Unconventional Monetary Policy and Wealth Inequalities in Great Britain

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This paper explores whether unconventional monetary policy operations have redistributive effects on household wealth. Drawing on household balance sheet data from the Wealth and Asset Survey, we construct monthly time series indicators on the distribution of different asset types held by British households for the period that the monetary policy switched, as the policy rate reached the zero-lower bound. Using this series, we estimate the response of wealth inequalities on monetary policy, taking into account the effect of unconventional policies conducted by the Bank of England in response to the Global Financial Crisis. Our evidence reveals that unconventional monetary policy shocks have significant and lingering effects on wealth inequality: the shock raises wealth inequality across households, as measured by their Gini coefficients, percentile shares, and other standard inequality indicators. Additionally, we explore the effects of different transmission channels simultaneously. We find that the portfolio rebalancing channel and house price effects widen the wealth gap, outweighing the counterbalancing impact of the savings redistribution and inflation channels. The findings of our analysis help to raise awareness of central bankers about the redistributive effects of their monetary policy decisions.

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1. Introduction

The Global Financial Crisis (GFC) led to a profound shift in monetary policy. As policy rates reached the zero-lower bound (ZLB), central banks employed unconventional monetary policy measures (UMP) aimed at boosting nominal spending, increasing liquidity, and reaching their inflation targets. UMP played a significant role in alleviating the impact of the crisis but also triggered policy concerns that such measures can have large effects on economic inequalities (Casiraghi et al., 2018; Colciago et al., 2019). Over the last 15 years, the UK has witnessed increasing levels of wealth inequality (Alvaredo et al., 2018). This study's estimations suggest that the share of net wealth held by the richest 10% of the population accounts for almost 50% of the country's total net wealth, while overall wealth inequality

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increased by more than 4% from 2006 to 2016.[1] Although there is by now a growing interest in exploring the relationship between monetary policy and income inequality,[2] the impact of monetary policy on wealth inequalities has received much less attention in the literature.[3] Yet, monetary policy, and particularly UMP, can influence household wealth shares by re-valuating and re-balancing their portfolios through different transmission channels (O'Farrell and Rawdanowicz, 2017; Colciago et al., 2019). Understanding the impact of monetary policy on wealth inequalities is of major policy importance because wealth is associated with households' financial health; it reflects future well-being; it is associated with political power (Cowell and Van Kerm, 2015); also, wealth disparities imply heterogeneous consumption elasticities which can function as a transmission mechanism of monetary policy themselves (Kaplan et al., 2018; Auclert, 2019; Arrondel et al., 2019).

This paper studies whether and how the UMP measures implemented by the BoE affected financial and housing wealth inequalities in Great Britain (GB) for the period 2006-2016. It contributes to the relevant empirical literature in the following ways:

This is the first study investigating the distributional effects of monetary policy on wealth inequality, for the UK, using low-level household balance sheet data at a relatively high frequency. The gap in the literature is not due to lack of research interest or policy relevance but mainly due to serious data limitations. Reliable data on the short term dynamics of household portfolios are scarce in most countries, but are a requisite for the investigation of the redistributive impact of monetary policy. Against this background, we draw on the Wealth and Asset Survey (WAS), a large sample survey on household finances, in which individual responses are balanced proportionately over time and geography, to construct monthly indices of net wealth inequalities for the period 2006—2016. In this way, our paper contributes to the broader wealth inequalities literature by providing a range of unique time-series of financial and housing wealth inequality estimates for the period preceding and following the Global Financial Crisis. We additionally assess whether our monthly sample distributions suffer from non-response bias, by comparing them to the representative WAS biennial sample across different points of the Cumulative Distribution Function (CDF) (Goldman and Kaplan, 2018). The application of this methodology strengthens the credibility of our results.

Second, most of the existing empirical literature applies static micro-simulation exercises (Doepke and Schneider, 2006; Adam and Tzamourani, 2016; Bunn et al., 2018) that typically provide information on household wealth or income distribution under policy scenarios which deterministically affect one or more of the distribution's components. These techniques fail to capture the underlying economic mechanisms at play, especially when the policy effects are indirect or take time to realize. They are also narrowed to the use of only a few time

[1]Authors' estimations using Wealth and Asset Survey data ONS (2019).

[2]See for example, Mumtaz and Theophilopoulou (2017); Coibion et al. (2017); Guerello (2018) and Colciago et al. (2019) for a literature review on the subject.

[3]Notable exceptions include Adam and Tzamourani (2016); Casiraghi et al. (2018); Lenza and Slacalek (2018); Hohberger et al. (2019)

points, that prevents a deep and dynamic exploration of the relationship (Colciago et al., 2019). To the best of our knowledge, this is the first paper that applies vector autoregressive (VAR) models to investigate the impact of UMP shocks on wealth inequality.[4] Furthermore, we adopt Bayesian methods to estimate our VAR and use a Gibbs sampling algorithm to approximate the posterior distribution of the model parameters. Recently, Bayesian VAR (BVAR) methodology has become a relevant tool for evaluation of the effects of monetary policy shocks (see, for instance, Bańbura et al. (2010); Galí and Gambetti (2015); Mumtaz and Theodoridis (2019)). As discussed in Koop and Korobilis (2010), this approach offers a convenient method to estimate precise error bands for impulse responses. The latter is an important tool of our analysis since it allows us to measure the impact of monetary policy on wealth inequality.

Third, our approach explores the effects of different transmission channels simultaneously. In contrast to most empirical literature on wealth inequality, which either focuses on the role of financial assets or investigates the transmission channels in isolation (see, for example, Adam and Zhu (2015); Inui et al. (2017); O'Farrell and Rawdanowicz (2017); Hohberger et al. (2019)), we specify the broader portfolio rebalancing mechanism functioning under periods of UMP. In particular, we measure the impact of the portfolio rebalancing channel by controlling for the effects of financial asset prices and corporate bond yields. In addition, we explore secondary effects by examining the impact of UMP on inequality via changes in housing asset prices (Joyce et al., 2012). Furthermore, we investigate the savings redistribution and the inflation channel from savers to borrowers. In comparison to the portfolio rebalancing channel, the last two channels function in the opposite direction, via lower borrowing rates and drops in the real value of nominal assets and liabilities.

Fourth, we further explore the effects of UMP shocks on wealth inequality correspondingly by carrying out counterfactual policy analysis. These experiments allow us to explicitly measure what would have happened to inequality had the BoE reversed its QE (Quantitative Easing) policy earlier. We also offer some evidence on the asymmetric impact of monetary policy on inequality across different policy regimes. To assess this, we use a Bayesian threshold VAR that allows us to endogenously identify ZLB versus non-ZLB states.

Two sets of results emerge from our analysis that shed light on theories linking monetary policy and wealth inequality. First, impulse response analysis suggests that unconventional monetary policy shocks elicit significant and persistent effects on wealth inequality: the shock raises wealth inequality across households, as measured by their Gini coefficients of total, housing, and financial net wealth, as well as across wealth percentile shares. In numbers, the shock is estimated to increase the Gini coefficient of total wealth by about 0.06 units one year after the change in policy. In addition, forecast error variance decomposition shows

[4]The available evidence on the use of multivariate time series models to examine monetary policy impacts on inequality is limited. Notable exceptions include Saiki and Frost (2014), Guerello (2018) and Inui et al. (2017), who focus on income inequality, and Curran et al. (2019), who focus on financial sector wages.

that the contribution of UMP shocks to fluctuations in the wealth Gini is around 11% at the first year horizon, suggesting that UMP measures did play an important role in the widening of the wealth gap over the forecasting period.[5]

Second, we find that the portfolio rebalancing channel, via the effect of elevated financial asset prices and lower corporate bond yields, plays an important role on the widening wealth gap. In addition, the redistributive effects of UMP from poorer to richer households are less prominent but still present through house price effects. This result echoes the home-ownership structure prevailing in GB and contradicts most empirical studies, which predict that house price increases offset the rise in inequality through portfolio rebalancing effects. On the contrary, UMP shocks lead to a fall in wealth inequality via the savings redistribution and the inflation channels, indicating that falls in borrowing rates and the nominal value of assets/liabilities do redistribute wealth from savers to borrowers. Yet, the latter channels are not strong enough to offset the upward pressures on inequality elicited by the former two channels.

The remainder of the paper is organized as follows. Section 2 discusses the underlying theoretical intuitions and the empirical background on how monetary policy influences wealth inequality. The section also identifies the key transmission channels behind the relationship, linking them to our empirical strategy. Section 3 presents the data sources of this study and describes the construction of monthly wealth time-series for GB. Section 4 illustrates the inequality series and their key components in relation to our research question. Section 5 discusses the empirical strategy and identifying assumptions behind the baseline model and its variants. Section 6 presents the main results and explores alternate mechanisms that may be driving the relationship between monetary policy and wealth inequality. In addition, it provides a number of robustness checks using different identification strategies. Section 7 concludes.

2. Monetary policy and wealth inequality in the literature

2.1. Transmission channels and household heterogeneity

Table 1 summarizes the effects and the mechanisms of the key channels of transmission of conventional (CMP) and unconventional monetary policy to wealth inequality as identified in the literature (Colciago et al., 2019). They include the portfolio rebalancing or portfolio composition channel, the effect via housing prices, the savings redistribution channel, and the inflation channel.

The portfolio rebalancing channel is a crucial transmitter of UMP to the financial system and the economy. Under imperfect substitutability of assets, the announcement of asset

[5]Note that our results remain invariant to alternative specifications of the BVAR. As we explain later in the text, we test the sensitivity of our results to alternative specifications of the benchmark BVAR, including different measures of monetary policy in the ZLB and measures of wealth inequality, different identification methods, and a medium-scale BVAR model that expands the information set in the benchmark case. Our results remain robust to all specifications.

Table 1—Monetary policy and wealth inequality : Transmission Channels

Channel	Monetary Policy	Effect	Mechanism	Key studies
Portfolio rebalancing/ Portfolio composition	UMP	Financial asset prices rise / Short term bond yields fall	Compositional/ Heterogeneity	Adam and Tzamourani (2016); Domanski et al. (2016); Casiraghi et al. (2018); O'Farrell and Rawdanowicz (2017); Bunn et al. (2018); Lenza and Slacalek (2018); Hohberger et al. (2019); De Luigi et al. (2019)
Housing asset price inflation	CMP/UMP	Housing asset prices rise	Compositional/ Heterogeneity	Adam and Tzamourani (2016); Domanski et al. (2016); Casiraghi et al. (2018); Bunn et al. (2018); Lenza and Slacalek (2018)
Savings redistribution	CMP/UMP	Interest payments and deposit rates on trackers fall	Compositional/ Heterogeneity	Casiraghi et al. (2018); Hohberger et al. (2019); De Luigi et al. (2019)
Inflation	CMP/UMP	Falls (rises) in the nominal value of debts (deposits)	Inflationary expectations	Doepke and Schneider (2006); Meh et al. (2010); Adam and Zhu (2015); Bunn et al. (2018)

purchases by the central bank can affect the composition of portfolios by influencing their relative supplies. If the assets purchased are not perfect substitutes for money, then the sellers of these assets rebalance their portfolios by replacing them with better substitutes. Hence, the price of the substitutes will increase to the point where the market for assets and money reaches an equilibrium. Increased asset prices imply lower yields, lower borrowing costs, and higher spending through wealth effects on consumption (Tobin, 1961; Brunner and Meltzer, 1973; Joyce et al., 2012). As far as wealth inequality is concerned, the increases in asset prices will result in capital gains. Capital gains, in turn, benefit particularly wealthier households who are the ones holding the bulk of these assets across the wealth distribution (Coibion et al., 2017; Inui et al., 2017; Hohberger et al., 2019).[6]

UMP may also imply redistributive wealth effects via the impact on housing prices. The effect of UMP on housing wealth is less straightforward than the portfolio rebalancing channel. This is because UMP affects the housing market in two ways: on the one hand, the purchase of mortgage-backed securities (MBS) by the central bank leads to large scale mortgage refinancing (Krishnamurthy et al., 2011) which increases net wealth (since mortgage debt payments fall) of indebted households.[7] On the other hand, UMP yields positive and persistent effects on house prices and residential investment (Rahal, 2016), assets which are

[6]An interesting extension of portfolio composition channels to periods of CMP has been proposed by Bagchi et al. (2019) who consider the presence of Cantillon effects in the relationship.

[7]The purchase of MBS, however, is more relevant in the case of the US than the UK, where the FED bought this type of assets aiming to support a housing market where excessive sub-prime loan-backed securities was one of the factors behind the sub-prime crisis.

mainly held by the middle and the upper parts of the total wealth distribution.[8] Henceforth, depending on the distribution of home-ownership, the value of housing assets, and the distribution of debts across households, wealth inequality may decelerate, stay intact, or accelerate.

Another transmission channel is the so-called savings redistribution mechanism which works via the impact on borrowing and deposit rates. Under expansionary monetary policy, indebted households standing on the bottom of the wealth distribution gain by experiencing a reduction in their interest payments on debt, while savers, standing on the top of wealth distribution, lose by experiencing lower returns (Bunn et al., 2018; Colciago et al., 2019). The saving redistribution channel may also have been reinforced by additional UMP measures other than asset purchases that were put forward by the BoE during that period. These include the introduction of a Funding for Lending Scheme (FLS) and enhanced liquidity support, aiming to maintain the flow of lending in the economy during the downturn.[9] Both schemes' association to the savings redistribution channel, depends on the degree that banks reduce their funding costs through the bank lending channel, which, in turn, is passed through to borrowers, who face lower borrowing rates.[10]

In a similar manner, unexpected inflation as a result of expansionary monetary policy, can lead to substantial redistributive effects. As evidenced by Doepke and Schneider (2006), when the price level rises faster than anticipated, the real value of debt declines. On the one hand, borrowers standing in the lower-middle part of the wealth distribution are better off, as indicated by increases in their net wealth. On the other hand, inflation makes lenders (who are standing in the middle-upper part of the net wealth distribution), worse off. Indeed, the amount of this wealth redistribution can be substantial, even following moderate inflation episodes (Doepke and Schneider, 2006).

It is worth mentioning that household heterogeneity is important for the propagation and amplification of UMP shocks on wealth inequality via the channels presented above. The number of households across the wealth distribution that hold a given share of real and financial assets and liabilities is key in shaping the impact of UMP shocks (O'Farrell and Rawdanowicz, 2017). For example, as shown in Figure 1, net housing wealth is more equally distributed than net financial wealth. This implies that a possible boost in financial asset prices may induce more unequal outcomes than housing price increases. Similarly, the share of households owning property drives the level of redistribution through the housing

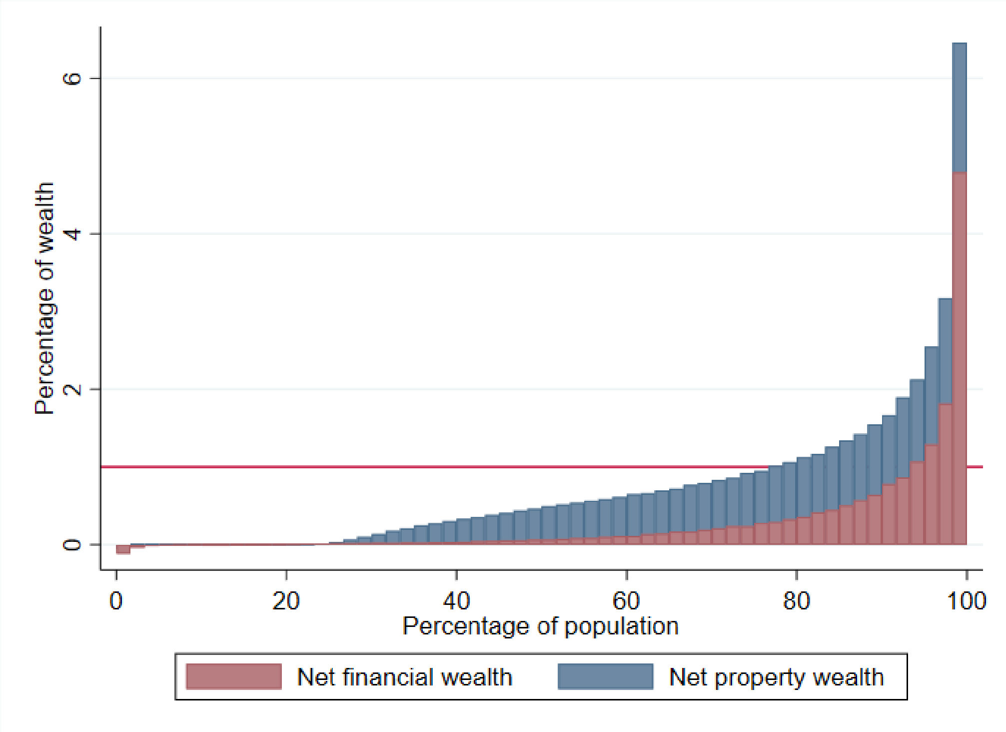
[8] Indeed, the strongest response in housing prices is observed in the UK and in the US, where housing and mortgage markets are more developed (Rahal, 2016).

[9] The FLS was launched in July 2012, designed to encourage banks and building societies to expand their lending to households and firms, by providing funds at cheaper rates than those prevailing in current markets (Churm et al., 2018). The Special Liquidity Scheme (SLS), launched in April 2008, aimed to improve the liquidity position of the UK banking system by allowing eligible institutions to finance assets that remained in their balance sheets after the GFC collapse (John et al., 2012).

[10] Although these policies are potentially captured by our main monetary policy shock instrument, the short-term shadow rates, disentangling between downward pressures on borrowing rates attributable to the schemes as opposed to asset purchases is out of the scope of this paper. An evaluation of the macroeconomic impact of the FLS has been performed by Churm et al. (2018).

prices channel. Also, the proportion of savers and debtors in the economy can influence the magnitude of the savings redistribution channel. As the magnitude of each channel's effects on the wealth distribution is *a priory* ambiguous, the evaluation of the overall UMP impact deserves an empirical investigation.

FIGURE 1. NET WEALTH COMPONENTS ACROSS THE WEALTH DISTRIBUTION



Note: Authors' estimations from Wealth and Asset Survey (2006 - 2016)

2.2. Empirical background

Only a handful of studies have yet investigated the relationship between monetary policy and wealth inequalities, particularly due to data limitations. Most of these studies focus on the portfolio composition channel, and mainly do so using micro-simulation exercises and local projections to produce impulse responses. For instance, Adam and Tzamourani (2016) who use the Household Finance and Consumption Survey, find that during the post-crisis period, Euro Area countries experienced an overall decrease in net wealth inequality, with increases in house prices counteracting the increase in wealth inequality caused by increases in equity prices. Their results vary depending on the relative distribution of housing and financial assets across countries. By contrast, Domanski et al. (2016) examine six advanced economies and find that net wealth inequality has risen since the financial crisis, with increases in equity prices outweighing house price increases. Casiraghi et al. (2018), using quarterly data for Italian households, simulate monetary policy impulses of household income and wealth statuses. Their evidence suggests a U-shaped response of net wealth on monetary policy, with poorer indebted households and asset-rich households mainly becoming better off, while those in the middle become worse off. Bunn et al. (2018), using a similar framework for a single wave of the WAS dataset for GB, suggest that the overall effect of monetary policy on standard relative measures of income and wealth inequality has been small.

Hohberger et al. (2019) study the distributional effects of monetary policy by estimating an open economy two-agent DSGE model that distinguishes between two types of households: non-liquidity constrained households that hold financial assets and receive capital income, wages, and transfers, and liquidity constrained households that receive only wages and transfers. They find that UMP shocks increase net financial wealth inequality but their effects are short-lived. In the medium term, UMP reduces the net financial wealth share of richer households, a result driven by the shrinking of the household's holding of interest-bearing long-term bonds and the reduction in private sector savings for an extended period.

Other studies impose estimated shocks, coming from time-series models, on cross-sectional survey data, and perform thought experiments on how the wealth distribution is affected. For example, Lenza and Slacalek (2018) and De Luigi et al. (2019) using the HFCS survey, simulate the short-run effects of UMP shocks on wealth and income inequalities for Euro-area countries. The former study suggests that monetary policy has only negligible effects on wealth inequality, while the latter finds a positive relationship, which is yet sensitive to the measure of wealth inequality employed. However, as pointed out by Colciago et al. (2019), most of these approaches are not well equipped for capturing the multiple distributional dimensions of monetary policy as reflected in theoretical models.

A few empirical studies focus on the inflation channel. In particular, Doepke and Schneider (2006) investigate the distributional consequences of the 1970s Great Inflation episode in the US. Meh et al. (2010) explore the distributional impact of inflation episodes and inflation targeting policies in Canada and, more recently, Adam and Zhu (2015) link Euro-area survey data with aggregated data on sectoral accounts, suggesting that unexpected inflation yields substantial wealth redistribution in the countries explored.

3. Data

3.1. Macroeconomic time series

The choice of the macroeconomic variables is based on a standard set of variables used for small open economies. In particular, we include: industrial production (IP), the consumer price index (CPI), the spread between the 10-year Government bond minus the 3-month rate, the nominal effective exchange rate (NEER) and, last, the short-term shadow rate (SSR) to measure the stance of UMP.

We begin by discussing the SSR. As per Colciago et al. (2019), the investigation of UMP effects on wealth inequality carries an additional identification choice. As the period of

UMP overlaps with the period of the ZLB, it is tricky to disentangle the impact of low interest rates, UMP, or the interaction of both. To identify UMP changes, we use the SSR as a measure of the monetary policy stance, extracted by modelling the term structure of the yield curve. To the best of our knowledge, only Inui et al. (2017) follow a similar identification approach to UMP shocks on inequality, for the case of Japan. The level and slope of the yield curve provides information on investors' perceptions and expectations with regards to future monetary policy actions and about the course of the interest rates. The strongest advantage of SSRs is that they are powerful instruments to predict the monetary policy stance at the zero lower bound (ZLB) with the data coming from the non-ZLB period in a fixed-parameter model (Bullard, 2012; Wu and Xia, 2016; Lombardi et al., 2018).

An additional advantage of SSRs over other proxies of UMP measures is that SSRs use information from the entire yield curve, including forward guidance, quantitative programmes, and their announcements.[11] Consequently, SSRs can capture the overall effects of a given measure.[12] For instance, Christensen and Rudebusch (2016) compare the performance of the SSR model to a Gaussian dynamic structure model on predicting bond yields at the ZLB, and show that the use of SSR indicates higher in-sample fit, matches the compression in yield volatility, and delivers improved real-time, short-rate forecasts than the standard model. In the present analysis we employ the two SSR rates for the UK, most cited in the literature. We use the SSR provided by Wu and Xia (2016) in our baseline specification and we test the robustness of our results by using the SSR series provided by Krippner (2014); Claus et al. (2018). The two series are presented in Figure B2 of Appendix B.[13]

Regarding the macroeconomic indicators, IP and CPI indices are used as the primary target variables of monetary policy. Given that the ultimate goal of monetary policy is to achieve price stability, we use the CPI index as a key variable to evaluate the impact of

[11] Because financial markets are forward looking, the impact of asset purchases on bond yields is likely to occur when expectations of purchases are formed and not necessarily when the purchases are realized. For instance, Joyce and Tong (2012) show that the biggest impact of QE1 on bond yields took place when the purchases were initially announced. With respect to forward guidance, three key announcements have been classified as such by the relevant literature (Moessner et al., 2017). The first announcement effectively introduced forward guidance, in August 2013, when the MPC "agreed its intention not to raise Bank Rate from its current level of 0.5% at least until ... the unemployment rate has fallen to a 'threshold' of 7%;" the second, in May 2013, stated that "all members agreed that, in the absence of other inflationary pressures, it would be necessary to see more evidence of slack reducing before an increase in Bank Rate would be warranted;" and the third, in February 2016, stated that, "The MPC judges it more likely than not that Bank Rate will need to increase over the forecast period to ensure inflation remains likely to return to the target in a sustainable fashion" (Moessner et al., 2017). Yet, in line with Domanski et al. (2016), we do not expect a direct impact on inequality driven by forward guidance, as the latter primarily targets bond yields rather than risky financial assets or housing. Differences in the concentration of fixed income claims between wealthy and poor households are relatively small compared to differences in capital gains arising from disproportionate holdings of risky assets and real estate, also influenced by UMP measures (Adam and Tzamourani, 2016; Rahal, 2016).

[12] Another common proxy of UMP is estimations from central bank balance sheets, for instance, total Bank's assets. Balance sheet proxies reflect central bank's purchases at the time they were implemented, if implemented, rather than announcement impacts. An interesting example of the difference was the ECB Open Market Operations (OMT) programme, which implied large quantitative effects when announced, but it was never actually implemented. As a result, a significant UMP event would not be captured by a central bank balance sheet proxy. As BoE implemented all of their announcements, there should be no issue with using either proxy in our case. Henceforth, we also run a robustness check using Bank's balance sheets in Section 6.6.2.

[13] The SSR series have been obtained from Cynthia Wu's website, which can be accessed here: https://sites.google.com/view/jingcynthiawu/shadow-rates, and from Leo Krippner's website, which can be accessed here: https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures

monetary policy on prices. Including CPI inflation rather than a GDP deflator in VARs is common practice in the monetary policy literature (see, Kim and Roubini (2000); Kim (2003)). Regarding the proxy for the business cycle, we use IP as a measure of economic activity, following other related studies that use VAR models to examine the impact of monetary policy transmission in the UK on a monthly basis (see, Kapetanios et al. (2012); Ellis et al. (2014)). Next, since we model a small open economy, business cycles are also influenced by exchange rate movements; thus, the use of the nominal exchange rate is required in order to put forward a set of assumptions to identify monetary policy shocks. Last, the use of the slope of the yield curve is motivated by the fact that the central bank, via QE, started to suppress longer-term yields while leaving the short-term rate unchanged in order to stimulate the economy. Similar to our study, other papers that seek to estimate the impact of unconventional monetary policy shocks using empirical VAR models include the slope of the yield spread in the matrix of endogenous variables (Baumeistera and Benati, 2013; Kapetanios et al., 2012).[14]

3.2. Constructing monthly estimates of wealth inequality in Great Britain

We now present the data employed for the estimation of household wealth and wealth inequality. Most existing time-series analyses estimating the impact of monetary policy shocks on wealth inequality are based on aggregate macroeconomic indicators regressed against partly disaggregate inequality measures (e.g., Gini coefficients of income, wages, consumption, and rarely wealth). A caveat of those approaches is the lack of reliable data, since surveys on household balance sheets are usually provided at a low frequency, typically every one or two years (Alvaredo et al., 2016). Annual or biennial wealth data would not allow us to assess short-term policy impacts of UMP shocks on the distribution of different wealth components. Instead, we require low level household balance sheet data held by households on a relatively high frequency, as well as information on the distribution of these items across wealth percentiles. To address this caveat, we estimate changes in wealth inequality using information from the Wealth and Asset Survey (WAS) for the period 2006 - 2016 (ONS, 2019). WAS is a longitudinal household survey in which households in GB are interviewed every two years.[15] Approximately 30,000 households were interviewed in wave 1, 20,000 in wave 2, 21,000 in wave 3, 20,000 in wave 4, and 18,000 in wave 5.[16] The total sum of weights for each wave is equal to the total number of households in the population. All households with missing values for assets or debts are dropped from the sample (less than 0.1% of the total sample). Our final sample is composed of more than 110,000 observations of household

[14] An alternative would be to use the 10-year interest rate rather than the slope of the yield curve. Note, however, that since our estimation period is from 2009-2016, the 10-year rate coincides with the term spread, given that the short-term interest rate is zero. As a robustness check, we re-run our model including the 10-year interest rate instead of the slope of the yield curve. Results (included in Appendix H) are largely unaffected.

[15] Excluding addresses north of the Caledonian Canal, the Scottish Islands and the Isles of Scilly.

[16] For cost-efficiency reasons, only 57% of the full sample of 30,595 responded to all components of their wealth in the first wave. Consequently, this sub-sample will be included in this analysis with regards to the first wave.

reported assets and liabilities for the entire period. This is a substantially large sample period for our purposes, as it covers the two major UMP rounds responding to the GFC and a pre-crisis sample, when the BoE implemented CMP.

It is important to stress that the WAS survey carries three features which are essential for the execution of our analysis properly. These include the proportional allocation of interviews over time and across geography, the constant two-year interval across waves, and the over-sampling of rich addresses. The following paragraphs describe these features and their relevance to our analysis.

First, interviews were allocated over the 24-month fieldwork period using systematic sampling with a random start point, such that interviewees' addresses were balanced proportionately over time and across space. Taking advantage of this feature, we follow the literature constructing time-series from survey data (see Cloyne and Surico (2016), Mumtaz and Theophilopoulou (2017), and Inui et al. (2017), for example), and split households to monthly samples based on the date of the interview. In particular, we break down the full sample population into 120 monthly sample cohorts, from the date the fieldwork commenced (July 2006) until the last released wave (June 2016). Each monthly sample comprises a minimum of 800 households, a number large enough to provide unbiased inequality estimations using the Gini coefficient.[17]

Although the survey design of WAS ensures that the interviews were spread proportionately, this property is not sufficient to ensure that the population representativeness is maintained across the constructed monthly samples. However, as pointed out in Grafström and Lundström (2013) and Grafström and Schelin (2014), in well-spread samples, the variance of commonly used estimators is typically low. We further adjust sampling weights for the monthly samples and observe that their sum remains rather stable for the entire period of our analysis (see Figure B1 in the Appendix) and close to the Census estimates of the GB household population (around 25.5 million households).[18] To further increase the credibility of our constructed samples, we proceed with additional checks by borrowing from the literature assessing household representativeness in survey samples that are likely contaminated by non-response bias. In short, we compare the distances in the distributions of demographic and financial variables between the constructed monthly samples and the broader representative WAS waves they lie on. We find no systematically large deviations in the distances, thus, we hold the assumption that our monthly cohorts largely maintain their population representativeness properties. Appendix A presents the analysis in full detail.

Second, by survey design, each interview on the longitudinal part of the sample has a

[17] According to Deltas (2003), the Gini can be biased downward in small samples. The reason is that for a given level of intrinsic inequality, a reduction in the sample size leads to reductions in apparent inequality, as measured by the Gini coefficient.

[18] The 2011 Census for GB reports 25.8 million households. See https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/populationandhouseholdestimatesfortheunitedkingdom/2011-03-21

two-year interval between two consecutive waves. In other words, no single household is interviewed more or less frequently than every two years and the survey provides wealth estimates which are based on a constant seasonal time point. The constant biennial time interval allows the estimates of change to be potentially comparable periodically and not be contaminated by seasonal effects on wealth holdings (ONS, 2019). Furthermore, the interval allows a substantially large period to update households' information set by capturing innovations in the perceived value of assets and liabilities.

Third, a typical shortcoming of wealth distribution analyses from survey data is the high non-response rates for the extremely rich households. Ideally, the distribution of wealth would be bench-marked against external controls for population totals using administrative personal wealth data. Unfortunately, there is no annual wealth tax in the UK, so we could not apply such a control to our survey estimates.[19] This lack of reliable data representing the richest wealth shares explains why analyses on the UK are largely missing from the recent wealth inequality literature (Alvaredo et al., 2016, 2018). A key feature of the WAS is that it over-samples the wealthy addresses and therefore has an improved representation of the right-skewed upper tail despite high non-response rates of the extremely rich.[20] Notwithstanding the oversampling, Vermeulen (2018) compared the second wave of WAS wealth estimates with those of the Forbes' Billionaires list and found that WAS underestimates the top 1% share of wealth by a factor of 1-5%. We acknowledge that potential under-representation of the extremely rich remains a weakness of our dataset which is not entirely corrected during the survey design stage. Nevertheless, the central scope of this paper is to capture short- and medium-term effects of UMP on housing and financial wealth inequality changes, rather than measuring wealth inequality for the entire population *per se*.

Armed with a decade of monthly household data for GB, we proceed to estimate the main wealth concepts and their corresponding inequality indexes.

4. Wealth Inequality Estimates for the period 2006-2016

4.1. Household assets and liabilities

The nature of wealth inequality often depends on the wealth definition being adopted. In the present analysis, following Cowell and Van Kerm (2015), we consider current net wealth as our standard wealth concept, namely the difference between assets and liabilities at a given point in time. It is defined as follows:

$$x = \sum_{j=1}^{m} \pi_j A_j - D \tag{1}$$

[19] Recent work by Alvaredo et al. (2018) addressed this caveat by imputing long-run estimates of wealth inequality since 1895 using the distribution of estates at death. However, their yearly estimates cannot be used for short-term analysis or for real and financial wealth decomposition.

[20] In particular, the survey is constructed such that it over-samples wealthy addresses using a factor of 3 for the wealthiest addresses (ONS, Wealth and Asset Survey Report).

Where $A >= 0$ is the amount held of asset type j, π is its price and D represents the call on those assets represented by liabilities.

Financial assets include formal investments such as bank or building society current or saving accounts, investment vehicles such as individual savings accounts (ISAs), endowments, stocks, and shares. Financial liabilities include outstanding balances on credit cards, arrears on household bills, and loans from formal sources.[21] The difference between financial assets and liabilities gives us the net financial wealth. Housing assets include self valuation of property owned, both main residence plus any other land or property owned in the UK or abroad. Housing liabilities refer to the outstanding value of any loans or mortgages secured on these properties. The difference between housing assets and liabilities gives us the net housing wealth. Since we consider only net wealth estimates, "wealth" and "net wealth" are, henceforth, used interchangeably in this study.

We exclude consumer durables such as automobiles and housing equipment. As suggested by Wolff and Zacharias (2009), although tangible assets carry a resale value, they can only accrue it by compromising current consumption. Other studies measuring wealth inequality from survey data use similar conventions (see Cowell et al. (2018), for example).

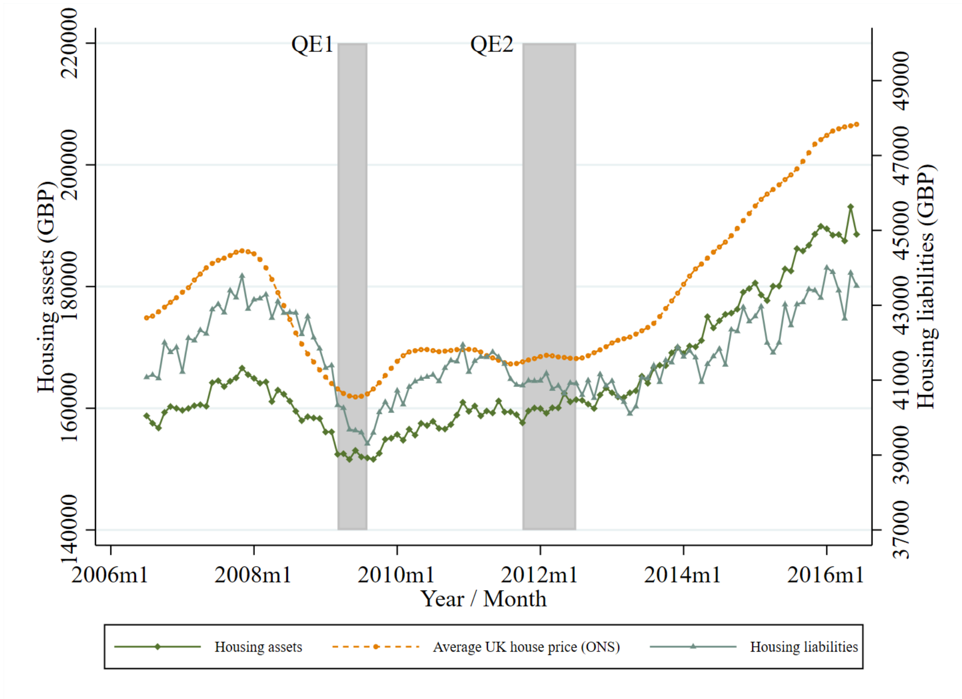
The economic unit is the household, where assets and debts are summed up for all household members. As there is currently no consensus in the literature on the need to equivalize wealth estimates, we do not adjust our wealth estimates for household composition.[22] Based on the definition in equation 3, we produce the two main components of net wealth, that is housing and financial net wealth, using the key components of each, namely assets and liabilities.

Figures 2 and 3 illustrate mean values for housing and financial assets and liabilities over the 10 year period, examined respectively. In Figure 2, we also included an index of the average house price in the UK, which serves as an external benchmark of the estimated housing wealth trends, as the latter capture the lion share of net wealth. The shaded areas in the graphs refer to UMP rounds as announced by the BoE for the period in question. The first round of UMP (QE1) was announced on March 2009, with an initial decision to purchase £75 billion worth of assets over 3 months, financed by the issuance of central bank reserves. The purchases increased to £200 billion over the next month, and the scheme was completed in January 2010. The second round of UMP (QE2) through asset purchases began in October 2011, in response to the impact of the Euro crisis. An additional £125 billion worth of asset purchases were completed in May 2012. Lastly, an additional £50 billion worth of asset purchases were announced in July 2012 and were completed in November 2012.

[21] We exclude informal financial assets, e.g., money under the bed or loaned to family or friends, children's assets, and pension wealth, i) to reduce measurement error, as formal financial assets and housing can be appraised by survey respondents with greater precision, and ii) because possible influence of monetary developments on informal assets and accumulated pension wealth is hard to capture in a structural model.

[22] If wealth is interpreted as future consumption, current household structure is of little use (Cowell and Van Kerm, 2015). Instead, it would only make sense to adjust wealth using a future household structure equalizer, which is clearly not observable at present.

Figure 2. Household housing assets and liabilities from 2006 to 2016

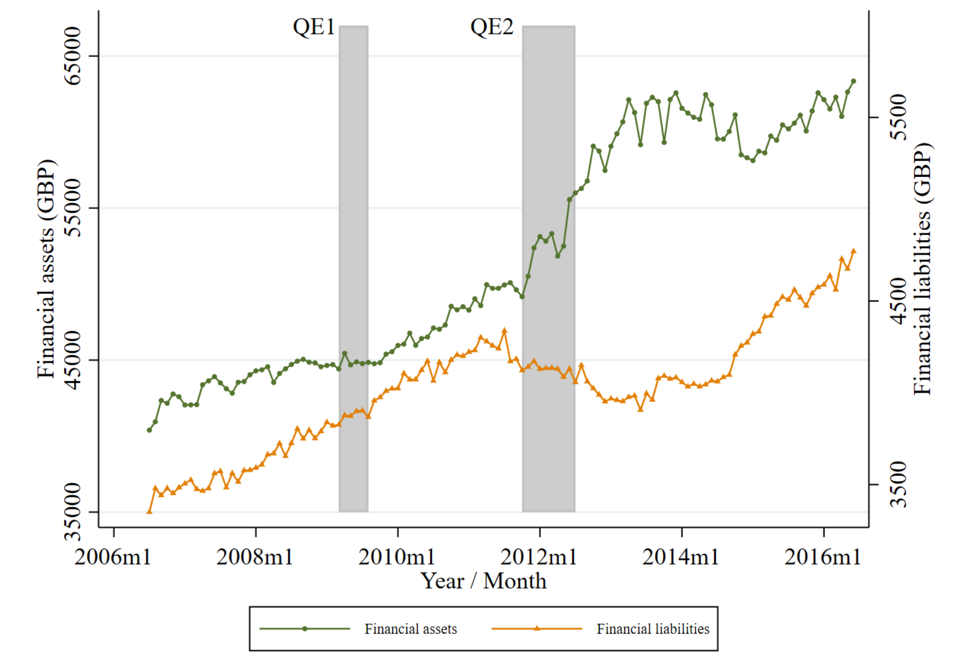


Source: Authors' estimations from the Wealth and Asset Survey (2006 - 2016). Average UK house prices are taken from the HM Land Registry, Registers of Scotland, Land and Property Services Northern Ireland, and Office for National Statistics.

Note 1: Monthly averages (six month moving average, seasonally adjusted).

Note 2: The shaded areas depict the announcements of UMP by the BoE.

Figure 3. Household financial assets and liabilities from 2006 to 2016



Source: Housing assets and liabilities are the authors' estimations from the Wealth and Asset Survey (2006-2016).

Note 1: Monthly averages (six month moving average, seasonally adjusted).

Note 2: The shaded areas depict the announcements of UMP by the BoE.

The mean value of all housing assets grew by 27%, which is lower than the overall increase in net wealth. Housing related liabilities increased by 11% and their trend largely mirrors that of housing assets (Figure 2). The announcements of two QE events and the rounds of asset purchases following them seem to be associated with accelerating trends in both housing assets and liabilities, the largest components of our net wealth index. The period associated with QE1, in late 2009, signals a reversal in the trend of housing components from negative to positive. Additionally, QE2 seems to mark the beginning of an upward housing wealth rally after a short period of stagnation. Interestingly, the average UK house price, our external benchmark, indicates a remarkably similar trend to our housing assets estimate, responding to QE events in the same way.

Financial assets are shown to exhibit the biggest growth rate compared to the rest of the net wealth components, accounting for 60% of the entire period (Figure 3). Their trend appears to accelerate following the announcements of asset purchases, and especially following QE2. The mean value of financial liabilities, the smallest component of our net wealth indicator, increased by 42% over the entire period, yet presented no clear link to QE announcements.

It is important to note that, although the series presented serve as stylized facts of the trends of various assets, it is impossible to distinguish the impact of asset purchase rounds from other factors affecting the price of these assets without a formal econometric model. This is because: i) financial assets were affected by other factors, including a distressed period in the Euro-area or prospects about corporate earnings and the stock market, and ii) anticipation about QE may have driven investors to price in the developments in advance (Joyce et al., 2012). Furthermore, the trends in housing assets and liabilities illustrate the average wealth holdings in our dataset. To make inferences about the concentration of these holdings across households, we proceed with the construction of proper inequality indicators.

4.2. Measuring wealth inequality across time

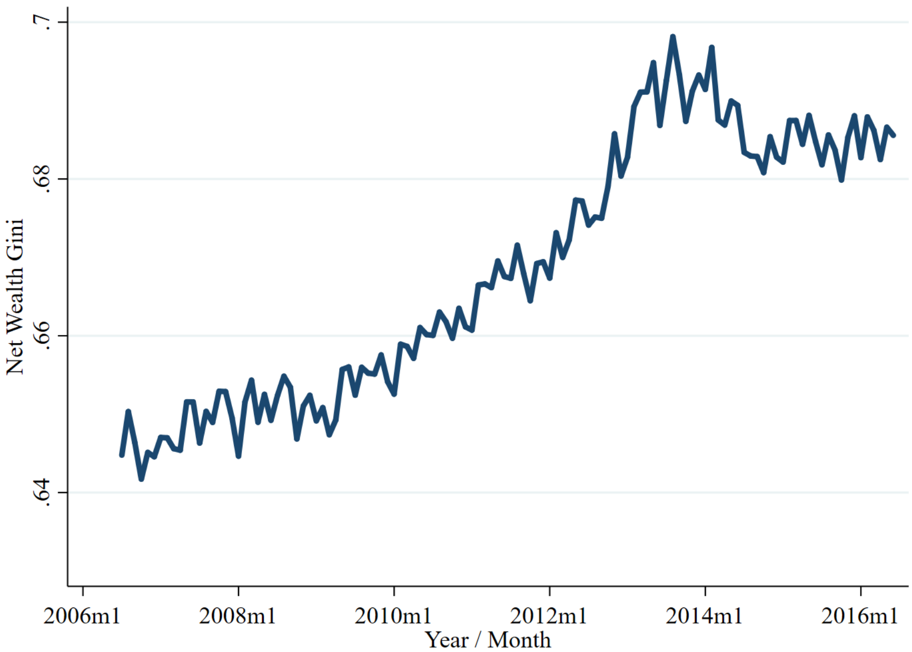
Moving to the dispersion of households' wealth, our main inequality measure is the Gini coefficient of household's net wealth ($G_{j,t}$), defined as follows:

$$G_{j,t} = \frac{\sum_{i=1}^{n_t} (2i - n_t - 1)x'_{i,t}}{n_t^2 \mu_t} \tag{2}$$

where j=3, depending on the measure of wealth that is used each time (total net wealth, net financial wealth, net housing wealth), t stands for the monthly sample when each interview took place, i is the household's rank order number, n is the number of all households present in each monthly sample, x_i is the household's i net wealth value, and μ is the population average. The standard coefficient ranges from 0 to 1, with 0 representing perfect equality and 1 representing perfect inequality. On top of being one of the most popular indicators of inequality, the Gini preserves its properties for negative values (Cowell and Van Kerm, 2015).[23] Allowing input values to be negative is crucial for measuring net wealth inequality, as a portion of the observations in our sample are lower than zero because debts may exceed assets at a given point in time.[24]

We next turn to trends in wealth inequality by applying the Gini coefficient on the 120 monthly samples of the WAS dataset. Figure 4 presents the results for household net wealth over the period 2006-2016. The Gini index on a monthly basis presents a substantial degree of variation compared to yearly or biennial estimates of wealth inequality, and makes it more relevant for the analysis of monetary developments. During our sample period, the monthly Gini coefficient for net wealth increased substantially from less than 0.65 in mid-2006 to about 0.68 in mid-2016. The index indicated a falling trend after 2009 and 2014, but kept increasing during all the other periods, peaking at 0.7 in 2013.

Figure 4. Net wealth Gini from 2006 to 2016



Source: Authors' estimations from Wealth and Asset Survey (2006 - 2016).

Note: Net wealth Gini coefficient (six month moving average). Net wealth refers to total household's assets minus liabilities, excluding pension wealth, tangible assets other than housing, and informal financial assets and debts.

While the net wealth Gini captures monthly variation in overall wealth dispersion, further decompositions would allow us to link the inequality index to the compositional nature of the channels discussed in Section 2. For example, the overall Gini, being too sensitive to

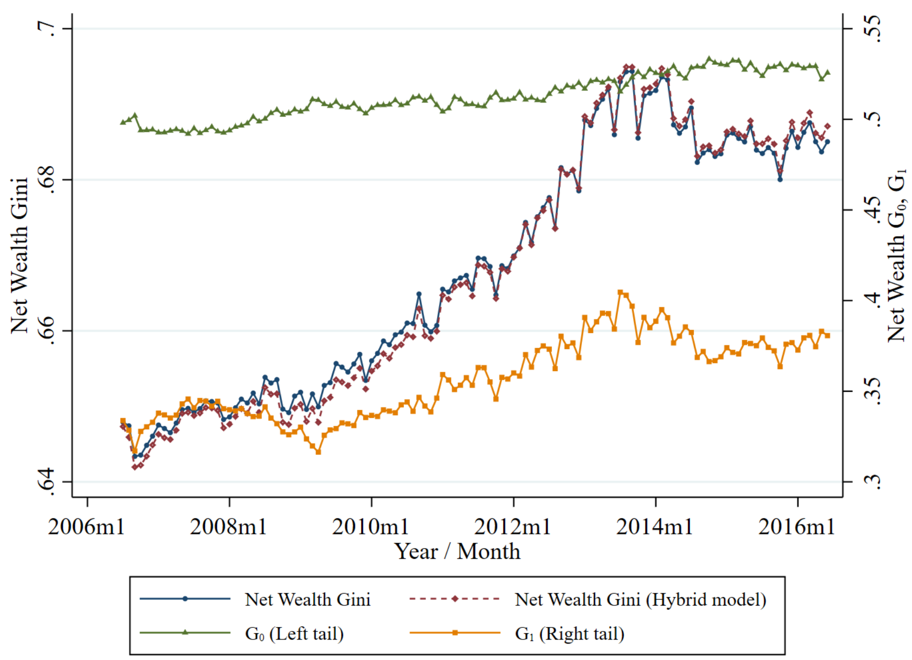
[23] Other desirable properties of the Gini as an inequality measure include scale independence, population independence, symmetry, and the axiom of transfers.

[24] Gini coefficient estimates with negative input values imply that the index is no longer upper bounded at 1, but can take any positive value. Regarding wealth estimates, there is no theoretical maximum for inequality since asset-free households can borrow infinitely to finance regressive transfers to rich ones (Cowell et al., 2017).

changes in the middle of the wealth distribution, may not reveal changes in trends driven by the two tails (see, Cobham et al. (2016)). This is particularly important in our analysis because, as shown in Figure 1, most net wealth is concentrated in the upper share of the distribution. To address this, Jantzen and Volpert (2012) propose a two-parameter model using the mathematical properties of the Lorenz curve, i.e., self-similar behavior at the two tails of the net wealth distribution, and the curve's relation to the Gini index. Specifically, they propose the split of the main Gini into two sub-indices. The two indices are associated with the left and the right tails of the distribution, and each captures the degree that changes in the tail are responsible for changes in overall inequality.

Following Jantzen and Volpert (2012), we fit a two-parameter hybrid model for the Lorenz curve on the wealth distribution of our monthly dataset. Using the parameters of the model, we estimate the two Gini sub-indices describing influence of the left (G_0) and right (G_1) tails on the main Gini index in isolation. The derivation of the two Gini indices is presented in Appendix C. The two indices provide a more detailed picture of how wealth is trending over time than the Gini index (G) alone, as they reveal which part of the distribution is primarily responsible for the overall inequality trend.[25]

FIGURE 5. FIT OF THE HYBRID MODEL AND ESTIMATION OF G_0 AND G_1



Source: Authors' estimations from Wealth and Asset Survey (2006 - 2016).

Note: Net wealth Gini coefficients (six month moving average). The derivation of the hybrid two-parameter model by Jantzen and Volpert (2012), used for the estimation of the Gini sub-indices, is discussed in Appendix C.

Figure 5 presents our estimations using the hybrid model of two-parameter Ginis, namely,

[25]The methodology has also been applied by Schneider and Tavani (2016) using historical US data on income inequality. Nonetheless, the present is the first study that applies this method to wealth data.

the overall Gini using the hybrid model and the two Gini sub-indices, G_0 and G_1. In addition, we plot again the overall net wealth Gini as presented in Figure 5, for comparison. The first thing to observe is that the Gini estimated from the parameters of the Lorenz curve overlaps with the main Gini to a large extent, suggesting that the hybrid model performs quite well. Second, the sub-Gini G_0, capturing the left tail of the wealth distribution, remains largely stable throughout our sample period, implying that changes in the lower end of the distribution do not drive changes in overall inequality substantially. Third, the sub-Gini G_1 seems to explain most of the changes in the overall Gini prior to 2009 and much of the trend in the subsequent period. Overall, the variation in wealth inequality is mostly driven by changes in the upper and the middle areas of the wealth distribution. Although the latter are not captured by the hybrid model, we can make this inference, as the middle area can be viewed as a residual in the model.

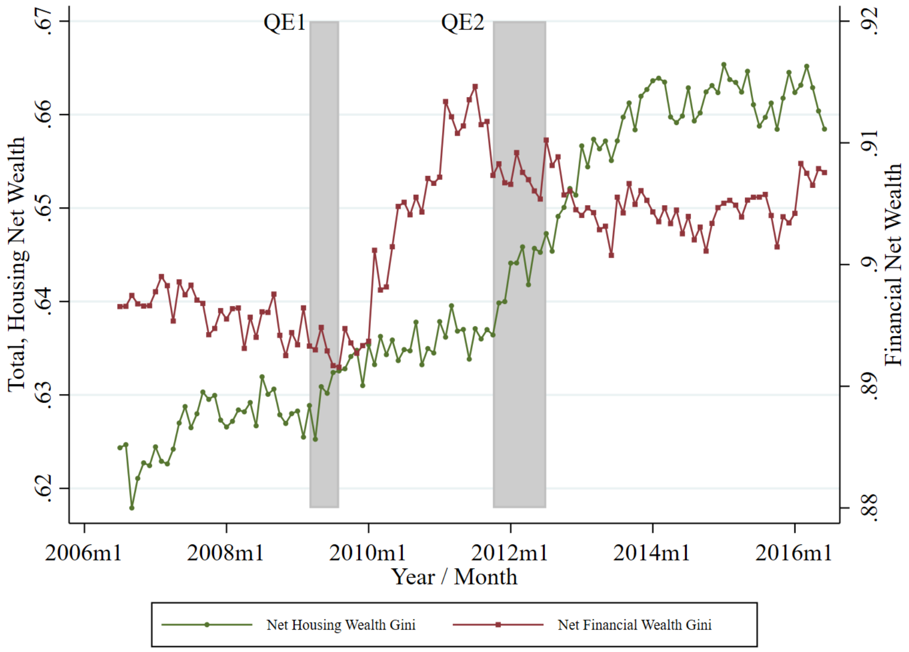
To shed further light on what drives variations in the overall Gini, we proceed by breaking it down to its two main components. Figure 6 shows the estimated Gini coefficients of net housing wealth and net financial wealth, evolving on a monthly basis from 2006 to 2016. By comparing the two components with the main net wealth Gini, we can make two interesting observations.

We observe that the housing net wealth Gini increases throughout the entire period, with some oscillations. Its strongest increase, however, is the one following QE2, leading to the peak of the index at almost 0.7. This increase seems to have substantially influenced the course of the main net wealth Gini index, as housing is the largest wealth component. We also observe a downward trend in the net financial Gini up to 2009, followed by a significant jump after the announcement of QE1. The same index oscillates in a downward trend following QE2. This trend is not shared by the steady increases in financial assets, shown in Figure 3 earlier, but matches empirical findings suggesting that the impact of QE1 on risky assets was larger than that of QE2 (Joyce et al., 2012). These assets are typically held by the richest households across the distribution.[26]

To sum up, our exploratory analysis on the estimated monthly Gini indices of inequality allows for two early conclusions. First, overall wealth inequality is mainly driven by changes in the upper and middle part of the wealth distribution. Second, the two components, housing and financial wealth, are both influencing overall wealth inequality, though in different ways and timing with respect to QE announcements. Being equipped with these series, in the next section we set-up our BVAR model to assess the role of UMP on wealth inequalities in GB.

[26]Disproportionate increases in risky assets may explain the increases in the net financial Gini and, in turn, the increases in total net wealth Gini after QE1.. See, Haliassos and Bertaut (1995); Calvet et al. (2009); O'Farrell and Rawdanowicz (2017), for example.

FIGURE 6. NET WEALTH GINI COMPONENTS FROM 2006 TO 2016



Source: Authors' estimations from Wealth and Asset Survey (2006-2016).
Note 1: Gini coefficients (six month moving average). Net housing wealth includes all housing assets held by the household minus mortgage debts. Net financial wealth includes all formal financial assets minus any type of formal debt collateralized on property.
Note 2: The shaded areas depict periods when UMP measures were announced and implemented by the BoE.

5. Model set-up

We estimate the impact of UMP shocks on wealth inequality by applying a structural Bayesian VAR model. Before we turn to the exposition of the econometric techniques, we motivate the model. The structural nature of our model allows us to use economic theory to decide which contemporaneous constraints are needed in order to identify the effect of monetary policy shocks. In our baseline model, we use a Cholesky structure that is the standard method for examining the effect of contemporaneous shocks.[27] Next, the use of Bayesian methods can be motivated from the following angles. First, BVARs improve the accuracy of estimates and subsequent forecasts by introducing appropriate prior information into the model. Second, structural analysis benefits from Bayesian VARs, as without prior information, it is hard to obtain precise estimates of so many coefficients and as a result, features such as impulse responses tend to be imprecisely estimated (Koop and Korobilis, 2010; Koop, 2017). The weight given to the prior information applied to our model is governed by a number of hyperparameters that we explain below. In this way, a posterior density function is obtained from which estimates and inference are derived.

The structural VAR model is defined as:

[27]Note that, later in the paper, we replicate the results from our baseline model by using alternative identification schemes. Results remain largely unchanged.

$$y_t = c + \sum_{j=1}^{p} y_{t-j} B_j + \nu_t \tag{3}$$

where y_t is a $n \times 1$ vector of endogenous variables, B_j are $n \times n$ matrices of the autoregressive parameters, p is the lag length, c is a $n \times 1$ vector of constants, and $\nu_t \sim \mathrm{N}(0, \Sigma)$ is a $n \times 1$ vector of white noise terms with a covariance matrix Σ. The covariance matrix of the residuals can be decomposed as $A_0 A_0' = \Sigma$, with A_0 representing the contemporaneous impact of the structural shocks, ϵ_t, where $\nu_t = A_0 \epsilon_t$. The matrix of endogenous variables includes IP, CPI, the yield spread, the nominal effective exchange rate, and the shadow rate, as discussed in 3. We augment our model with the inequality measure described in detail in 3, in order to estimate the impact of the monetary policy shock on wealth inequality. All variables except the shadow rate, the yield spread, and the inequality measure enter in log differences. Based on information criteria, we estimate the BVAR with four lags, considering alternative lag lengths in the robustness section.[28]

We estimate the model in 3 by using the Bayesian shrinkage approach proposed by Bańbura et al. (2010). In a Bayesian framework, the parameters are treated as random variables and their posterior distribution is estimated via the imposition of prior beliefs on their distribution. Following Bańbura et al. (2010), we impose a natural conjugate prior which is a variation of the Minnesota prior. The Minnesota prior, originally developed by Litterman (1986), imposes a random walk representation for all variables. This is a plausible prior assumption for the majority of macroeconomic variables apart from the ones characterized by substantial mean reversion. The main issue with the Minnesota prior is the imposition of a fixed and diagonal covariance matrix of the residuals that excludes possible correlation among residuals of different variables. Kadiyala and Karlsson (1997) therefore suggest a natural conjugate prior that maintains the principles of the Minnesota prior but relaxes the assumptions on the covariance matrix structure of the residuals.

To present this prior, consider the compact form of the VAR in equation 3:

$$Y = X\bar{B} + U \tag{4}$$

where $Y = \{y_1, y_2, \ldots, y_T\}'$ is a $T \times n$ matrix where T is the number of observed time periods, $X = \{X_1, X_2, \ldots, X_T\}'$, with $X_t = \{Y'_{t-1}, Y'_{t-2}, \ldots, Y'_{t-p}, 1\}'$ is a $T \times k$ matrix where $k = np + 1$, $\bar{B} = \{B_1, B_2, \ldots, B_p, c\}'$ is a $k \times n$ matrix containing all parameters, and $U = \{\nu_1, \nu_2, \ldots, \nu_T\}'$ is a $T \times n$ matrix of the error terms. The prior for the VAR coefficients $\bar{B}$ is normal and given by: $vec(\bar{B})|\Sigma \sim \mathrm{N}\left(vec(\bar{B}_0), \Sigma \otimes \Xi\right)$. The prior distribution of the

[28] The choice of four lags reflects convention in empirical studies employing similar VAR models to monthly data (Bekaert et al., 2013) and seems to be sufficient to capture the dynamics of the model. We check the robustness of our results by estimating alternative versions of the baseline model with a lag length of three, five, and six, respectively. Note that, as we were constrained by the relatively short sample period, and the fact that we are estimating a rather large number of parameters, we did not go beyond six lags.

covariance matrix Σ is inverse Wishart: $\Sigma \sim \mathrm{IW}\left(\bar{S}, \alpha\right)$, with prior scale matrix $\bar{S}$ and prior degrees of freedom α.

We implement these priors by adding dummy observations. The advantage of this methodology is that it matches the Minnesota moments while at the same time, it works as a regularisation solution to the matrix inversion. Following Bańbura et al. (2010), it can be shown that adding T_D dummy observations Y_D and X_D to the system in 4 is equivalent to imposing the natural conjugate prior with $\bar{B}_0 = (X_D' X_D)^{-1}(X_D' Y_D), \Xi = (X_D' X_D)^{-1}, \bar{S} = (Y_D' - X_D\bar{B}_0)^{-1}(Y_D' - X_D\bar{B}_0)$ and $\alpha = T_D$. Intuitively, one can think of dummies in terms of artificial data featuring pseudo observations for each of the regression coefficients with properties specified by the prior beliefs on the VAR parameters and blending this with the real data. This prior is implemented as follows:

$$Y_D = \begin{bmatrix} diag(\delta_1\sigma_1, \ldots, \delta_n\sigma_n)/\lambda \\ 0_{n(p-1)\times n} \\ \cdots\ \cdots\ \cdots\ \cdots\ \cdots\ \cdots \\ diag(\sigma_1, \ldots, \sigma_n) \\ \cdots\ \cdots\ \cdots\ \cdots\ \cdots\ \cdots \\ 0_{1\times n} \end{bmatrix} X_D = \begin{bmatrix} J_p \otimes diag(\sigma_1, \ldots, \sigma_n)/\lambda & 0_{np\times 1} \\ \cdots\ \cdots\ \cdots\ \cdots & \cdots\ \cdots\ \cdots \\ 0_{n\times np} & 0_{n\times 1} \\ \cdots\ \cdots\ \cdots\ \cdots & \cdots\ \cdots\ \cdots \\ 0_{1\times np} & c \end{bmatrix}$$

with $J_p = diag(1, 2, \ldots, p)$.

To give an intuition behind the expressions above, both matrices Y_D and X_D are made of three blocks. The first block is related to the moment of the VAR coefficients corresponding to the endogenous variables of the model. The second block deals with the residual variance-covariance matrix while the third block, represents the moments of the coefficient for the constant term. In particular, δ_i's denote the prior mean of the coefficients on the first lags in the Minnesota prior. They are chosen as the Ordinary Least Squares (OLS) estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample. Next, σ_i's are the scaling factors and are set using the standard deviation of the OLS residual obtained from these preliminary AR(1) regressions. Also, c reflects the uninformative prior for the intercept and is set equal to a very small number.

Finally, λ controls the overall tightness of the prior distribution and it reflects the relative importance of the prior beliefs with respect to the information contained in the data. Essentially, if $\lambda = 0$ the posterior equals the prior and the data do not influence the estimates. If $\lambda = \infty$ on the other hand, posterior expectations coincide with the OLS estimates. As λ increases, the 'looser' the prior is, which allows the coefficients to have increased variance in the structural form, in effect permitting the model to move away from a random walk in the reduced form. The choice of prior is important since if the prior is too loose, overfitting is hard to avoid; while if it is too tight, the data is not allowed to speak. We set a relatively loose prior $\lambda = 1$. As suggested by Canova (2011); Dieppe et al. (2016) and

Chiu et al. (2017) , these values work reasonably well in similar macroeconomic applications and should be used as starting points. Last, it is worth noting that our dummy prior is consistent with the prior belief that variables can be represented by unit root and potential cointegrating processes (see more details in Bańbura et al. (2010)). We use a Gibbs sampling algorithm to approximate the posterior distributions of the model parameters. The details of the posteriors are described in the Appendix D.

Regarding the identification of the UMP shock, we follow the relevant literature on the monetary policy transmission popularized by Christiano et al. (1999, 2005) by adopting a recursive ordering of the variables based on the Cholesky decomposition of the Σ matrix: $\Sigma = A_0 A_0'$ as described earlier. With respect to the ordering of the variables, the monetary policy instrument is ordered after economic activity, inflation, and the inequality index, and before the yield spread and NEER. These restrictions on the macroeconomic variables are fairly standard in the literature and imply that output and prices react to monetary policy changes with a lag, while a monetary policy shock is allowed to affect financial variables contemporaneously. Note that the results from the main specification are robust to different identification schemes that we describe later in the paper.

6. Results

6.1. The response of wealth inequality to UMP shocks

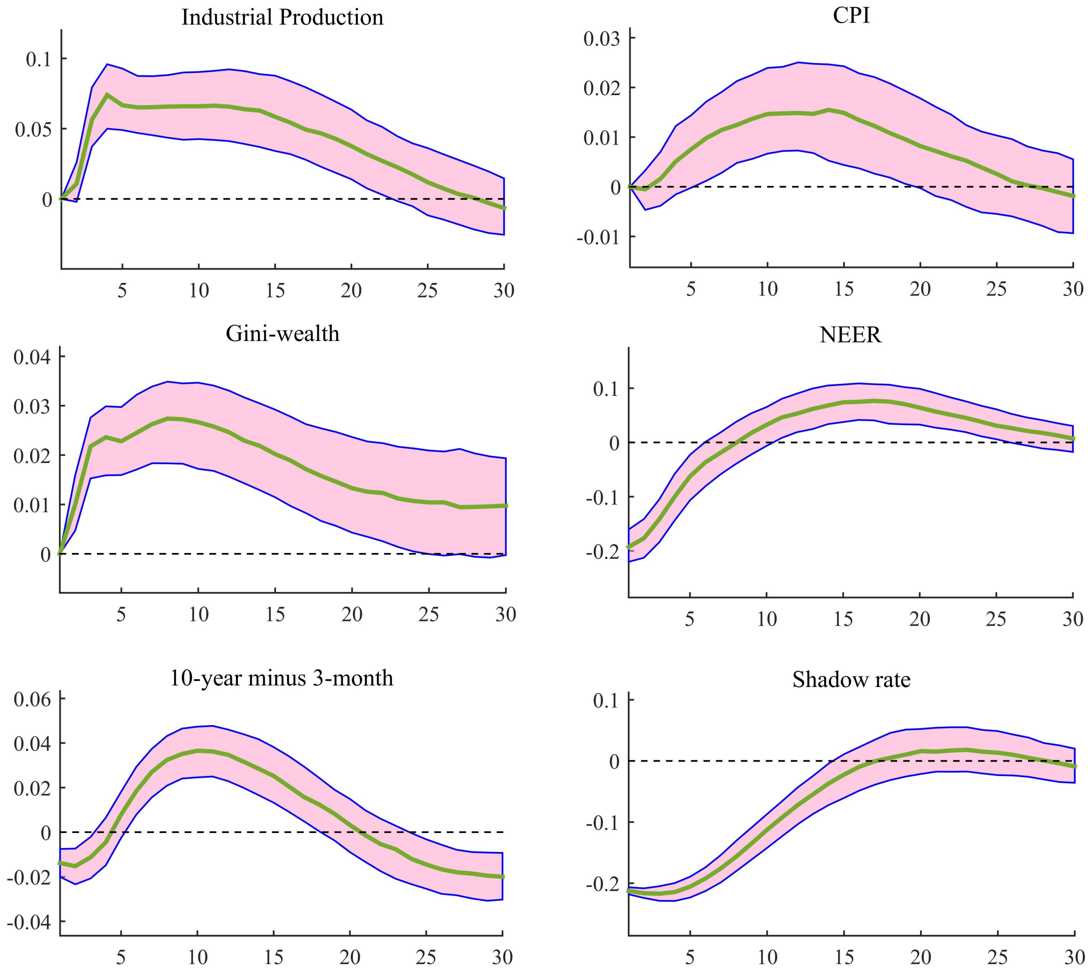
Figure 7 shows the impulse responses over 30 months of all variables to one standard deviation shock in the shadow rate. The green line is the median estimate and the pink shaded area depicts the 68 percent error bands.[29] Our results indicate that the shock leads to a significant increase of the net wealth Gini coefficient. The impact of UMP shocks on increasing wealth inequality has lingering effects as it persists for the whole forecasting horizon. Regarding the magnitude of the effect, we observe that the UMP shock is estimated to increase the Gini coefficient by 0.06 original units one year after the change in policy. This result contradicts predictions of DSGE models suggesting short-lived effects (Hohberger et al., 2019).

In terms of the responses of the core macroeconomic variables to UMP shocks, we note a positive reaction of IP by around 0.07% four months after the shock, and a gradual increase in the CPI that reaches its peak (increase of 0.015%) one year after the shock. This result highlights the short-term benefits of UMP; that is, to support economic growth and boost inflation. The reduction in the shadow rate elicits a fall in the nominal effective exchange rate on impact, as expected. Last, the yield spread falls in response to the shock and then increases. The increase however is not persistent as it later becomes insignificant.[30] Our

[29]Note that in contrast to the frequentist approach, 68 percent is quite common in the Bayesian VAR literature (see Sims and Zha (1999); Bańbura et al. (2010); Liu et al. (2014); Alessandri and Mumtaz (2019), among others).

[30]The initial short term fall of the yield spread is consistent with literature of event studies which explores explicitly the impact of UMP shocks and/or announcements on the yield curve of nominal interest rates, focusing on the period

FIGURE 7. THE IMPULSE RESPONSE OF THE GINI COEFFICIENT TO A MONETARY POLICY SHOCK



Note: The vertical axis of each plot shows the responses in percent (apart from the shadow rate that is in percentage points). Time intervals on the x-axis are months. The green line is the median estimate and the pink shaded area depicts the 68 percent error bands.

results are consistent with other empirical studies (Kapetanios et al., 2012; Baumeistera and Benati, 2013; Weale and Wieladek, 2016; Meinusch and Tillmann, 2016), suggesting that asset purchases exert a powerful effect on both economic growth and inflation.

6.2. *Robustness checks of benchmark model*

We test the robustness of the main findings by implementing an extensive sensitivity analysis. First, considering that the SSR series may vary depending on modeling assumptions (Krippner, 2019), we test the sensitivity of our estimates by employing an alternative SSR series as defined in Krippner (2014) and Claus et al. (2018). Second, we re-estimate our model by providing alternative estimation of UMP shocks based on BoE total assets. A number of papers suggest that innovations on central bank assets do capture UMP innovations during the period of the GFC (Gambacorta et al., 2014; Saiki and Frost, 2014). Although total assets capture only the quantitative effects of UMP, they remain observable variables and as such, they serve as a good robustness check for our purposes. To identify this, we adopt sign restrictions as described in Baumeistera and Benati (2013) and Boeckx et al. (2017). Accordingly, we assume that the contemporaneous impact on output and prices of a shock that increases the balance sheet is positive, while the same expansionary balance sheet shock decreases the yield spread and leaves the short-term rate unchanged. Regarding the mechanics of the process, we follow Rubio-Ramirez et al. (2008) by letting $\Sigma_t = PDP'$ be the eigenvalue-eigenvector decomposition of Σ_t and set $\bar{\Sigma}_0 = PD^{1/2}$. We then draw an $r \times r$ matrix K from $N(0, 1)$ and we compute Q such that $K = QR$. Having these in hand, we compute the structural impact matrix as $\Sigma_0 = \bar{\Sigma}_0 Q'$ and maintain it, if it satisfies the sign restrictions. Note that we also address the problem described in Fry and Pagan (2011) under which the sign restrictions methodology presents impulse responses from different models rather from than a single model, which could be misleading as a description of a single economy. To avoid this, we include a median target approach that selects the A_0 matrix that is closest to the median from a given number of draws from the algorithm.

Next, we replicate the benchmark analysis by using two alternative identification schemes. Specifically, we estimate a version of the model by adopting a stronger restriction that forces all the variables in the system to respond to UMP shocks with a lag, i.e. a cut in the shadow rate has a zero impact on all variables contemporaneously; we achieve this by ordering the shadow rate last and after the financial variables. Secondly, we use sign restrictions based

close to the date of the announcements (see, among others, Krishnamurthy et al. (2011); Altavilla and Giannone (2017); Fratzscher et al. (2018)). Regarding the subsequent increase in the yield spread, similar evidence has also been documented by Weale and Wieladek (2016); Puonti (2019), while Schenkelberg and Watzka (2013) particularly allowed for this hypothesis in their model. Also, Ambler and Rumler (2019) suggest that the impact of UMP measures on yields can be positive, depending on the degree to which the measures have been anticipated by markets. A plausible conjecture is that long-term nominal yields could rise in response to UMP, due to rising inflation expectations. Indeed, if market participants believe the central bank intervention is successful in stimulating the economy by increasing aggregate demand and therefore boosting economic growth and inflation (which is also evident by looking at the corresponding responses of IP and CPI in Figure 7), then real rates are likely to rise in the near future (see, for example, the theoretical work of Eggertsson et al. (2003) or Svensson (2003)). As a result, inflationary expectations as of today should rise and long-term nominal yields should also rise, thus increasing the yield spread.

on Uhlig (2005) and assume that an expansionary UMP shock leads to a contemporaneous decrease in the shadow rate and the yield spread, a rise in inflation and IP, and a decrease in the effective exchange rate.

Furthermore, we estimate two additional versions of the benchmark model, this time by checking whether our results are sensitive to the use of alternative inequality measures. We first re-estimate the benchmark model by replacing the Gini coefficient with the 20:20 ratio of net wealth. The 20:20 ratio compares the share of wealth of the 20% wealthiest households with the share of wealth of the 20% poorest, effectively depicting the wealth of the rich as a multiple of the poor's wealth. In other words, the 20:20 ratio is equal to $(100 - Q_{80})/Q_{20}$, where Q_{20} and Q_{80} stand for the quantile shares of order 0.2 and 0.8, respectively. In the second specification, we use a popular alternative to the Gini, namely the coefficient of variation. The coefficient of variation is estimated by dividing the standard deviation of the net wealth distribution by its mean. The more equal a wealth distribution is, the smaller the standard deviation and consequently, the coefficient of variation will be smaller in more equal distributions.[31]

In addition, we examine potential sensitivity of our results to prior selection by estimating three different versions of our baseline model. We discuss the alternative priors in the Appendix, 'Prior Sensitivity'. In this section we report the results when an independent normal Wishart prior is considered while responses from the other specifications are shown in the Appendix. We shall only highlight here that results are largely unchanged across all specifications, pointing to a significant and persistent increase of inequality, in response to UMP shocks.

Last, the findings are robust to perturbations to the benchmark VAR specification, such as the addition of extra lags and the inclusion of additional endogenous variables. Specifically, in the former case, we re-estimate our model by including six lags.[32] In the latter case, we augment the vector of endogenous variables by including a large number of macroeconomic and financial variables.[33] [34] Note that in the latter case, the size of the BVAR increases significantly. This inevitably leads to the curse of dimensionality, which refers to the large number of parameters that have to be estimated in the model. We deal with this issue by

[31]The coefficient of variation is the only inequality measure within the Generalized-Entropy class that is applicable to wealth distributions (Cowell et al., 2018). However, in contrast to the Gini index, the measure is very sensitive to outliers in the two tails, and thus it is more appropriate when the distribution approaches normality. To address this problem, we top-coded the richest and the poorest 1% of our sample and then estimated the coefficient of variation for household net-wealth. Although this is a rough approach to correct for extreme values at the two tails, potentially leading to underestimation of inequality, it is still widely used in the relevant literature (see, Mumtaz and Theophilopoulou (2017); Coibion et al. (2017)) and can help reduce measurement bias of the coefficient of variation estimates (Colciago et al., 2019).

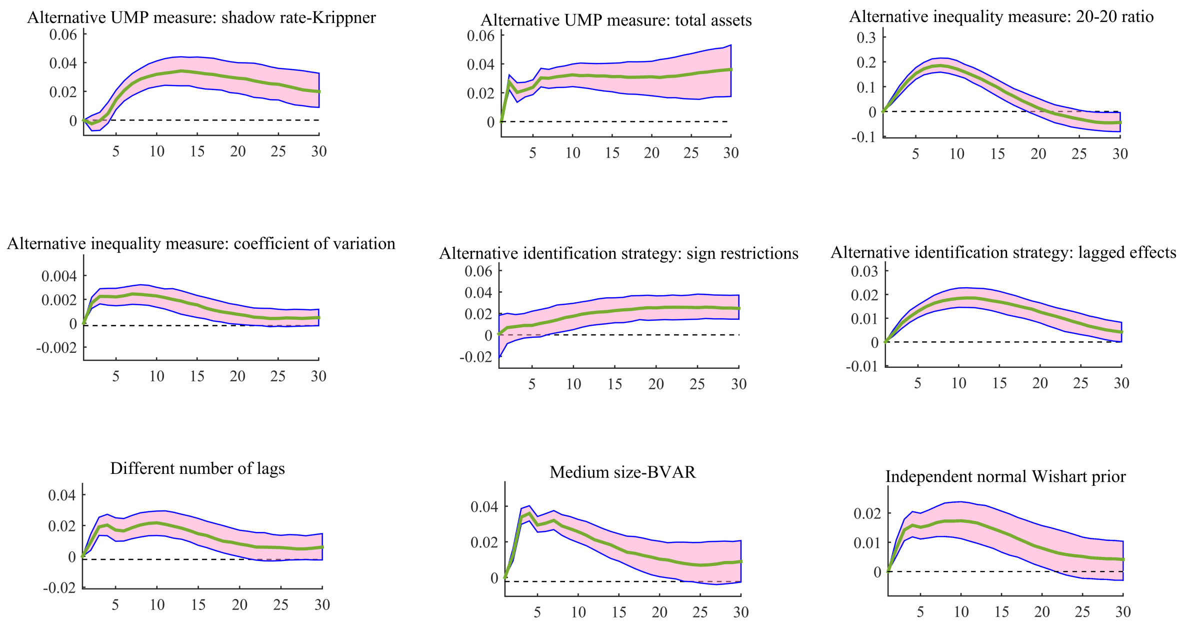
[32]We also consider alternative specifications with a lag length of three and five, in the Appendix. Results are largely unchanged, indicating a positive and significant response of inequality to UMP shocks across all three specifications.

[33]We augment the initial vector of endogenous variables by adding: the UK all share index, the crude oil price in dollars, imports, exports, government consumption, unemployment rate, weekly earnings, the 3-month Treasury bill rate, the 5-year Government bond yield and, last, the 10-year and the 20-year Government bond yields.

[34]Note that we estimate another specification of our baseline model where we consider unemployment rate instead of IP as a proxy for the business cycle in the UK. Our results confirm that IP is a better proxy than unemployment. Details and discussion of the results are provided in the Appendix.

adopting a dummy observation prior as described in Bańbura et al. (2010) and Blake and Mumtaz (2012), to achieve Bayesian shrinkage. Practically, the hyperparameter that controls the overall tightness λ of the prior distribution is set in relation to the size of the BVAR so that the higher the number of variables, the more the parameters should be shrunk to avoid overfitting.

Figure 8. Robustness checks of the baseline result



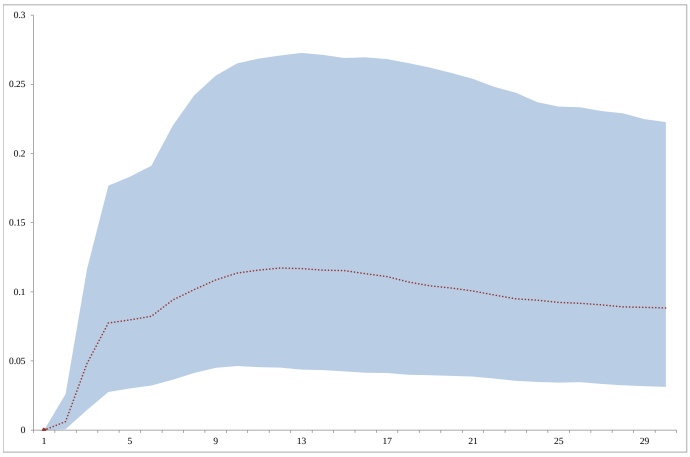
Note: The vertical axis of each plot shows the response in percent. Time intervals on the x-axis are months. The green line is the median estimate and the pink shaded area depicts the 68 percent error bands.

The results from all different specifications described above are depicted in Figure 8. Note that we only show the response of the inequality measure, as this is the variable of main interest. We observe that the responses of the inequality measure in all cases convey a similar message to the benchmark case, generating a significant increase of wealth inequality that persists over the forecasting horizon. Regarding the other variables of the system, the macroeconomic responses (not reported here but available upon request) are similar to the benchmark case, with the UMP shocks generating a positive reaction of IP and CPI and a negative response of the term spread and the NEER on impact.

6.3. *Unconventional monetary policy on wealth inequalities: variance decomposition*

Another way to highlight the role played by UMP shocks in driving fluctuations in the Gini coefficient is by looking at the forecast error variance decomposition. Figure 9 plots the contribution of the UMP shock to the forecast error variance of the inequality measure. The red dotted line shows the median estimate and the light blue shaded area is the 68% error band. We observe that the median contribution of the UMP shock to fluctuations in the wealth Gini is around 11% at the first year horizon, suggesting that UMP measures did play an important role in the widening of the wealth gap over the 2009-2016 period.

Figure 9. Percentage contribution of unconventional monetary policy shocks to the forecast error variance of the net wealth Gini coefficient.



Note: Percentage contribution of UMP shocks to the forecast error variance of the Gini coefficient. The red dotted line is the median estimate and the light blue shaded area depicts the 68% error bands.

6.4. *Unconventional monetary policy on wealth inequalities: capturing the channels*

Next, we augment our main BVAR specification by adding five variables in order to examine the means through which UMP affects wealth inequality. First, as discussed in Section 2, the impact of central bank asset purchases on equity prices is established in the UMP literature and functions through the portfolio-rebalancing channel (Joyce et al., 2012; McLaren et al., 2014; Neely, 2015). The announcement of central bank purchases implies a simultaneous increase in asset prices and a drop in corporate bond yields (Joyce et al., 2012; Neely, 2015). As investors rebalance their portfolios from risk-free government bonds to more risky assets, the risk-premium for holding equities is reduced, and upward pressure is put on their prices (Joyce et al., 2011, 2012). To capture the simultaneous impact of QE on corporate bond yields and equity prices, we use the "UK all share index" taken from the Federal Reserve Economic Data database (FRED), and the Sterling (GBP) corporate bond yields on all issuers (including financials) rated AAA-BBB, taken from the millennium of macroeconomic database of BoE.[35] Both variables allow us to quantify the impact of the portfolio rebalancing channel on wealth inequality changes.

Second, we investigate the channel that works via higher asset prices through housing wealth. To do this, we augment our BVAR with the housing market index taken from

[35]See, www.bankofengland.co.uk/publications/quarterlybulletin/threecenturiesofdata.xls

Gov.UK as an additional variable. As mentioned earlier, UMP can affect the housing market by inflating house prices and boosting residential investment (Rahal, 2016). Given the more even distribution of housing wealth compared to financial wealth, the expected effect of UMP on housing wealth inequality can go in either way.

Third, we look at the savings redistribution channel as proxied by the effect of a decreased borrowing rate on the net wealth position of borrowers and savers (Inui et al., 2017; Casiraghi et al., 2018). Our hypothesis is that when the savings redistribution channel is open, QE affects the borrowing. Consequently, borrowers are likely to be better off as interest payments on debts fall more than interest payments on savers' deposits. We use the mortgage interest rate and the unsecured loan rate taken from the millenium macroeconomic database of BoE in order to uncover the potential impact of this channel.

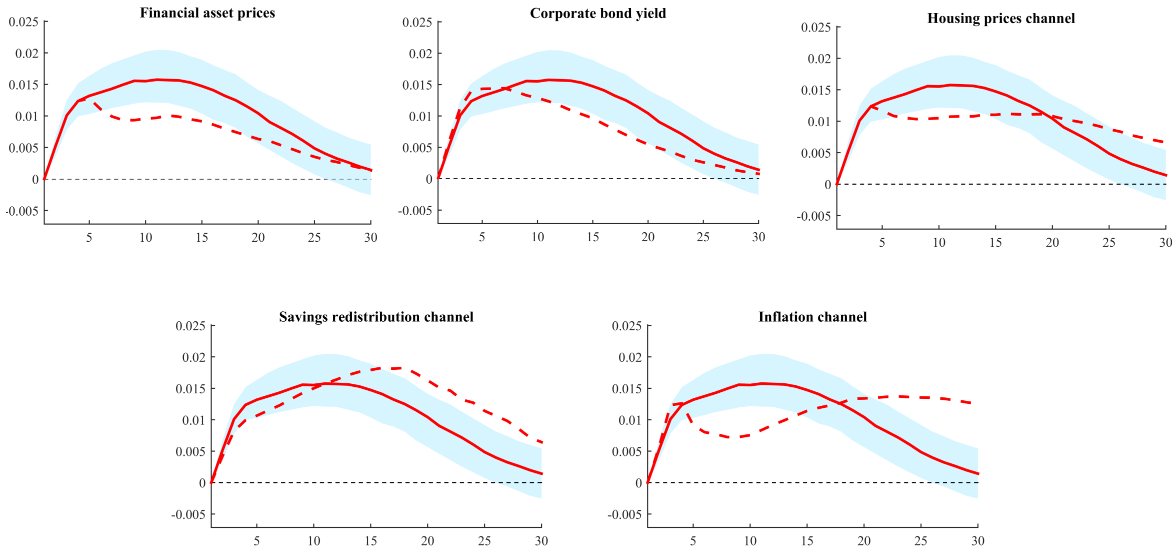
Fourth, we examine the inflation channel by using the CPI. Unanticipated changes in the price level directly lead to wealth redistribution, as inflation reduces the real value of nominal assets and liabilities, effectively redistributing wealth from lenders to borrowers (Doepke and Schneider, 2006; Adam and Zhu, 2015). The magnitude of the effect can vary depending on the presence of nominal rigidities or disproportional changes in the nominal value of different assets driven by other channels.

We build the counterfactuals as hypothetical impulse responses which depict only the direct impact of UMP shocks on inequality and neutralize the indirect effects through each of the four transmission channels. This is done by constructing a counterfactual sequence of shocks to the variables such that the impulse response to UMP shocks of each of the additional variables described above is equal to zero at all horizons. The comparison of the counterfactual responses of Gini with the actual responses estimated in the unrestricted model provides us a measure of the relative importance of each of these channels on the transmission of UMP to households' wealth dispersion.

Figure 10 shows the results. The red solid lines represent the median responses of the net wealth Gini index, computed in the unrestricted BVAR together with the 68% confidence bands, while the dotted lines show the median response of the Gini from the counterfactual experiment. We observe that shutting down the share index and the corporate spread to UMP shocks leads to significant declines of the responses of Gini (note that both counterfactual responses are below the responses of the unrestricted model, while they also lie outside the error bands for most of the forecasting horizon). This indicates that the portfolio rebalancing channel has an important role in increasing wealth inequality. Our results confirm empirical works suggesting a positive effect of the portfolio composition channel on wealth inequality Domanski et al. (2016); Casiraghi et al. (2018); Adam and Zhu (2015); Lenza and Slacalek (2018) for other countries, but contradict theoretical predictions implying that the effect is short-lived and changes direction in the medium-run (Hohberger et al., 2019).

Next, we observe that when the housing prices channel is shut down, the counterfactual

FIGURE 10. UNCONVENTIONAL MONETARY POLICY ON WEALTH INEQUALITY: TRANSMISSION CHANNELS



Note: The red line shows the median estimate and the blue shaded area depicts the 68% error bands. The dotted lines show the median response of Gini from the counterfactual experiment.

response of Gini in the first twenty months after the shock is lower in magnitude compared to its counterpart in the unrestricted case, thus exerting extra pressure on the widening of the wealth gap. This finding comes in contrast to most of the simulations literature which predicts that housing price increases offset the regressive outcomes of financial asset price increases.(Adam and Tzamourani, 2016; Lenza and Slacalek, 2018; Bivens, 2015; Bunn et al., 2018). As this finding is partly driven by the share of households in GB with no housing assets at all (around 25% according to our estimates), it adds to the policy relevant literature suggesting that the promotion of home-ownership for lower wealth groups should lead to lower wealth inequality (see, Kaas et al. (2019)).

The reverse effect is observed when we switch off the savings redistribution channel (i.e. setting the coefficients of both the mortgage interest rate and the unsecured loan rate to zero). The counterfactual response of Gini appears to be significantly higher 15 months after the shock onward, indicating that the savings redistribution channel acts as a counterbalancing force since the fall in wealth inequality offsets the upward pressures on inequality elicited by the other two channels.

A similar result is obtained when we control for the effect of CPI on the response of the Gini coefficient through the inflation channel. According to the right bottom IRF in Figure 10 when the CPI channel is switched off, the inequality index presents a substantial and lingering response to the UMP shock in the medium term. This finding confirms existing micro-simulation studies arguing for persistent wealth redistribution effects of inflation from asset-rich lenders to asset-poor borrowers (Doepke and Schneider, 2006; Adam and Zhu, 2015).[36] Interestingly, in the beginning of the period, inequality is responding less when the inflation channel is switched off. This finding can be potentially attributed to nominal rigidities in wage contracts, which put downward pressure on the real income and saving rates of poorer households in the lower end of the distribution.

6.5. Heterogeneity of responses across the net-wealth distribution

To explore further the drivers of the response of wealth inequality to the UMP shocks as witnessed above, we examine how households at different points of the distribution respond to the same UMP shock.

First, we repeat the same exercise as in Section 6.6.1, except that now we are replacing the Gini index with household's net wealth quantile shares as an inequality measure. Percentile shares are common in studies tracking inequality over time (Atkinson et al., 2011; Piketty and Saez, 2014), as they quantify proportions of total outcome, e.g., wealth, that correspond to different population groups, defined in terms of their relative ranks in the distribution.[37]

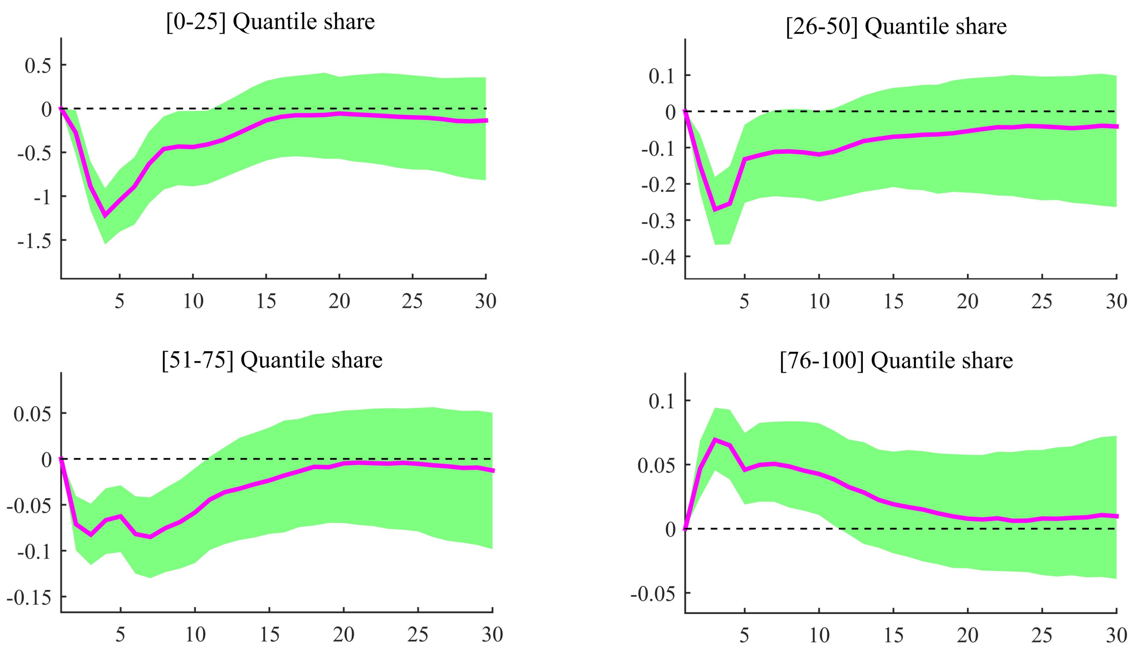
The impulse responses of quantile shares (i.e., 0-25; 26-50; 51-75; 76-100) to UMP shocks are shown in Figure 11. The results suggest that all shares respond negatively to an UMP shock except those standing on the fourth quantile (76-100). In particular, the UMP effect for the richest quantile is positive and significant for an entire year after the shock. The effect for the first three quantiles is the other side of the same coin, since gains in the share of the richest shares are mirrored in losses of the remaining shares. Unsurprisingly, the first percentile (0-25), exhibits the strongest decrease in its wealth share, as households in this rank possess limited financial assets and nearly zero housing assets, as shown in Figure 1 earlier. Households in the second and the third percentile (26-50, 51-75) also exhibit falls in their relative wealth shares, but of a smaller scale than the first percentile. This can be explained by their large possession of housing assets (Figure 1), which moderates the redistributive effect of UMP in the middle of the wealth distribution. While these results do not rule out the possibility that each of the four quantiles may have experienced wealth gains in absolute terms following the shock, they clearly suggest that the gains exhibited by the richest quantile outweigh those of the first three. As can be observed in Figures G1 and G2 in Appendix G, similar patterns emerge if we decompose the wealth shares into their two main components, financial and housing net wealth. Although the effect on the top quantile share is falling, it never becomes negative as it does in the case of the poorer quantiles.

[36] The standard way to account for the inflation channel in these studies is by specifying the household portfolio share that is exposed to inflation (e.g., net nominal position), impose on it a hypothetical inflationary shock, and evaluate the distributional changes it brings. While this approach is convenient for studies focusing on CMP periods, its application may be problematic in the case of UMP. This is because, under UMP, the portfolio rebalancing channel revaluates financial assets, which are largely the same assets taken into account for the specification of net nominal asset position. As a result, netting out the effect of portfolio rebalancing and inflation is tricky in micro-simulation approaches.

[37] Note that, by construction, the percentile shares sum to one. In other words, increases in the share of a given percentile share ineluctably lead to a drop in the total share of all other percentiles. The shares have been estimated using the Stata package "Pshare" (Jann, 2016).

This finding hints on the magnitude of the portfolio rebalancing channel, as highlighted in Section 2.2.1, and contradicts estimates from estimated DSGE simulations suggesting that gains from revaluations turn negative after a number of periods due to capital income losses for asset-rich households (Hohberger et al., 2019).

FIGURE 11. IMPULSE RESPONSES OF NET WEALTH QUANTILE SHARES



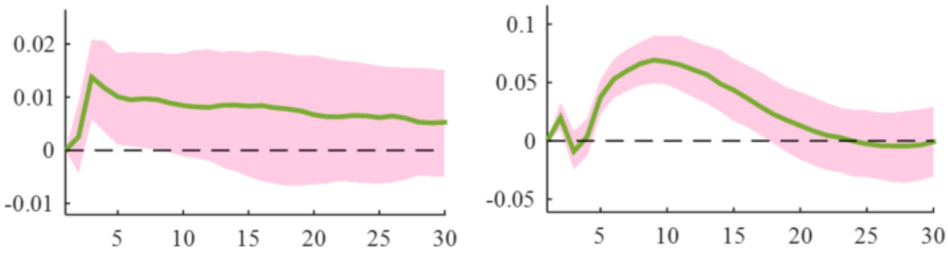
Note: The vertical axis of each plot shows the response in percent. Time intervals on the x-axis are months. The pink line is the median estimate and the green shaded area depicts the 68 percent error bands.

Second, we re-run the model using the two Gini sub-indices presented in Section 4, to capture how UMP shocks affect the two tails of the net-wealth distribution.[38] We now observe that the response of sub-index G_1, reflecting the upper part of the wealth distribution, shown in panel b of Figure 12, is about five times more than the response of G_0, which reflects the lower part of the distribution, shown in panel a. This result comes in agreement with the IRFs of the quantile shares, implying that the UMP-induced wealth inequality is mostly driven by changes in the upper parts of the wealth distribution.

Following the theoretical channels described in Section 2 and the results shown Section 2.2.1, a conjecture for these results is that UMP improves the relative net wealth position of asset-rich households compared to the asset-poor ones. This result is in line with the literature on portfolio composition which suggests that richer households show a greater degree of diversification in their portfolios and re-balance more actively (Haliassos and Bertaut, 1995; Vissing-Jørgensen and Attanasio, 2003; Calvet et al., 2009). The strong increases in the

[38]Alternatively, we could have used a series tracking the path of the bottom or the upper 1%, 5%, or 10% percentile share over time. Yet, we wish to avoid potential sampling error due to the fact that the construction of these shares would require a much larger sample on a monthly basis. This is why we chose to use the two sub-indexes proposed by Jantzen and Volpert (2012).

FIGURE 12. IMPULSE RESPONSES OF THE TWO GINI SUB-INDICES, G_0 AND G_1



(a) G_0 (Left tail) (b) G_1 (Right tail)

Note: The left panel presents the Gini sub-index driving the lower part of the wealth distribution (G_0), and the right panel shows the response of the Gini sub-index driving the upper part of the wealth distribution (G_1). Time intervals on the x-axis are months. The green line is the median estimate and the pink shaded area depicts the 68 percent error bands.

response of the upper quantile reinforce the finding that the portfolio re-balancing channel and the house prices channel, inflate assets held by richer households, thus outweighing the effects of the savings redistribution and inflation channel.

6.6. *Counterfactual policy analysis*

The analysis so far has focused on the role of UMP shocks in driving wealth inequality in the ZLB period. In this section, we explicitly measure the impact of UMP on inequality by focusing on the period before the implementation of the last round of QE, in August 2016, where the BoE had already completed a total of 435 billion worth of purchases. In particular, we are interested in exploring what would have happened to the wealth inequality if the BoE had reversed its QE policy earlier. We construct two counterfactual experiments to measure the impact of QE on the Gini coefficient: the first counterfactual is based on out-of-sample forecasts from our BVAR while the second one is based on a different, more structural approach by using sign restrictions.

In the first experiment, following the spirit of Kapetanios et al. (2012), our BVAR is used to simulate the economy one period ahead, conditional on specific counterfactual policy paths. We estimate the BVAR from 2009:01 up to 2014:12 and then we carry out the counterfactual experiment from 2015:01 to 2016:06. The counterfactual experiment involves two conditional forecasts that we call the 'QE-scenario' and the 'non-QE scenario'. Specifically, the experiment is based on the structure of our benchmark specification, where we assume that QE affects the economy by reducing the shadow rate. The first conditional forecast uses the shadow rate as a measure of monetary policy over the forecasting horizon (QE scenario), while in the second conditional forecast, we replace the values of the shadow rate with the actual policy rate over the forecasting horizon (non-QE scenario); this latter can be seen as quantitative tightening.

Figure 13 illustrates the results. The blue line shows the actual data for the Gini coefficient, the red line shows the median conditional forecast of the Gini coefficient under the non-QE

FIGURE 13. THE IMPACT OF QE ON GINI COEFFICIENT

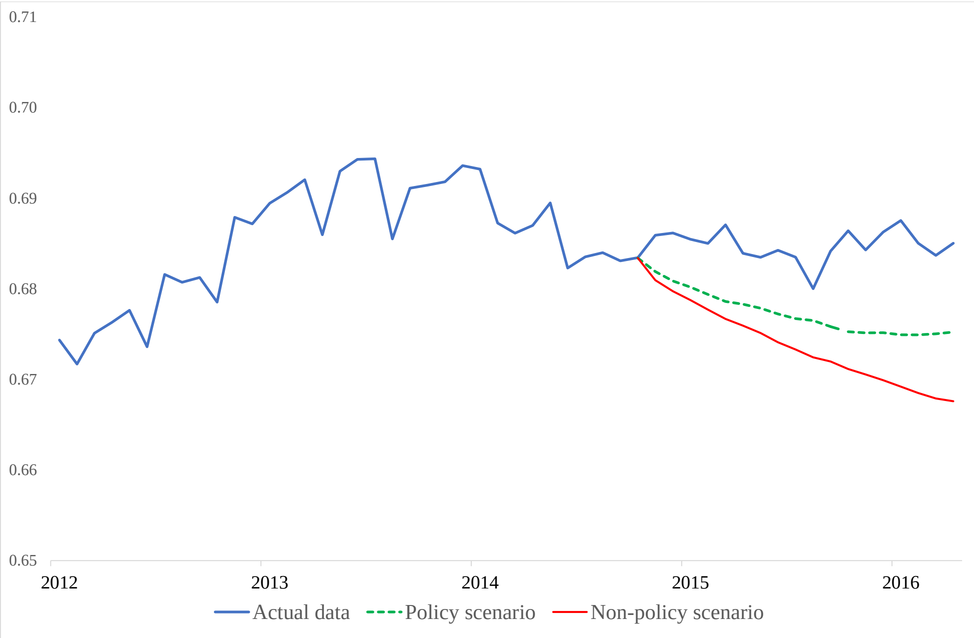
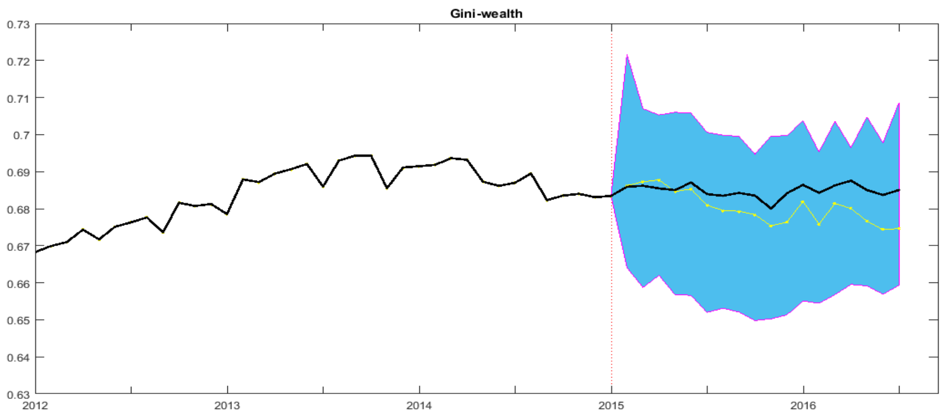


FIGURE 14. THE IMPACT OF QE ON GINI COEFFICIENT FROM A TV-VAR MODEL



Note: The yellow starred line shows the counterfactual path while the blue line shows the actual data. The light blue shaded area depicts the 68% bands.

scenario, while the green dotted line shows the median conditional forecast under the QE scenario. Comparing the green with the red line, we conclude that forecasts of the wealth Gini coefficients are much higher in the QE scenario as opposed to the non-QE scenario, throughout the forecasting period. This result suggests that UMP measures inflated the wealth of the rich and therefore widened inequality.

We should highlight that this approach is based on out-of-sample forecasts from the BVAR model. Thus, the forecast distributions linked with this scenario can be extremely wide, while the median forecast may deviate from the actual data, indicating that the estimates are uncertain. This is also in line with Kapetanios et al. (2012) and Mumtaz and Theophilopoulou (2017) who suggest that the estimates from similar applications can be uncertain. We, therefore, seek to check the robustness of our results by adopting a different, structural approach based on Baumeistera and Benati (2013).

Specifically, we employ a time varying VAR model (TV-VAR). We describe the model in detail in the Appendix E. The model is estimated from 2009:01 to 2016:06. The innovation here with respect to the previous counterfactual is that we use a time-varying parameter specification which allows us to capture the changing macroeconomic structure in place in the aftermath of the Great Recession while tracing the effects of unconventional monetary policies. Also, we use sign restrictions in order to be able to identify a shock to the shadow rate. The process that we follow is similar to the identification scheme proposed by Baumeistera and Benati (2013). In particular, we assume that a contractionary monetary policy shock consistent with quantitative tightening increases the shadow rate contemporaneously and leads to a rise in the term spread and a fall in inflation and IP. Having identified the shadow rate shock, we conduct a counterfactual experiment from 2015:01 to 2016:06 where we scale the shock such that the counterfactual value of the shadow rate is higher than the actual value by 100 basis points; essentially, what we get is the counterfactual path in the absence of QE.

Figure 14 presents the results. To examine whether QE could have affected the wealth Gini coefficient, we compare the implied path of the Gini coefficient obtained by the counterfactual scenario described in the previous paragraph, with the actual path. The yellow line shows the counterfactual path while the black line shows the actual data. The light blue shaded area depicts the 68% bands linked to the simulation. Although the result is not statistically significant, it should be noted that the mass of the counterfactual distribution for the Gini series lies below the observed data during the whole forecasting period. This finding suggests some evidence for our hypothesis that UMP aggravated wealth inequality, in line with our previous results.

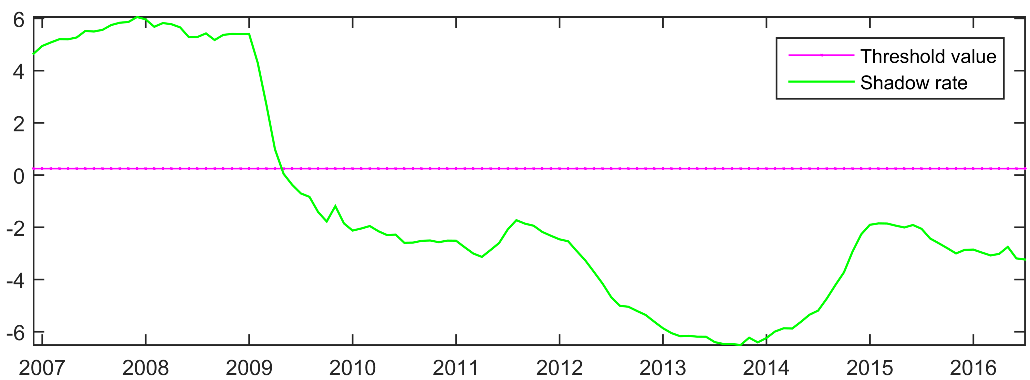
6.7. Conventional Monetary Policy versus Unconventional Monetary Policy on wealth inequality

As discussed in Section 2, the portfolio composition channel is the most crucial one for the transmission of unconventional monetary policy to the wealth holdings, and this takes place through portfolio rebalancing by investors, which, in turn, affects the price of assets held by households. Still, the other main channel, namely savings redistribution via the borrowing rate, does also function under periods of CMP. The evidence from the literature is mixed when it comes to the distributional consequences of CMP and most of the studies suggest that if any relationship exists, it favours the poorer parts for the wealth distribution (Meh et al., 2010; Doepke and Schneider, 2006; Adam and Zhu, 2015), with only a few studies suggesting the opposite case (for example, Bagchi et al. (2019)).

To strengthen our case for the redistributional consequences of UMP, we investigate whether the effects of monetary policy shocks on wealth inequality differ depending on two monetary policy states, i.e. the ZLB state where UMP measures are implemented and the non ZLB state where CMP is implemented. To do this, we use a Bayesian threshold VAR (TVAR) model that allows us to endogenously identify these monetary policy states with respect to one transition variable which, in our case, is the shadow rate. The two different monetary policy states are determined by the value of this transition variable with respect to a certain threshold that is estimated within the model. We use the six variables as defined in the benchmark specification while the monetary policy shock is identified using the same recursive identification scheme discussed in Section 5. The model is run over the full sample period, i.e. from 07/2006 to 06/2016. We describe the model in detail in the Appendix F.

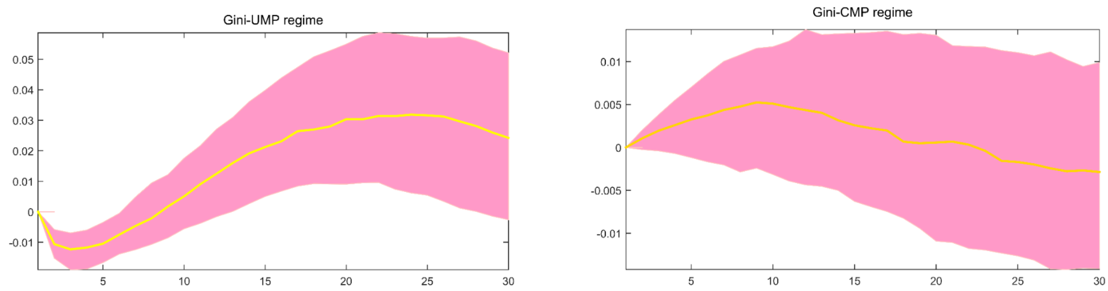
Figure 16 presents the impact of a one standard deviation shock in the shadow rate on the Gini coefficient, in both conventional and unconventional monetary policy regimes. Before we discuss this figure, it is worth inspecting Figure 15. The graph reveals that our TVAR successfully identifies the two monetary policy regimes that took place from the beginning of our sample until 2016, in the UK. In particular, the estimated threshold and the threshold variable show that regime one persisted up to early 2009 while from that point onward, regime two prevailed. Therefore, we interpret the negative shadow rate shock in regime one as representative of expansionary monetary policy via conventional measures, i.e. typical interest rate cuts, while we interpret the same shock in regime two as indicative of UMP shocks.

FIGURE 15. ESTIMATED THRESHOLD AGAINST THE THRESHOLD VALUE



Back to Figure 16, the right graph shows that in the conventional policy regime, an expansionary policy shock leads to a gradual rise in the Gini coefficient; note however that the null hypothesis that this effect equals zero cannot be rejected. On the other hand, the left graph shows that after a short-lived initial fall, we observe a continuous increase of the Gini

FIGURE 16. IMPULSE RESPONSES OF CMP AND UMP ON THE GINI COEFFICIENT OF WEALTH INEQUALITY



(a) UMP (b) CMP

Note: The vertical axis of each plot shows the response of Gini coefficient in percent. Time intervals on the x-axis are months. The yellow line is the median estimate, and the pink shaded area depicts the 68 percent error bands.

coefficient that becomes positive and significant, reaching a peak approximately after two years (note that the magnitude of the response is very close to the one obtained under our benchmark model). Overall, the results indicate that conventional interest rate cuts up to early 2009 did not worsen wealth inequality while UMP measures implemented thereafter have contributed to the surge of wealth inequalities.

Our results are in line with the evidence coming from the existing literature suggesting that expansionary CMP does not increase wealth inequality. Yet, they should be read with caution as our dataset covers only a fraction of the long period during which CMP was implemented before the bank rate touched the zero level. Further work is needed that delves deeper into analyzing the effect of CMP on wealth inequality from a historical perspective.[39] Still, the juxtaposition of two different monetary policy states coming from the same model, clearly strengthens the case put forward in this study in favour of regressive redistributive effects of UMP.

7. Concluding Remarks

We illustrated that UMP shocks have significant effects on wealth inequality: an expansionary monetary policy as illustrated by a decrease in the shadow rate, raises the observed inequality across households as measured by their Gini coefficients and quantiles of net wealth, housing wealth, and financial wealth. Additional counterfactual policy experiments confirm the UMP did play an important role in the widening of the inequality gap. With respect to the pass through mechanism of UMP shocks, portfolio rebalancing is the most prominent channel in increasing wealth inequality and as our results show, it is activated through wealth effects via higher financial asset prices and drops in corporate bond yields.

We also presented evidence of a regressive distributive effect activated through the housing prices channel. This result contradicts the intuition of theoretical and empirical works investigating the relationship between monetary policy and wealth inequality. These papers

[39] Bagchi et al. (2019) and El Herradi and Leroy (n.d.) are recent works on these grounds.

typically predict that housing revaluation effects offsetting the financial asset revaluation effects of UMP (see for example, Adam and Tzamourani (2016); Lenza and Slacalek (2018); Bunn et al. (2018)). Our results suggest that home-ownership only moderates the redistributive effect of UMP only in the middle of the wealth distribution. This is attributed to the relatively small share of home-owners in GB and the revaluation effect of UMP on house prices, which takes more time to reveal than the corresponding effect on financial assets. In addition, we presented evidence in favour of the savings redistribution and the inflation channel, which transfer wealth from richer savers to poorer borrowers whose balance sheet items track variable interest rates or are exposed to inflation. Nevertheless, these channels are not strong enough to counterbalance the upward pressures on inequality driven by the pressures of the portfolio rebalancing channel and the housing price channel. Last, as expected, the results reveal that UMP is shown to present more regressive redistributive effects than CMP.

While our analysis captured a rich set of dynamics, it narrowed its focus to a partial equilibrium perspective, by evaluating the impact of UMP shocks on wealth distribution variables rather than focusing on their impact on other welfare measures such as income or consumption. These measures are most likely affected by UMP in an heterogeneous way, depending on the income structure and the consumption patterns of the economy. Yet, evidence from Mumtaz and Theophilopoulou (2017) complements our analysis by providing evidence that QE worsened income and consumption inequality in the UK, on top of wealth inequalities addressed here. Taking all the evidence together, the message is that UMP in the UK worsened overall economic inequalities.

Our results have important policy implications at a time when major central banks are moderately switching from unconventional to conventional monetary policy. Although UMP measures have proven to be a powerful monetary instrument to boost liquidity and investment when the ZLB is binding, they need to be qualified by acknowledging their undesirable side effects, namely widening wealth disparities. Policies that induce regressive redistribution outcomes may not be desirable for the UK given the central role of underlying social inequalities on the rise of populism (Goodwin and Heath, 2016; Piketty, 2018) and possibly on the British referendum vote to leave the EU (Fetzer, 2019).

Alternatives to UMP have been proposed, including fiscally-oriented transfer policies, by crediting (poorer) households with means-tested stipends, refundable tax credits targeted to poorer families, and unemployment insurance extensions.[40] Although the effectiveness of fiscal transfers in raising output and stabilizing investment under a binding ZLB is still debated (Eggertsson and Krugman, 2012; Mehrotra, 2018), such measures are likely to have less regressive side-effects when it comes to wealth redistribution, due to the lower prevalence of the asset revaluation channel documented in the present study. Thus, the redistributive

[40]See for example Muellbauer (2014) and Baldwin (2016), among others.

effects of fiscal versus monetary policy under the ZLB serve as a straight avenue for future research. The study of Bivens (2015) focusing on income inequality for the US case is a good starting point on this research agenda.

Finally, growing theoretical and empirical work suggests that wealth distribution disparities, on top of being an outcome of monetary policy, function as a transmission mechanism of monetary policy to consumption through varying marginal propensities to consume for different net wealth profiles (Auclert, 2019). Thus, an avenue for future research would be the investigation of monetary policy-induced inequality as an endogenous variable in the monetary policy transmission and its effects on the economy-wide equilibrium.

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Assessing the population representativeness of the constructed monthly wealth series

The wealth inequality measures in this study are estimated after we break the five biennial waves of WAS (2006-2016) on a monthly basis. In this section, we assess whether our monthly samples maintain the representativeness of the British population, as initially ensured in the construction of WAS.[41] To achieve this, we borrow from the literature investigating whether non-response bias in internet surveys leads to under-representation issues (see, for example, Groves (2006); Smyk et al. (2018)).

A challenge in assessing the representativeness of our samples is that the proportion of a population in a given demographic group is likely to change over time. Consequently, when evaluating potential deviations between the constructed sample and the one representing the population, it is tricky to identify whether these deviations arise due to actual population trends or representation bias in the construction of our samples. Ideally, we would benchmark the distributions of auxiliary variables in the monthly samples with similar variables from actual population estimates, to assess whether they retain their representativeness properties.[42]

In the absence of another representative sample with similar frequency, our strategy is to compare the distributions of key variables in our monthly samples and assess whether they indicate large systematic deviations from the original representative WAS waves. Evidence of such deviations would imply that the estimated monthly distributions do not maintain their representativeness and may contaminate our analysis with measurement error and representation bias. By contrast, no evidence of large deviations, although not securing population representativeness from a strictly statistical viewpoint, serves as a robustness check pointing that our monthly samples represent the population subgroups sufficiently when compared to the original survey.

The variables considered in our tests are: i) demographic variables, namely gender and age, and, ii) the target variables employed in the study, namely household net wealth and its components. Demographic variables are crucial for the tests as they hint on the representation of various population groups and remain largely stable over time.[43] The only continuous demographic variable we can test is the age of the household's reference person (HRP). Age is a key variable for our purposes, both because of its standard use of evaluating the representativeness of a sample compared to population (Smyk et al., 2018), but also

[41]We are grateful to an anonymous referee for suggesting the assessment of the represenativeness of the constructed monthly samples.

[42]An intuitive definition of a representative sample is the following: Let two auxiliary variables, gender (young or old) and gender (male or female). Then, old male subjects constitute a coherent subset of the population. A representative sample must have the same proportion of old male subjects as in the population (Grafström and Schelin, 2014).

[43]The typical selection of variables for testing nationally representative samples, satisfying the criteria of random sampling by most statistical offices, include age, gender, and residence. The underlying assumption is that, if the random sample matches these characteristics with population, the measurement of other characteristics is thought equivalently good, as if each household from the population participated in the survey (Smyk et al., 2018). We included only age and gender as WAS does not disclose information on household residence due to confidentiality reasons.

because substantial jumps in the age structure of the population may lead to different life-cycle patterns and therefore different wealth distribution outcomes (see, Almås and Mogstad (2012)).

The only categorical variable considered is gender. For this variable, we use the T-test to compare the means of the distributions. With respect to continuous variables testing, the most popular test for evaluating equality of distributions is the Kolmogorov-Smirnov (KS) test (Kolmogorov, 1933).[44] A caveat of the KS test is that is not very sensitive in the tails of the distribution (Eicker, 1979; Jaeschke, 1979). As discussed earlier, the wealth distribution is highly skewed to the right, leading us to reservations on its use for assessing representativeness between continuous variables. To address this caveat, we employ the recent multiple testing procedure of Goldman and Kaplan (2018). This distance test is superior to KS in that it does not only answer whether or not two distributions are identical, but also indicates the points of the Cumulative Distribution Functions (CDF) where the null hypothesis of identical distributions can be rejected. Importantly, by distributing power more evenly across the entire distribution, the test is more sensitive to differences in the tails.

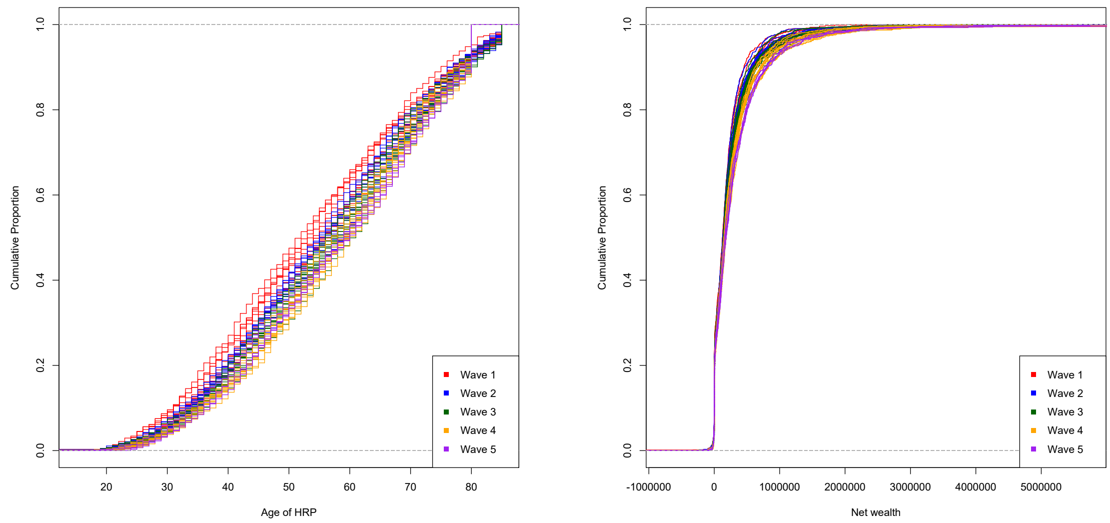
Before performing the tests, we plot the CDFs of age of HRP and net wealth, for all 120 monthly sub-samples estimated (Figure A1). Each CDF on the plot stands for a monthly sample, while its colour represents the corresponding WAS wave it belongs. With the exception of wave 1, CDFs for age are largely blurred across waves and follow a similar pattern.[45] Interestingly, the CDFs for net wealth indicate a slight shift to the right in the middle of the CDF, implying that, in the early years of the survey, more households reported higher wealth in the middle range of the wealth distribution. More importantly, the monthly subsets in both variables maintain remarkably the shape of the wave's CDF they belong, hinting that the population representativeness of the original survey may be retained after the break. This intuition remains to be confirmed using formal tests.

Table A1 presents the p-values of the t-test and the CDF distance tests across the actual five WAS waves. The rows stand for the different variables examined and the columns compare each wave to the subsequent one. The t-test evaluates the null hypothesis that there is no difference in the proportion of households in each group from one wave to the next, while the distance test for continuous variables evaluates the null hypothesis that the two distributions are similar between waves. The 0% rejection rate for gender, the only categorical variable, signals no differences in means across waves. Rejection of H0 would imply that the proportion of different groups in the population has varied over time from 2006 to 2016. Moving to the continuous variables, the null hypothesis of equality is

[44] The test evaluates the maximum vertical distance between two ECDFs, and if those are in agreement, the null hypothesis cannot be rejected, and representativeness across the samples is ensured.

[45] Note that wave 1 of WAS refers to the period between June 2006 and July 2008, when no UMP measures had yet been taken, and is thus not considered in most of our analysis.

FIGURE A1. CUMULATIVE DISTRIBUTION FUNCTIONS OF CONSTRUCTED MONTHLY SAMPLES



(a) Age CDF (b) Net wealth CDF

Note: The graph depicts the empirical cumulative distribution functions for 120 monthly subsets of the WAS corresponding to the five survey waves from 2006 to 2016.
Source: Authors' estimations based on WAS Data (ONS, 2019).

rejected in almost all continuous variables except age of HRP, where it cannot be rejected in three out of four wave comparisons. This is an unsurprising finding for age, implying no considerable trends in age representation across waves. The distributions of the financial variables naturally differ across the biennial waves.

Table A1—Tests for equality of categorical and continuous variables across subsequent WAS waves

Variable	W_1 - W_2	W_2 - W_3	W_3 - W_4	W_4 - W_5	Rejection rate
Female HRP*	0.21	0.17	0.42	0.88	0%
Age of HRP	0.01	1.00	1.00	1.00	25%
Total wealth	0.00	0.00	0.00	0.00	100%
Net wealth	0.00	0.01	0.00	0.00	100%
Housing wealth	0.00	0.00	0.00	0.00	100%
Financial wealth	0.07	0.00	0.00	0.02	100%
Mortgage debt	0.00	0.09	0.07	0.09	100%
Non-mortgage debt	0.07	0.00	0.00	0.02	100%

Note: The estimation of differences in the proportions of the only categorical variable, namely female Household Reference Person (HRP), has been performed using t-tests across subsequent WAS waves. Comparisons of continuous variable distributions have been performed using Goldman and Kaplan (2018) test. The table reports p-values from both tests. Rejection rate refers to the percentage that the null hypothesis of equality between the two distributions is rejected at 10%.

While the wave-on-wave comparisons are interesting on their own, they provide no new information on how well our monthly estimates are sufficiently representative of the population. To assess this, we compare the rejection rates of Table A1 with similar statistics coming from the comparison of the distances between the distribution of the monthly samples and the biennial wave each monthly sample belongs.

Table A2 summarizes the results. The columns stand for the comparison between each monthly sample, s_i, with the wave it lies on, W_j, set minus the sample s_i.[46] For the categorical variable, gender, rows stand for the number of cases that the null hypothesis of equality between the means of the two distributions can be rejected under the t-test. For the continuous variables, the rows stand for the number of cases that the null hypothesis can be rejected under the Goldman and Kaplan (2018) test of distance across distributions. Beginning with the demographic variables, gender and age, only in a handful of cases can the null hypothesis of equality of distributions be rejected, as the rejection rates range between 2.5 to 5%. In particular, for gender, the null hypothesis can be rejected in only 6 cases out of 120 and, for age, in 3 cases out of 120. The results on the demographic variables confirm our hypothesis that the age structure of the representative WAS waves is maintained throughout the monthly samples. Also, these rejection rates are not systematically larger than the corresponding ones between the subsequent WAS waves, shown in Table A1 earlier. The same

[46]In this way, we rule out the possibility that potential similarity between the distributions is driven by the presence of the monthly subset within the broader wave.

test on wealth variables and its components rejects the null hypothesis in a much higher rate, ranging from 15% for mortgage debt to 43.3% for net wealth. Note that, despite being higher than those for demographic variables, the rates for target variables are substantially smaller than those coming from the same test across waves, where the null hypothesis was rejected universally.[47] On the basis of these results, we could not provide evidence of large systematic deviations between the WAS representative waves and the monthly subsets constructed in this study. We, thus, hold the assumption that the monthly estimates of wealth maintain their representativeness properties.

[47] Applying the KS test on continuous variables yields similar results, though we do not present them, to economize on space. They can be provided by the authors upon request.

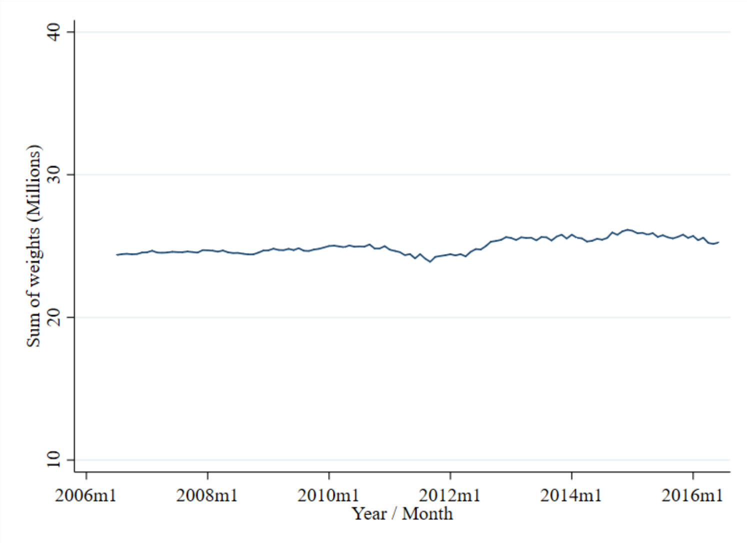
Table A2—Differences in proportions of continuous variables across subsequent waves

Variable	$(W_1 \setminus S_{i,1})$ - $S_{i,1}$	$(W_2 \setminus S_{i,2})$ - $S_{i,2}$	$(W_3 \setminus S_{i,3})$ - $S_{i,3}$	$(W_4 \setminus S_{i,4})$ - $S_{i,4}$	$(W_5 \setminus S_{i,5})$ - $S_{i,5}$	Rejection rate
Female*						
Reject H0 (#)	2	2	1	0	1	5%
Age of HRP						
Reject H0 (#)	0	2	1	0	0	2.5%
Total wealth						
Reject H0 (#)	11	9	10	9	8	39.2%
Net wealth						
Reject H0 (#)	11	10	13	12	6	43.3%
Housing wealth						
Reject H0 (#)	10	9	9	5	5	31.7%
Financial wealth						
Reject H0 (#)	8	4	8	7	6	27.5%
Mortgage debt						
Reject H0 (#)	6	3	1	5	3	15%
Non-mortgage debt						
Reject H0 (#)	5	8	6	7	5	25.8%
N	24	24	24	24	24	

Note: The table presents differences in the distributions between monthly subsets, s_i, and the WAS waves to which the subsets belong, W_j, excluding subset s_i. The estimation of differences in the proportions of the only categorical variable, namely female HRP, has been performed using t-tests. Comparisons of continuous variable distributions have been performed using Goldman and Kaplan (2018) test. H0 stands for the evaluated null hypothesis of equality between the distributions compared. The columns below names of continuous variables stand for the number of times the H0 can be rejected. The rejection rate refers to the percentage that the H0 can be rejected at 10% across all monthly samples of our data-set, i.e., a total of 120.

Descriptive statistics and Additional Figures

Figure B1. Sum of adjusted monthly household population weights



Source: Authors' estimations from Wealth and Asset Survey (2006 - 2016).

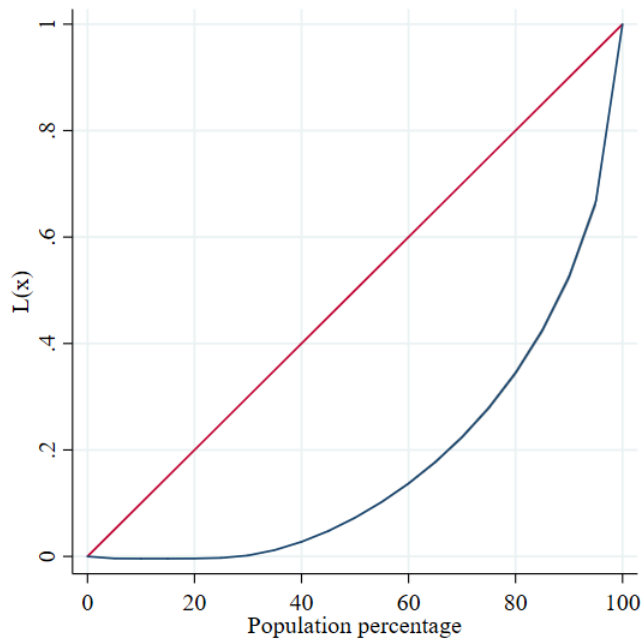
Figure B2. The shadow rate as a proxy of Unconventional Monetary Policy

Source: Wu and Xia (2016); Krippner (2014), FRED.

Applying the two-parameter Gini Hybrid Model on wealth distribution data

Jantzen and Volpert (2012) proposed a novel method to estimate income inequality and derive a two-parameter index following the properties of the observed Lorenz curve. The index is estimated based on the empirical fact that the top ends of the right tail and the left tail of the income distribution Lorenz curve are remarkably self-similar. The authors incorporate the properties of left- and right self-similarity asymptotically towards the two tails of the income distribution and derive two Gini sub-indices capturing inequality at the right and the left tail respectively.

Figure C1. Estimated Lorenz curve for wealth inequality



Source: Authors' estimations from Wealth and Asset Survey (2006 - 2016).

Note: The blue line presents the Lorenz curve of the full sample and the red line presents the hypothetical case of total equality.

Taking advantage of the finding that the ends of wealth distributions in the UK follow similar power laws with income (Drăgulescu and Yakovenko, 2001; Vermeulen, 2018), we estimate a two-parameter net wealth Gini model for GB. Figure C1 illustrates the estimated Lorenz curve, $L(x)$, for the wealth distribution of our dataset, compared to the 45 degree line of perfect equality. Following Jantzen and Volpert (2012), the right tail of the distribution is assumed to follow a Pareto-distribution with a Lorenz curve of the form $L(x) = 1 - (1 - x)^q$, where x stands for the cumulative proportion of the population owning $L(x)$ share of total net wealth. The left tail of the wealth distribution is assumed to follow a power law of the form $L(x) = x^p$. The combination of the two tails gives the hybrid two-parameter model of the Lorenz curve with the following form:

$$L(x;p,q) = x^p(1-(1-x)^q) \tag{C1}$$

The parameters p and q can be estimated from Lorenz curve coordinates using nonlinear least squares,[48] while the traditional Gini index based on C1 can be evaluated exactly in terms of the Gamma function:

$$G = 2\int_0^1 x - x^p(1-(1-x)^q)dx = 1 - \frac{2}{(p+1)} + 2\frac{\Gamma(1+q)\Gamma(p+1)}{\Gamma(2+p+q)} \tag{C2}$$

where Γ stands for the Gamma function. As shown in Figure 5 of the main text, the hybrid model fits the traditionally estimated Gini index remarkably well. Following the authors, we use this model to estimate the two inequality indices, relying only on information from the two parameters p and q, and the degree of left and right tail self-similarity, respectively. Solving C2 for the Lorenz curve function, $L(x)$, for each of the two tail distributions, gives us the two sub-indices, G_0 and G_1. G_0, or "low end" Gini index, captures inequality at the left of the observed net wealth distribution, while G_1, or "high end" Gini index, captures inequality at the right of the net wealth distribution:

$$G_0 = \frac{p}{p+2} \tag{C3}$$

$$G_1 = \frac{1-q}{1+q} \tag{C4}$$

Bayesian VAR estimation

Define $Y^* = \begin{pmatrix} Y \\ Y_D \end{pmatrix}, X^* = \begin{pmatrix} X \\ X_D \end{pmatrix}$. That is, Y^* and X^* are obtained by concatenating the dummy observation matrices at the top of the actual data matrices Y and X. Given the natural conjugate prior, the conditional posterior distributions of the VAR parameters $\bar{B}$ and Σ take a simple form and are defined as:

$vec(\bar{B}|\Sigma) \sim \mathrm{N}\left(vec(\mu^*), \Sigma \otimes (X^{*'}X^*)^{-1}\right)$

$\Sigma \sim IW\left(\bar{\Sigma}, T^*\right)$

The posterior means are given by $\mu^* = (X^{*'}X^*)^{-1}(X^{*'}Y^*)$ and $\bar{\Sigma} = (Y^* - X^*\mu^*)'(Y^* - X^*\mu^*)$. T^* denotes the number of rows of Y^*, that is, the total number of time periods obtained from adding the actual and simulated time periods. A Gibbs sampler is used to simulate the posterior distributions of $\bar{B}$ and Σ by drawing successively from these conditional posteriors. We run 40,000 draws and discard the first 30,000 to ensure convergence.

[48]The Lorenz curve coordinates were estimated using the Stata package "Glcurve7" (Van Kerm and Jenkins, 2001) and two parameters p and q were estimated using Stata's nonlinear least squares command, nl, similar to Schneider and Tavani (2016).

Time varying VAR model

We use a TV-VAR model in order to conduct a counterfactual policy scenario to measure the impact of UMP on inequality as described in section 6.6.6. This approach was proposed by Baumeistera and Benati (2013), who identified a shock to the 10-year government bond spread in order to examine the macroeconomic effects of a yield spread compression. Consider again the structural VAR in equation 3 but, this time, following Primiceri (2005), the covariance matrix Σ_t is decomposed as:

$$\Omega_t = A_t^{-1} H_t \left(A_t^{-1}\right)'$$

In our four VAR specification, the time-varying matrices H_t and A_t are defined as follows:

$$H_t = \begin{bmatrix} h_{1,t} & 0 & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 & 0 \\ 0 & 0 & 0 & h_{4,t} & 0 \end{bmatrix} \text{ and } A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21,t} & 1 & 0 & 0 & 0 \\ a_{31,t} & a_{32,t} & 1 & 0 & 0 \\ a_{41,t} & a_{42,t} & a_{43,t} & 1 & 0 \end{bmatrix}$$

where H_t is a diagonal matrix of the stochastic volatilities and A_t is a lower triangular matrix which captures the contemporaneous interactions of the endogenous variables. Following Primiceri (2005), the elements of $B_{i,t}, h_{i,t}, a_{ii,t}$ are modeled as random walks. The advantage of this approach is that we allow for permanent shifts while we reduce the number of parameters to be estimated in an already heavily parameterized model. In particular, denoting $h_t = [h_{1,t}, h_{2,t}, h_{3,t}, h_{4,t}]'$ and $a_t = [a_{21,t}, a_{31,t}, \dots a_{43,t}]'$, we have that:

$lnh_t = lnh_{t-1} + n_t$

$B_t = B_{t-1} + \eta_t$

$a_t = a_{t-1} + \tau_t$

where $h_{i,t}$ evolves as a geometric random walk and B_t, a_t evolve as driftless random walks. We assume that the vector $[\varepsilon_t, \eta_t, \tau_t, \nu_t]'$ is distributed as:

$$\begin{bmatrix} v_t \\ \eta_t \\ \tau_t \\ n_t \end{bmatrix} \sim N\left(0, V\right), \text{ with } V = \begin{bmatrix} \Sigma & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & Z \end{bmatrix}$$

Estimation of the TV-VAR Model

The model is estimated using Bayesian methods. In the following sections, we describe the prior distributions and the estimation algorithm.

Prior Distributions

The initial conditions for the VAR coefficients B_0 are obtained via an OLS estimate of a fixed VAR using the first T_0 observations; the prior distribution for B is defined as $B_0 \sim N\left[\hat{B}_{OLS,}, 4x\hat{V}\left(\hat{B}_{OLS}\right)\right]$. For the prior of h, let $\hat{\Sigma}_{OLS}$ be the estimated covariance matrix of ν_t from the estimation of the time-invariant version of equation 3 and let K be the lower triangular Choleski factor under which $KK' = \hat{\Sigma}_{OLS}$. The prior is then defined as $lnh_0 \sim N\left(ln\mu_0, 10 \times I_3\right)$ where μ_0 is a vector collecting the logarithms of the squared elements on the diagonal of K. For the prior of the off-diagonal elements of A, we set $a_0 \sim N\left[\tilde{a}_0, \tilde{V}\left(\tilde{a}_0\right)\right]$ where $\tilde{a}_0$ are the off-diagonal elements of $\hat{\Sigma}_{OLS}$, where each row scaled by the corresponding element on the diagonal, while $\tilde{V}\left(\tilde{a}_0\right)$ is a diagonal matrix with each element (i, i) being 10 times the absolute value of the corresponding i-th element.

Regarding the prior distributions for the hyperparameters, the prior of Q is assumed to be inverse Wishart distribution $Q \sim IW\left(T_0\breve{Q}, T_0\right)$. The scale parameter is equal to $T_0\breve{Q}$, where $\breve{Q} = \rho \times \hat{\Sigma}_{OLS}$, and $\rho = 0.0001$. The prior distribution of the elements of S is assumed to be inverse Wishart $S_i \sim IW\left(S_{\mu 0_i}, S_{v0_i}\right)$ where i indexes the blocks of S where $S_{\mu 0_i}$ is a diagonal matrix with the relevant elements of $\tilde{a}_0$ multiplied by 10^{-3} (see also Mumtaz and Theophilopoulou (2017) who use this prior specification). Finally, for the variances of the stochastic volatility innovations, we set an inverse Gamma distribution for the elements of Z, $\sigma_i^2 \sim IG\left(\sigma_{\mu 0} = \frac{0.0001}{2}, \sigma_{\sigma 0} = \frac{1}{2}\right)$.

A Gibbs sampling algorithm is used to sample from the posterior distribution. The details of each conditional distribution are provided below.

1st step; drawing the coefficient states B_t

Conditional on $A_t, H_t V$, the observation equation 3 is linear with Gaussian innovations and a known covariance matrix. Therefore, we draw B_t using the Carter and Kohn (1994) algorithm as follows. The conditional posterior distribution of $p\left(B^T \setminus Y^T, A^T, H^T, V\right)$ is written as $p\left(B^T \setminus Y^T, A^T, H^T, V\right) = p\left(B_T \setminus Y^T, A^T, H^T, V\right) \prod_{t=1}^{T-1} p(B_t \setminus B_{t+1}, Y^T, A^T, H^T, V)$. The first term on the right hand side equation, i.e. the posterior distribution of B_t is distributed as $p\left(B_T \setminus Y^T, A^T, H^T, V\right) \sim N\left(B_{T|\mathrm{T}}, P_{T|\mathrm{T}}\right)$. The second element, i.e. the posterior distribution of B_t, is distributed as $p\left(B_t \setminus B_{t+1}, Y^T, A^T, H^T, V\right) \sim N\left(B_{t\setminus t+1}, P_{t\setminus t+1}\right)$. The simulation proceeds as follows. First we use Kalman filter to draw $B_{T|\mathrm{T}}, P_{T|\mathrm{T}}$ and then we proceed backwards in time by using $B_{t\setminus t+1} = B_{t\setminus t} + P_{t\setminus t}P_{t\setminus t+1}^{-1}\left(B_{t+1} - B_t\right)$ and $P_{t\setminus t+1} = P_{t\setminus t} + P_{t\setminus t}P_{t\setminus t+1}^{-1}P_{t\setminus t}$.

2nd step; draw the covariance states a_i

Before describing this step, we note that ν_t, the VAR residuals, can be written as with $var\left(\varepsilon_t\right) = H_t$. This is a system of linear equations with time varying coefficients and heteroskedasticity which has a known form. The j_th equation of this system is given as

$\nu_{jt} = -a_{jt}\nu_{-jt} + \varepsilon_{jt}$, where the subscript j denotes the $j_t h$ column of ν_t, while $-j$ denotes columns 1 to $j-1$. Note that this is a system of equations with time varying coefficients a_t. Following Primiceri (2005), we simplify the analysis by allowing the covariance of τ_t, S, to be block diagonal, that is, the shocks to the jth equation $\tau_{j,t}$ are uncorrelated with those from other equations. Given this diagonal form, the elements of A_t can be drawn by using the standard Carter and Kohn (1994) algorithm.

3rd step; Draw the volatility states, h_t

Following Cogley and Sargent (2005), the diagonal elements of H_t are sampled using a Metropolis Hastings algorithm. To see this, we write the following equation as before, $A_t\nu_t = \varepsilon_t$, where, $var\left(\varepsilon_t\right) = H_t$. Now, conditional on B_t and A_t, the distribution of h_{it} is given by:

$$f(h_{it}/h_{it-1}h_{i,t+1,}\varepsilon_{it}) = f\left(\varepsilon_{it} \setminus h_{it}\right) x f(h_{it} \setminus h_{it-1}) x f\left(h_{it+1} \setminus h_{it}\right)$$

$$= h_{it}^{-0.5} exp\left(\frac{-\varepsilon_{it}^2}{2h_{it}}\right) x h_{it}^{-1} \exp\left(\frac{-(lnh_{it}-\mu)^2}{2\sigma_{h_i}}\right)$$

where μ and σ_{h_i} denote the mean and variance of the log-normal density $h_{it}^{-1} \exp\left(\frac{-(lnh_{it}-\mu)^2}{2\sigma_{h_i}}\right)$. Following Jacquier et al. (2002), we use this log normal density as the candidate generating density with the acceptance probability defined as the ratio of the conditional likelihood $h_{it}^{-0.5} exp\left(\frac{-\varepsilon_{it}^2}{2h_{it}}\right)$ at the old and the new draw. This algorithm is applied at each period in the sample to deliver a draw of the stochastic volatilities.

4th step, draw the hyperparameters, Q, S, Z

Conditional on B_t, A_t, H_t, we sample the hyperparameters as follows: Q is sampled from the inverse Wishart distribution using the scale matrix $\eta_t'\eta_t + Q_0$ and degrees of freedom $T + T_0$. Next, S is sampled from the inverse Gamma distribution with scale parameter $\tau_t'\tau_t + S_i$ and degrees of freedom $T + T_0$. Last, we draw the elements of Z from its inverse Wishart distribution with scale parameter $\frac{(lnh_{it}-lnh_{it-1})'(lnh_{it}-lnh_{it-1})+\sigma_{\mu 0}}{2}$ and degrees of freedom, $\frac{T+\sigma_{\sigma 0}}{2}$. The algorithm is run for 100,000 iterations discarding the initial 60,000 as burn-in sample.

Threshold VAR

The TVAR is defined as:

$$y_t = c_1 + \sum_{j=1}^{p} B_{1j} y_{t-j} + v_t, \quad v_t \sim N\left(0, \Sigma_1\right), \text{if } Y_{it-d} <= Y^*$$
$$y_t = c_2 + \sum_{j=1}^{p} B_{2j} y_{t-j} + \epsilon_t, \quad \epsilon_t \sim N\left(0, \Sigma_2\right), \text{if } Y_{it-d} > Y^* \tag{F1}$$

where Y_{it-d} is the threshold variable, which in our case is the shadow rate, d is the time lag that is assumed to be known, and Y^* is the threshold level. Based on standard information criteria, the specification that we follow is an one-lag VAR with the threshold variable delayed by two periods.

Estimation of the TVAR

Following Bańbura et al. (2010), we introduce a dummy observation prior for the VAR parameters $\mathrm{b_i} = \{\mathrm{c_i}, \mathrm{B_i}\}$, where i=1,2. The prior means are chosen as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample. As is standard in the literature, we set the overall prior tightness $\lambda = 0.1$. Next, we assume that the prior of Y^* follows the normal distribution with $p\left(Y^*\right) \sim N\left(\bar{Y}^*, \sigma_{Y^*}\right)$. We follow Blake and Mumtaz (2012) by using the mean of the threshold variable as $\bar{Y}^*$ and the variance of the series as σ_{Y^*}.

For simplicity, denoting the right hand side variables of the TVAR as X_i , we can write the conditional posterior distribution of b_i that is standard and follows the normal distribution as:

$$H\left(b_i \backslash \Sigma_{i,} y_i, Y^*\right) \sim N\left[vec\left(B_i^*\right), \Sigma_i \otimes \left(X_i^{*\prime} X_i^*\right)^{-1}\right] \tag{F2}$$

where $B_i^* = \left(X_i^{*\prime} X_i^*\right)^{-1} X_i^{*\prime} y_i^*)$ and $y_i^*, \mathrm{X_i^*}$ denote the transformed data in regime i augmented with the dummy observations that define the prior for the left and the right hand side of the TVAR respectively. The conditional posterior distribution of Σ_i is given by the inverse Wishart distribution:

$$H\left(\Sigma_i \backslash b_{i,} y_i, Y^*\right) \sim IW\left(S_i^*, T_i^*\right) \tag{F3}$$

where $S_i^* = \left(y_i^* - X_i^* * b_i\right)' \left(y_i^* - X_i^* * b_i\right)$ and T_i^* denotes the number of rows in Y^*.

The Gibbs sampler cycles through the following steps: (i) the parameters are sampled in each regime according to the conditional posterior distributions F2 and F3. Then, given the values for coefficients and covariances, (ii) we sample the threshold value, Y^* by using a Metropolis Hastings random walk algorithm as follows.

We draw a new value of the threshold from the random walk process: $\mathrm{Y}^*_{\text{new}} = Y^*_{\text{old}} + \Psi^{1/2} e$,

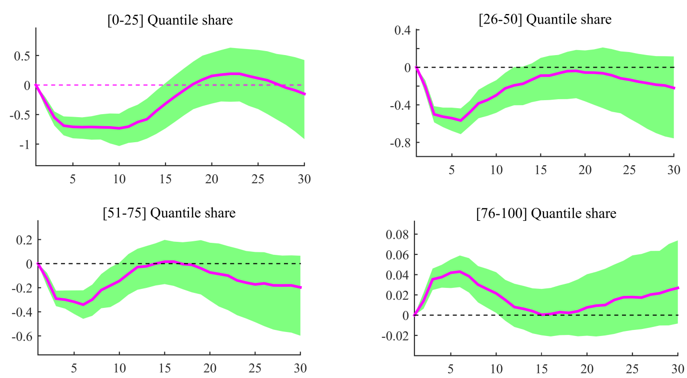
$e \sim N(0, \Sigma)$, where $\Psi^{1/2}$ is a scaling factor that is chosen so as to ensure that the acceptance rate is in the 20–40% interval. Next, we compute the acceptance probability:

$$a = \frac{F\left(y \backslash b_i, \Sigma_i, Y^*_{new}\right) p\left(Y^*_{new}\right)}{F\left(y \backslash b_i, \Sigma_i, Y^*_{old}\right) p\left(Y^*_{old}\right)} \tag{F4}$$

where $F\left(y \backslash b_i, \Sigma_i, Y^*_{new}\right)$ is the likelihood of the parameters as the product of the likelihoods in the two regimes. The log likelihood in each regime is defined as: $lnF = \left(\frac{T}{2}\right) log \left|\Sigma_i^{-1}\right| - 0.5 \sum_{t=1}^{T} \left[(Y_{i,t} - X_{i,t}b_i\ )'\Sigma_i^{-1}\ (Y_{i,t} - X_{i,t}b_i)\right]$ .We then draw $u \sim U(0,1)$. If $u < a$, accept Y^*_{new}, else maintain Y^*_{old}. We run 100,000 draws and discard the first 60,000 to ensure convergence.

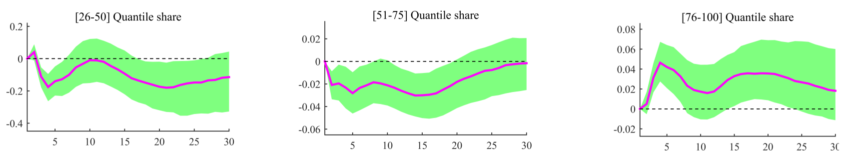
Additional estimates

Figure G1. Impulse responses of net financial wealth quantile shares



Note: The vertical axis of each plot shows the response in percent. Time intervals on the x-axis are months. The pink line is the median estimate and the green shaded area is the error band.

Figure G2. Impulse responses of net housing wealth quantile shares

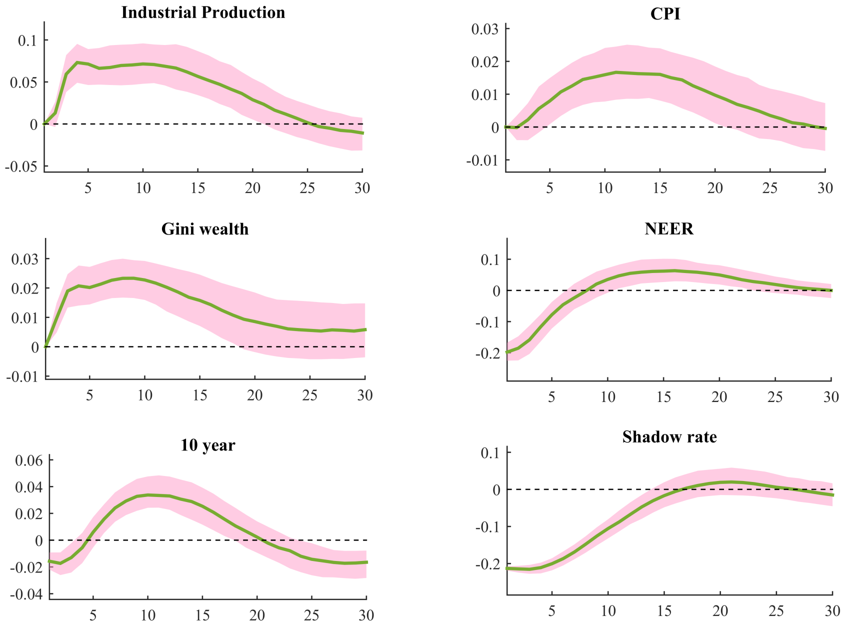


Note: The vertical axis of each plot shows the response in percent. Time intervals on the x-axis are months. The pink line is the median estimate and the green shaded area is the error band.

Additional robustness checks

We estimate an alternative version of our baseline model using by including the 10-year interest rate instead of the slope of the yield curve. As Figure H1 shows, results are largely unchanged.

Figure H1. Alternative specification with 10-year rate instead of the slope of the yield curve



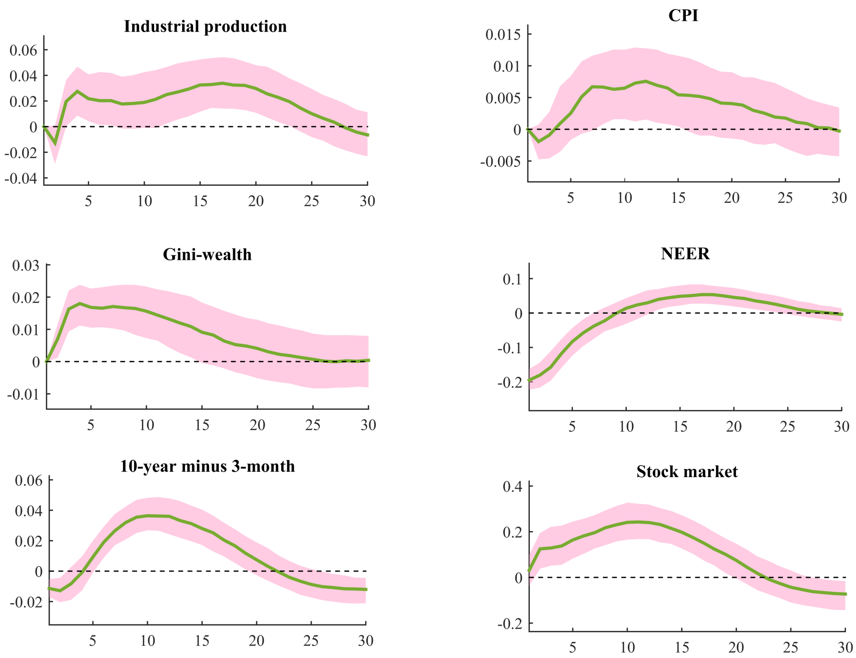
Note: The vertical axis of each plot shows the responses in percent (apart from the shadow rate that is in percentage points). Time intervals on the x-axis are months. The green line is the median estimate and the pink shaded area depicts the 68 percent error bands.

We next wish to see whether the response of wealth inequality to monetary policy shocks is not affected by the addition of an asset price indicator. For this reason, we estimate another version of our baseline by adding the UK all share index (Figure H2). The results suggest that both macro variables respond positively to the shock, as in the baseline. More importantly, we witness clear evidence that the shock leads to a significant and persistent increase of the net wealth Gini coefficient, exactly as in our baseline model.

In addition, we estimate another version of our baseline model by using the rate of unemployment instead of IP, as a proxy for the business cycle. In particular, we estimate a specification that includes: unemployment rate, CPI, 10y yield, shadow rate, NEER, Gini, the UK all share index, and the housing price index. The results are presented in Figure H3.

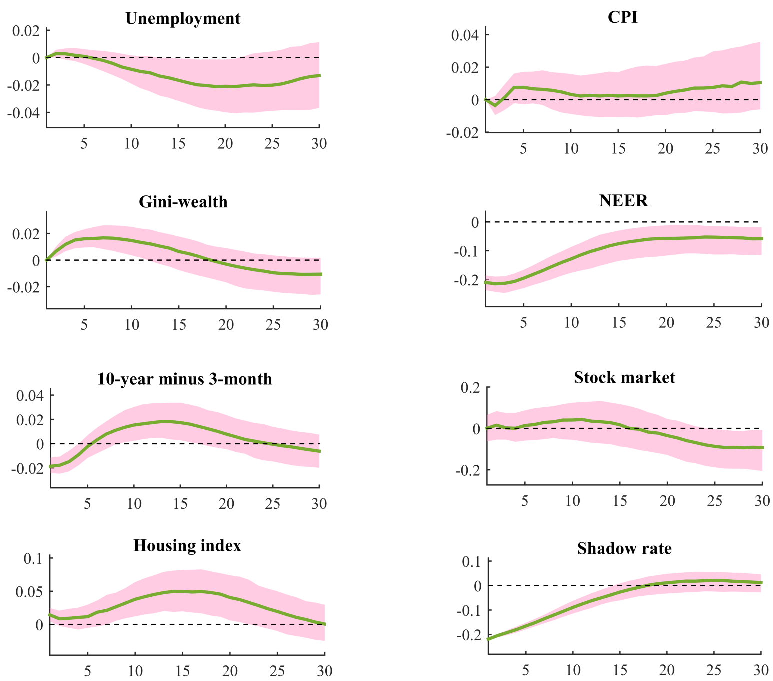
The response of the inequality measure conveys a similar message to the baseline case, as it generates a significant increase of wealth inequality. Moreover, regarding the impact of the shock on macroeconomic aggregates, as expected, the shock leads to an increase in economic activity as evidenced by the decrease in unemployment. Note, however, that the effect is not as strong and persistent as the response of IP in our baseline model, since the response of unemployment is marginally significant. For prices, while there is some evidence that inflation rises, the response remains subdued compared to our baseline, with the error bands including zero. The latter findings are in contrast to the related literature on the macroeconomic impact of asset purchases in the UK. In particular, Kapetanios et al. (2012); Baumeistera and Benati (2013); Weale and Wieladek (2016) suggest that asset purchases

Figure H2. Alternative specification with the addition of a stock market indicator



Note: The vertical axis of each plot shows the responses in percent (apart from the shadow rate that is in percentage points). Time intervals on the x-axis are months. The green line is the median estimate and the pink shaded area depicts the 68 percent error bands.

Figure H3. Alternative specification including unemployment rate instead of IP



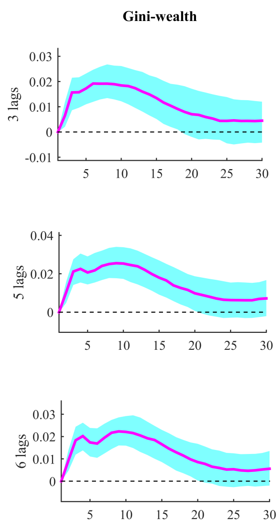
Note: The vertical axis of each plot shows the responses in percent (apart from the shadow rate that is in percentage points). Time intervals on the x-axis are months. The green line is the median estimate and the pink shaded area depicts the 68 percent error bands.

exert a powerful effect on both economic growth and inflation, and also that, without QE, economic growth would have fallen by even more during 2009, and inflation would have reached low or even negative levels. Overall, our alternative specification does not confirm the findings of the related studies (and our baseline model) that UMP has a strong impact on economic activity and prices. Thus, it is safe to assume that IP is a better proxy than unemployment rate.

Alternative lags

We check the robustness of our results by estimating alternative versions of the baseline model with a lag length of three, five, and six. Note that, as we were constrained by the relatively short sample period and the fact that we are estimating a rather large number of parameters, we did not go beyond six lags. Figure I1 depicts the results. The positive response of inequality is robust across all four prior specifications.

Figure I1. Responses of inequality to UMP shocks when alternative lags are considered



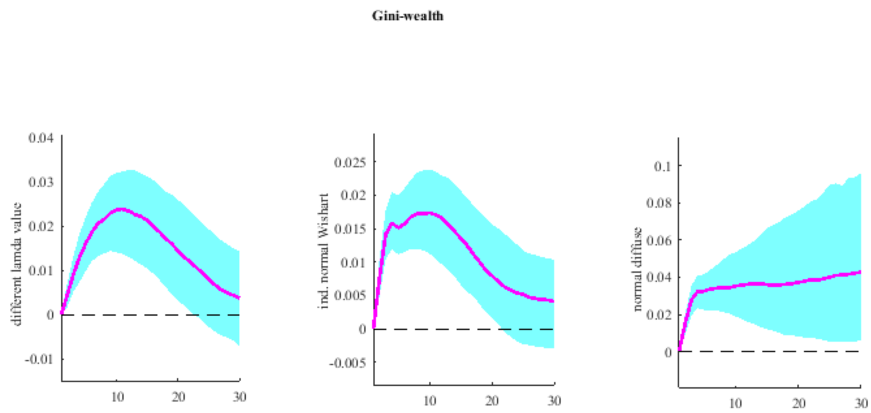
Note: The vertical axis of each plot shows the responses in percent (apart from the shadow rate that is in percentage points). Time intervals on the x-axis are months. The purple line is the median estimate and the light-blue shaded area depicts the 68 percent error bands.

Prior Sensitivity

We examine potential sensitivity of our results to prior selection by estimating three different versions of our baseline model. First, we consider λ which controls the overall tightness of the prior distribution equal to $\lambda = 2$. Our second alternative is to consider the independent normal Wishart prior. As noted by Koop and Korobilis (2010), one drawback of the natural prior is that it relies on the Kronecker structure of the prior variance covariance matrix which hinders the use of structural VAR specifications. This is because for each equation, this structure creates a dependence between the variance of the residual term and the variance of the VAR coefficients, which may be an undesirable assumption. Thus, by assuming prior independence between residual variance and coefficient variance, we can gain flexibility in the structure of the prior. Last, we impose the so-called normal-diffuse prior distribution (also called Jeffreys prior). The specificity of this prior is that it relies on a non-informative prior for the variance covariance matrix. Details on the implementation of these priors are provided in Blake and Mumtaz (2012) and Dieppe et al. (2016).

Visual inspection of J1 shows that the positive response of inequality to an UMP shock is robust across all three prior specifications. Note however that when selecting the diffuse prior, the effect is very persistent and the error bands wider. This is not surprising as it is a non-informative prior.

FIGURE J1. PRIOR SENSITIVITY

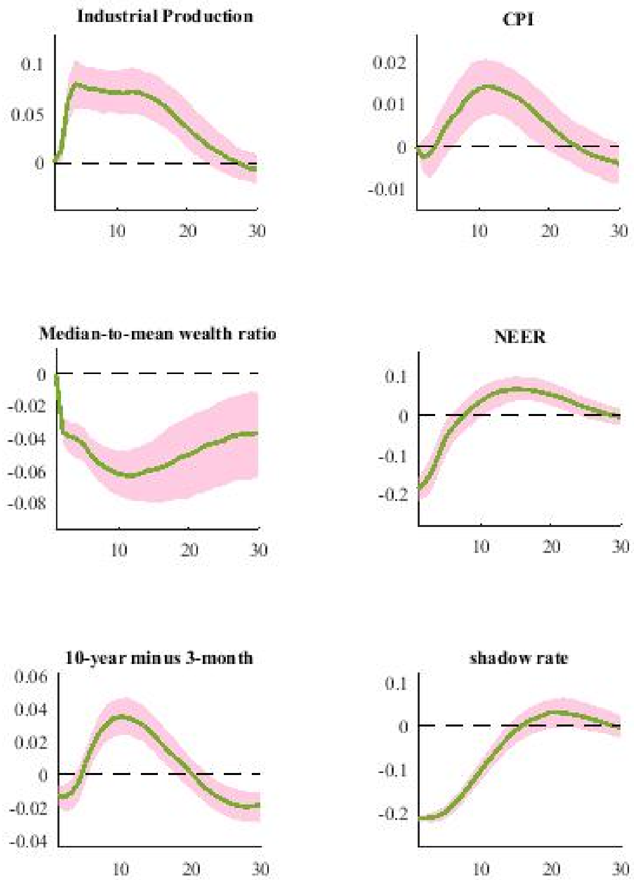


Note: The vertical axis of each plot shows the responses in percent (apart from the shadow rate that is in percentage points). Time intervals on the x-axis are months. The purple line is the median estimate and the light-blue shaded area depicts the 68 percent error bands.

ALTERNATIVE MEASURE OF INEQUALITY

We last check the robustness of our results by estimating our baseline model using the ratio of median over mean net wealth. Note that lower figures of the ratio indicate that a significant mass of people is experiencing net wealth levels that fall below the average of the sample population. Figure K1 illustrates the results. The large negative response of the median-to-mean ratio supports our initial hypothesis of UMP driving increases in wealth inequality.

FIGURE K1. ALTERNATIVE MEASURE OF WEALTH INEQUALITY



Note: The vertical axis of each plot shows the responses in percent (apart from the shadow rate that is in percentage points). Time intervals on the x-axis are months. The purple line is the median estimate and the light-blue shaded area depicts the 68 percent error bands.