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# Deleverage and Defaults in UK

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**Abstract**

This paper studies the effect of monetary policy on debt deleveraging in the United Kingdom finding that households' credit quality functions as a transmission channel for monetary policy. I use a VAR model to estimate the effect of monetary policy on household debt deleverage measuring both the response of the overall debt stock and the number of individual insolvencies. This has implications for monetary policy rules targeting financial stability. I find that a monetary tightening produces defaults. A time-varying causality test confirms that causality goes from house prices to real debt and shows that the bank rate predicts insolvencies when it is high.

JEL Codes: E52, E58

## Introduction

In the United Kingdom the number of household insolvencies has continuously risen from their post-Crisis trough in 2015, and, in 2018 the number stood as high as at 2010, close to 130,000 year-end new defaults. By the end of the same year, the real household debt stock exceeded its all time historical level previously set in 2008.[1] The Bank Rate, on the other hand, is unprecedentedly low at 0.1%. It is therefore topical to understand how a recessive monetary shock might impact financial stability in such a context.

The effect of monetary policy on financial variables has received great attention in recent works, with a number of authors arguing for a tightening of monetary policy in situations of rising house prices or rising debt [Borio and Lowe, 2011, Gambacorta and Signoretti, 2014], to '*lean against the wind*'. The advantage of such a stance appears to be particularly relevant for highly levered economies, where local policymakers might want to cool down debt accumulation and asset prices. Several empirical papers have indeed found an effect of monetary policy on debt showing a marked deleverage effect coupled with a decline in house prices [Hofmann and Peersman, 2017, Robstad, 2018, Laseen and Strid, 2018] (henceforth 'papers by HPRLS').

The aim of this paper is to extend this empirical framework to understand if the responses of personal insolvencies to a monetary policy shock warrant particular policy attention. To do so, I set up a Vector Autoregression (VAR) model akin to the ones present in the papers by HPRLS. The Hofmann and Peersman paper has investigated a panel of economies, whereas the latter two focused on Norway and Sweden respectively. Here I will concentrate on the United Kingdom. The elements of novelty of my work consist in including the number of individual insolvencies among the regressors and using an external instrument to identify the dynamic system. I highlight the role of defaults, which are only tangentially treated in the papers by HPRLS. In particular, my VAR

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[1] Data sources are in Appendix A.

analysis delivers a response on impulse of household insolvencies to a monetary shock, among to other variables common to the literature.

The first contribution of this paper is to show that households' credit quality makes up a separate channel of monetary transmission. A policy contraction produces some sudden and disorderly deleverage, thereby increasing the aggregated insolvency level. In the VAR, Insolvencies react much quicker than deleveraging and I find that a monetary tightening leads to an uptick in individual insolvencies, they peak at 2.2% after 8 quarters versus 0.36% debt reduction at the same horizon. I then conjecture that household insolvencies might be part of a *financial accelerator*-like mechanism feeding back to financial variables.

Moreover, the instrumental VAR model results also deliver policy relevant answers in regards of a flexible inflation targeting. Debt-to-GDP ratio in UK is not significantly different from zero upon a tightening and it is therefore an ineffective measure when targeting financial stability. UK Debt-to-Income ratio declines but the Granger causality test confirms that real debts are endogenous to house prices, and house prices as a policy target are the object of a vast literature.

The importance of households' credit risk in the monetary policy transmission has implications for macro-prudential policy. The HPRLS papers have generally assumed that debt deleverage would be orderly and neutral to households' credit quality. However theory [Bernanke et al., 1999] and empirical evidence suggest that more defaults happen in distressed environments. The papers by HPRLS don't reconcile this twofold aspect of debt deleverage, implicitly assuming that families either pay back their debts, stop rolling them over or renounce to take additional leverage after an interest rate tightening. Following this line of thought, a policy induced deleverage might even be desirable from a macro-prudential angle. But what if this produces more defaults?

'*Leaning against the wind*' stance postulates the use of interest rate to target financial variables, this translates into monetary policy what is a common macro-prudential principle: creating risk buffers at the cycle height to counter down swings (e.g. the Countercyclical Capital Buffer measure).[2] That raises the question of whether traditional macro-prudential policy would be better in achieving financial stability rather than interest rate policy. Given that disorderly insolvencies are an important part of the transmission of monetary policy then there is a potential welfare case for using the interest rate in lieu of other more apt instruments.

Since VAR models are sensitive to identification assumptions, I also explore various alternative sign-restriction identification schemes under a Bayesian approach in Section 4 as a robustness check. The result is that the baseline model inference continues to hold also when the shock is sign-identified.

I present the results of time-varying Granger causality tests to uncover the causal direction between two variables at the time (Section 5). Such tests identify the changing points of causal relations among variables, thereby addressing the discontinuity represented by the 2008 crisis. This Granger causality testing is performed on a reduced form version of the model, is not dependent on the modelling choices established in the first part of this paper. The policy rate Granger-causes insolvencies when it is high, ceasing to be relevant to bankruptcies from when it plummeted to 2%. House prices drive debt dynamics whilst the opposite only holds during recessions.

The paper is structured as follows: in the first section I present the literature behind household credit decisions and the transmission of monetary policy. I shall devote the second section to comparing different UK papers and how they have dealt with the identification challenge in retrieving structural innovations. My model is then presented in Section 3 with impulse response analysis. The remaining sections present the sign-restriction approach and the time-varying Granger test.

# 1 Related Literature

The concept of credit risk features prominently in the seminal theoretical literature on '*financial market frictions*'. The fact that borrowers may fail in honouring their debts provides a micro-foundation for costly-state verification Bernanke et al. [1999] and collateral constraints Kiyotaki and

[2]'*the countercyclical capital buffer regime may also help to lean against the build-up phase of the credit cycle in the first place. In downturns, the regime should help to reduce the risk that the supply of credit will be constrained by regulatory capital requirements that could undermine the performance of the real economy and result in additional credit losses in the banking system.*' BIS description of Countercyclical Capital Buffer (CCyB) (underline mine).

Moore [1997] models. These efforts have established how lenders and borrowers optimising decisions can produce stronger fluctuations in production and investments through oscillation in firms' net worth in a New-Keynesian general equilibrium context.

In real life, economy-specific structural factors such as the proportion of adjustable rates over fixed and the average loan maturity dictate whether household would either take up more debt or deleverage on the back of shorter-term attrition in lending rates and house prices. This makes the theoretical impulse response functions bounded to their own model hypotheses and represents the reason why the problem at hand has been often approached from an empirical angle.

This paper retains an applied approach and is similar in spirit and methodology to three papers developed by authors affiliated to Central Banks (HPRLS papers). The aim is to shed light on how household finance responds to tight monetary policy shock and the methodology is a Vector Autoregression analysis. In this section I will mainly focus on these three papers with an eye on a few selected general equilibrium models that have discussed a '*leaning against the wind'* stance.

As the Swedish Riksbank '*leant against the wind'* to curb house prices through targeting the private debt stock, a discussion arose regarding the trade-offs of setting monetary policy in response to asset prices and debt variables. Gambacorta and Signoretti [2014] present such framework in a DSGE environment, finding that a mixed policy rule produces greater gains in a highly leveraged economy.

An opposite conclusion appears in the theoretical framework laid by Svensson [2014] , who argued that a rule responding to household debts has little effect on the overall stock since income reacts to policy adjustment faster than debts producing recessive consequences. Hence the cost of deviating from inflation targeting is higher than the benefit as it bears a disproportionate effect on output and inflation. [3] Laseen and Strid [2018]'s paper is a direct response to Svensson [2014] and finds a strong decline in real household debts and Debt-to-GDP ratio following a tightening. The IV-VAR presented below in this paper supports this household debt dynamics with UK data, although capturing no significant movement of Debt-to-GDP ratio.

Hofmann and Peersman [2017] takes a slight different angle, hinting a *'debt service channel'* for monetary policy transmission by which interest and principal payments relative to the existing household debt stock become more onerous as lending rates increase with a monetary tightening. This makes the economies with a higher stock of household debts more prone to a deterioration on a interest rate contraction. My position is conceptually similar to theirs in arguing for a credit quality channel of monetary transmission. Not only a rate tightening impacts households' debt burden but pushes some into default. This aspect is lacking in Hofmann and Peersman [2017], who assume a benign debt deleverage, i.e. driven by principal repayments, a view generally common across HPRLS.

To summarise the literature up to this point: whilst the effect of tight monetary policy is well understood in regards of debts and house prices, there is no consensus on the gains in terms of financial stability. I therefore contribute to this debate by adopting the HPRLS VAR framework and supplement it with individual insolvencies. I also discard the Cholesky identification to avoid defending a particular recursive ordering, relying instead on an external series of shocks. Hopefully, this effort will help nuancing more the effects of a mixed policy aimed to stabilise credit aggregates.

The paper most similar to mine is Piffer [2018], who tries to reconcile the '*financial accelerator'* model [Bernanke et al., 1999] with an Instrumental VAR akin to the one proposed below. He specifically includes delinquencies in his analysis on US and investigates whether a policy easing shock causes more or less defaults. This research question stems from partial equilibrium models of the risk-taking channel of monetary transmission. In a lower interest environment, lenders may have the incentive of targeting riskier clients to increase their interest income. This may lead to a deterioration of lending portfolios and therefore the increase of non-performing loans. Piffer [2018] empirically finds that an increase in wealth dampens default. This finding is consistent with Bernanke, Gertler, and Gilchrist's DSGE model holds with positive net-worth effects prevailing over risky lending pitfalls.

Nevertheless, debt might build up in periods of relative financial quietness. A prolonged period

[3] Using a calibration for the Swedish economy.

of low inflation may be conducive to a crisis [Borio and Lowe, 2011] as supply side developments may feed into an overly positive sentiment causing lending and asset prices booms. Credible monetary policy reinforces the low risk perception and adds to the general exuberant feeling [Borio and Lowe, 2011]. The loosening of credit standards coupled with yield compression often precedes the downturn and have the potential of exacerbating the ensuing crisis. This connects back to New-Keynesian DSGE models as many credit variables are pro-cyclical as net-worth is.

DSGE models don't account directly for defaults [Goodhart and Tsomocos, 2011, Gambacorta and Signoretti, 2014] but they are a normal feature of the economic cycle [4] and they increase in crises. Household insolvencies endogenously arise from net-worth down-movements, which are reinforced by falling house prices in downturn periods. Feedback effects from banks' balance-sheet may also result in a reduced credit supply and amplify the cyclical swing. The recessive potential of a monetary policy rule that purposely reacts to credit variables deteriorating household finances is therefore still to be fully investigated.

# 2 The Identification Challenge

## 2.1 Monetary Policy in UK

In this section I briefly outline the history of monetary policy in the UK, since this is relevant for the identification of monetary policy shocks. In recent history the Bank of England (BoE) has not been bound by a single monetary rule. It targeted the money supply from 1976 to transition to the exchange rate, at first informally tracking the Deutsche Mark (1987-88) and from '89 by maintaining a floating band around a fixed basket of ECU participating currencies within the of Exchange Rate Mechanism (ERM) [King, 1997]. Following Black Wednesday and its withdrawal from the ERM, UK moved towards pure inflation targeting in October 1992. A change of monetary regime happened when the new Labour executive granted to BoE operational independence in 1997, although it did not change in the focus on inflation targeting. With the Bank of England Act of 1998, the Monetary Policy Committee (MPC) was given the responsibility of formulating monetary policy in lieu of acting on a target rate set by the Treasury. The main policy instrument is the Bank Rate but asset purchases have been performed as the Bank rate reached zero lower bound in March 2009.

Concomitantly to this policy shifting in the early '90s, the Bank of England underwent a series of structural reforms to improve the transparency of the decision making process [King, 1997]. It published its first Inflation Report in August 1993 and set a fixed calendar for MPC meetings and the publication of the relevant minutes thereafter to counter-balance Treasury's discretionality and, to the extent possible, separate the rate-setting process from the Government political agenda. The management of expectations has become a separate channel of transmission and unconventional policy gaining prominence since. From March 2009, the MPC also voted on the size of assets purchase programmes. The Central Bank adopted an additional communication lever, a *'forward guidance'* policy aimed to clearly communicate under which conditions monetary policy is to be tightened and quantitative easing modified [Dale and Talbot, 2013].

## 2.2 Identification of Exogenous UK Policy Shocks

The policy regime is not irrelevant to VAR identification and bears powerful consequences on the model-implied conclusions. Interest rate is endogenous to the state of the economy therefore to assess the impact of shocks, one would need to find interest rate developments that are plausibly exogenous. The Cholesky identification is the most used strategy in structural VARs literature but presents a number of issues that I will discuss below. Because of its properties, it has been considered unreliable to retrieve UK policy shocks. I shall outline what I mean by identification and survey alternative approaches used in the British VAR literature.

Generally, identification boils down to performing a discretionary orthogonalisation of the time-regression residuals. Such transformation is needed to interpret errors as exogenous shocks originat-

[4] As Goodhart and Tsomocos [2011] note, very seldom the repayment rate is 100%.

ing outside of the system [Sims, 1980]. This means that the researcher has to formulate and make clear some valid hypotheses to back the identification decision before estimating the VAR equations. Finding an economically suitable identification is per se a daunting task, [5] which requires careful pondering as it reflects assumptions on behaviour of the analysed economy and on causal chains linking the regressors.

A straightforward method to achieve full identification is to impose restrictions on contemporaneous reactions of macro-variables to monetary policy shock such that each variable respond to impulse with a time lag from the one ordered right before. This recursive identification is computationally inexpensive and is achieved by operating a Cholesky decomposition on the reduced for residual covariance matrix.

Such triangular system has a number of drawbacks: (1) progressive delayed reactions are difficult to defend with lower frequency data or including financial variables, which are likely to adjust simultaneously with the macro ones. (2) Cholesky-identified VARs tend to produce at times puzzling impulse response functions with results at odds with textbook theory. This may be due to the omission of forward looking variables that the Central Bank uses to inform its decision. An incorrect identification may pick up the endogenous component of interest rates, i.e. when the Monetary Authority moves the rate with a predictable rule, responding to developments in the other endogenous variables [Arias et al., 2019]. (3) when different monetary regimes coexist within the same sample, instrumenting the interest rate in a Cholesky ordering may be incorrectly identifying policy shocks [Rusnak et al., 2013].

A key difference between the papers by HPRLS and the literature regarding the UK is that the former all use a Cholesky decomposition, [6] which has been openly impugned and discarded in many of the UK papers. A reason behind that choice might be that in the British cases researchers have endeavoured to achieve, either directly or indirectly, a double goal: trace the effects of a monetary policy shock and assess the transmission mechanism over a very long sample. The need for a different identification is dictated by the length of the period analysed and the breadth of the research questions tackled, almost assuming a historical perspective. [7]

We have seen in the previous paragraph that the shift to inflation targeting is a source of discontinuity in the data. Cloyne and Hürtgen [2016] addresses that including in a VAR a novel narrative series as endogenous regressor, this means supplementing an otherwise standard system with new information. They find that the response of inflation to monetary innovations is similar if taken pre and post 1992. What changes is the volatility of exogenous shock series, which is significantly reduced arguably thanks to a more attentive steering of monetary policy by the BoE.

Ellis et al. [2014] make explicit the historical dimension of their study as they set out to deal with different policy regimes analysing a sample from 1975 to 2005. A Factor Augmented VAR model is meant to mitigate the omitted variable problem by including factors from some 350 variables the Central Banker might react to. Structural changes in UK policy making show in time-varying impulse responses, as prior to 1992 monetary policy was neutral to inflation. After that date, monetary policy gained in efficiency producing clear responses in CPI and asset prices to a monetary tightening.

Analysing an overlapping time span (1974 - 2005), Mountford [2005] finds that monetary policy accounts for a limited variation of output. Monetary policy reaction to the other variables in the VAR are thus quantitatively more important than exogenous monetary shock, hence the title of the paper is *'Leaning into the wind'*.

So we have established some econometric issues when applying VAR analysis to UK: (1) There is a clear policy change in 1992, (2) monetary policy might endogenously react to variables that are either inside or outside the VAR, (3) previous UK studies have all been concerned in disentangling actual shock from the '*systematic component*' of monetary policy (as defined in Gerko and Rey [2017]).

[5]'*The number of structural VARs is limited only by the inventiveness of the researcher*' [Stock and Watson, 2001]. Indeed, many different identifications have been proposed so far, such as sign or long run restrictions". For a survey see Ramey [2016]

[6]Although Robstad [2018] also proposes an alternative sign restriction identification and different Cholesky ordering.

[7]A tabular summary of key cited studies is presented in Appendix B with a comparison of their research questions and sample periods.

My approach differ from the historical one, as I am estimating a VAR on a circumscribed time period, broadly coinciding with BoE reforms on adopting an inflation targeting. Nevertheless, the IV-VAR is apt to produce more reliable results with low-frequency data as opposed to a Cholesky decomposition, as it allows to disregard a battery of rather mechanical assumptions about the system ordering.

Gerko and Rey [2017] and Cesa-Bianchi et al. [2020] articles are more recent and they translate to the UK the Instrumental VAR methodology that I shall describe in the next paragraph and use for my analysis. Gerko and Rey [2017] finds a significant price and production puzzles when applying the Cholesky identification to 1982-2015 data which an instrumental identification mitigates. In that instance, a monetary tightening is neutral to RPIX and Industrial Production and drives up lending spreads. That weak response might again be due to the length of sample and policy heterogeneity. The significant pass-trough of the interest rate shock on corporate and mortgage spreads is shared with Cesa-Bianchi et al. [2020], who in turn find a significant decrease in economic activity measured by a rise in unemployment.

# 3 The Instrumental Vector Autoregression Approach

## 3.1 The Model

The model is an Instrumental Vector Autoregression (VAR-IV). Since monetary policy might be endogenous to the other variables, I use an external instrument to identify the interest rate equation. Following this stream of empirical research, I identify the shock using an index of daily surprises on the Sterling Deposit Future adopting the approach pioneered by Gertler and Karadi [2015] and Mertens and Ravn [2013], although with lower frequency data and applied to UK variables.

High frequency identification aims to isolate exogenous shocks which are not connected to the other time series in the VAR [Ramey, 2016]. To do so we need firstly a reduced form VAR that takes the following shape:

$$y_t = C + \sum_{j=1}^{p} \underbrace{A_p}_{B_0^{-1}B_j} y_{t-j} + \underbrace{u_t}_{B_0^{-1}w_t} \tag{1}$$

And then we need identifying restriction on the matrix $B_0^{-1}$ to retrieve the monetary policy shocks. Here an instrument $Z$ respecting the following conditions comes handy:

$$\mathbf{E}[Z_t w_t^{p'}] = \phi \tag{2}$$

$$\mathbf{E}[Z_t w_t^{q'}] = 0 \tag{3}$$

Z must be correlated to monetary policy shocks $w_t^{p'}$ and uncorrelated to the other structural shocks $w_t^{q'}$.

So, as in Mertens and Ravn [2013] and Gertler and Karadi [2015], I proceeded estimating a two stage regression (TSLS) following these steps:

1. Retrieve the error $u_t$ from the reduced form representation.

2. Compute the following regression $u_t^p = a + xZ_t + e$, of which fitted values are $\hat{u_t^p}$.

3. Estimate $u_t^q = \frac{s^q}{s^p}\hat{u_t^p} + \xi$.

Where the first stage isolates the exogenous part dependant on the instrument $Z_t$ and the second stage yields an estimate of the ratio $u_t^q = \frac{s^q}{s^p}$. The separated $s^q$ and $s^q$ can be obtained from partitioning of the structural coefficients matrix $B$ and covariance matrix $\Sigma$ given the restrictions $\Sigma = \mathrm{B}_0^{-1}\mathrm{B}_0^{-1'}$ and $u_t^q = \frac{s^q}{s^p}$.

$$B_0^{-1} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \qquad \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix} \tag{4}$$

Were $\beta_{11}$ and $\Sigma_{11}$ are $k \times k$ instruments used (here a scalar) and $\beta_{21}$ and $\Sigma_{21}$ are then $k \times (n-k)$. The identification is thus provided by the closed form solution firstly derived by Mertens and Ravn [2013].

$$\beta_{21}\beta_{11}' = \frac{s^q}{s^p} \tag{5}$$

$$\beta_{12}\beta_{12}' = (\Sigma_{21} - \frac{\beta_{21}}{\beta_{11}})'Q^{-1}(\Sigma_{21} - \frac{\beta_{21}}{\beta_{11}}\Sigma_{11}) \tag{6}$$

$$Q = \frac{\beta_{21}}{\beta_{11}}\Sigma_{11}\frac{\beta_{21}'}{\beta_{11}} - (\Sigma_{21}\frac{\beta_{21}'}{\beta_{11}} + \beta_{21}\beta_{11}\Sigma_{21}') + \Sigma_{22} \tag{7}$$

$$\beta_{11}\beta_{11}' = \Sigma_{11} - \beta_{12}\beta_{12}' \tag{8}$$

The first column of $\Sigma$ can then be used to compute the impulse response functions for the monetary policy shock. Reduced coefficient estimates are reported in Appendix **??**.

### 3.2 Stationarity and Data

In my baseline VAR specification I use UK Bank Rate, GDP, GDP Deflator, House Prices, Real Household Debt, Individual Insolvencies in this order. Data are taken in log-levels and are quarterly, spanning from Q1 1987 to Q4 2018 for a total of 128 data points.[8] An element that differences the present work from previous UK studies and the papers by HPRLS is the inclusion of Individual Insolvencies, which are compiled by the UK Insolvency Service and composed of Individual Voluntary Arrangements, Debt Relief Orders and Bankruptcies. Real debt series comes from ONS' Households Loans series, which includes secured debt (mortgages and equity releases) and unsecured debt (as credit cards and student loans). House Prices series is the UK average house price. This series follows exactly the same dynamics of the house price index, which is calculated normalising the average house price, and has the advantage of being measured in GBP.

I include 2 lags in accordance with the Bayesian Information Criterion (BIC), which is both consistent and parsimonious in the lag selection. The VAR system is stationary being the eigenvalues of the companion-form matrix outside the unit circle.

Cheng et al. [2019] deal with potential non-stationarity of series in a IV-VAR estimation finding that for the estimated coefficient the error is '*asymptotically negligible*'. In presence of non-stationarity, IRFs are asymptotically normal with the covariance matrix depending on the persistence of each series. Cheng et al. [2019] hence derive a GMM estimator for IRFs with an optimal weighting matrix based on a consistent covariance estimator which enables the computation of IRFs that are robust to non-stationarity of regressors. I've used that method to derive non-stationarity robust IRFs as part of my robustness checks (reported in Appendix D.3).

The external instrument $Z_t$ I use to pin down the exogenous component of reduced form residuals spans from 1997 to the end of the sample. It is calculated around specific monetary policy events from a handpicked dataset. In accordance with the literature, my dataset of policy events includes three macro-categories of BoE appointments: announcements, MPC Minutes disclosures and Inflation Report publication.

Monetary policy is announced roughly every six weeks by BoE and the MPC meeting minutes are disclosed on the following day. In terms of communication, BoE has been publishing the Inflation Report since August 1993 and the minutes of monthly MPC meetings since August 1996 no later than six weeks after the meeting (two weeks from 1998). From 2015 MPC minutes Inflation Report

[8]Sources and Charts are reported in Appendix A.

and have been disclosed on the meeting day. In November 2019, the Infation Report changed name into Monetary Policy Report and now carries more background information on the overall economic conditions underpinning the monetary policy decision.

### 3.3 The Instrument

Following the existing high-frequency IV-VAR literature on UK Cesa-Bianchi et al. [2020], Gerko and Rey [2017], I use the ICE LIFFE Three Month Sterling (Short) Future.[9] This future contract captures the three-month ahead interest rate and thus is a forward looking measure of interest rate surprises. According to papers mentioned, the instrument can capture the surprises associated with unconventional monetary as the publication of Inflation Reports and MPC Minutes update the expectations of the public with fresh information on the state of the economy and on what motivated the policy decision [Gerko and Rey, 2017].

The instrument is then calculated as follows:

$$Z_t^{daily} = -(P_{t,\tau+1}^{daily} - P_{t,\tau}^{daily}) \tag{9}$$

Since the Sterling Future is quoted at discount ($P_t = 100 - InterestRate$), the minus sign before the parentheses in Equation 9 denotes that positive monetary surprises corresponds to an increase in the interest rate. The subscript $\tau$ is the day of the relevant policy event and $\tau+1$ is the day after.

In their paper Cesa-Bianchi et al. calls their surprise index 'daily' or 'high frequency', whereas here I reserved the label 'daily' to my indicator. [Cesa-Bianchi et al., 2020] it is more of a 'trading time' indicator, being constructed on a database of tick-by-tick data around monetary policy events (exactly 10 minutes before and 20 after). My indicator uses the daily difference in settlement prices for that derivative contract, thus it constitutes a lower frequency instrument than what is normally used in the literature. The contract settles at 11.00 a.m. therefore daily differences capture the money surprises as the announcement is disclosed at 12.00 a.m.

My first-stage regression (See 2) displays a F-Statistic (1,85) of 41.56 and R-squared is 0.32, meaning that the instrument is a strong one. These results exceed the 10 F-Statistic threshold Stock and Yogo [2005] a rule of thumb under which the power of the instrument is deemed weak.[10]

Similarly to Gertler and Karadi [2015], I derived a monthly and quarterly series by cumulating and differencing the rough surprises series in the following fashion:

1. I've calculated the daily surprise in Eq. 9 as at the days in which took place a relevant policy making decision (meaning monetary policy committee announcements, minutes or inflation report disclosures),
2. I cumulated them and
3. took a 31 days rolling average.

The monthly indicator is then the end of month first difference of the series obtained with step (3). Similarly, the quarterly surprises series that I've used as an external instrument in my baseline specification took a 3-period sum of monthly surprises.

Figure 1 represents the three instrumental variables side by side both in their monthly formulation (top pane) and quarterly aggregated (bottom pane). In Cesa-Bianchi et al. [2020], the largest surprise is the one associated with the interest rate cut from 5% to 0.5% from September 2008 to March 2009. Gerko and Rey [2017] choose to omit policy rate announcements from their dataset. This is because they think that announcement press releases don't provide any new information due to their brevity.

In this paper I include base rate announcements and, due to these differences, my monthly surprise series is closer to the Cesa-Bianchi et al. one, though being more volatile. Monetary

[9] Intercontinental Exchange Website.

[10] I have used Gerko and Rey [2017] and Cesa-Bianchi et al. [2020] instrument in my baseline specification finding that the former is not a useful measure in my context [F-stat(1,69) = 0.63, $R^2 = 0.01$], whereas the latter makes a strong instrument [F-stat(1,70) = 21.74, $R^2 = 0.24$].

'surprises' that are only present in my dataset are in March and May 2018, when the market started to price July 2018 tightening, updating its expectation thanks to policy's forward guidance. In general, I detect a slight increase in volatility from 2017 probably due to general markets' expectations of an upcoming policy normalisation after an extended period of low interest rate and the Brexit vote induced rate cut of 2016.

**Figure 1:** UK Money Surprises

I derived a daily frequency indicator of monetary surprise as in Cesa-Bianchi et al. [2020] (solid blue line). In my case money surprise is the change in price for a 3-month sterling derivative future during the day of a monetary policy announcement.


### 3.3.1 Instrument Robustness

Cesa-Bianchi et al. [2020] propose a Sargan-Hansen over-identification test to control for non-monetary information potentially 'contaminating' the instrument. Under the null hypothesis there is no correlation between instruments and reduced form residuals (i.e. the instruments are both valid). Since this statistical testing strategy requires more instruments than endogenous variables, I then leverage on the Cesa-Bianchi et al. [2020] dataset using their high frequency indicator alongside with Cloyne and Hürtgen [2016] narrative series as joint excluded instruments (quarterly re-sampled).

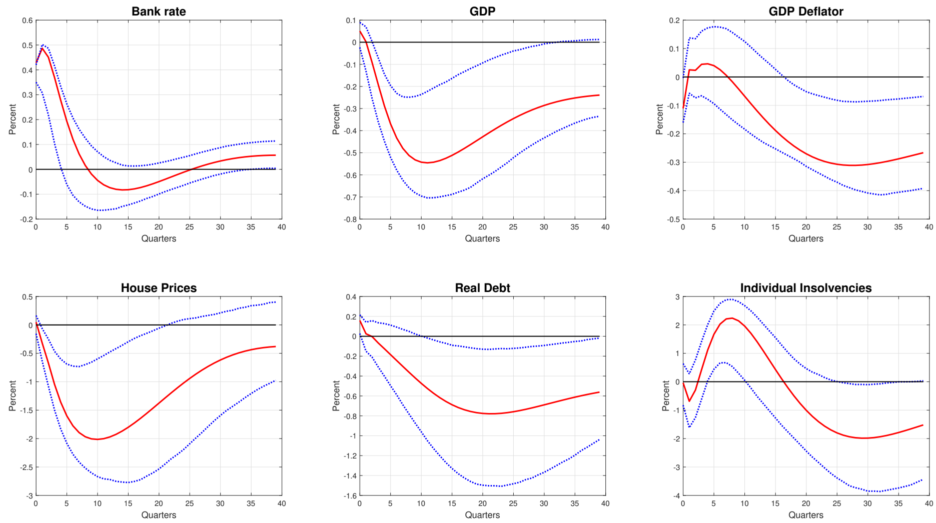
I perform this test twice, coupling my baseline instrument separately with both the externally available series. In both cases I cannot reject the null hypothesis with 0.01 significance level, concluding that the daily instrument derived in the above section is apt to identify the exogenous monetary shocks. This result is particularly important when using the Cloyne and Hürtgen series, which is based on a narrative approach and explicitly excludes other factors influencing monetary policy [Cesa-Bianchi et al., 2020].

To further gauge the robustness of my baseline model, I have tried a variety of instruments as alternatives to the bank rate either in the VAR or as excluded instruments for monetary policy surprises. These instruments include: the 5, 10 and 20 years UK ZCB rates, 3 month, 2, 5 and 10 years nominal par yields, the 3 months Libor swap rate and 3 months GBP/USD forward rate. Shorter rates produce similar results, with lower first stage statistics than the combination of policy rate and instrument I end up using in the baseline model.

## 3.4 Impulse Response Functions

**Figure 2:** Structural Impulse Responses of the Baseline IV-VAR(2) model on UK Data.

Solid line represents point estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times




The purpose of this section is to trace the effects of a monetary tightening - a one standard deviation monetary surprise - to the six variables in the dynamic system, providing intuition for the different channels at play (Figure 2). Confidence bands are derived using a wild bootstrap method as originally proposed in Gonçalves and Kilian [2004] and later widely adopted in the IV-VAR literature (e.g. Mertens and Ravn [2013], Gertler and Karadi [2015]).

The responses on a monetary impulse of GDP and inflation are consistent with textbook macro-models, with a rate hike reducing investments and price level on the back off demand-side developments. If seen through DSGE lenses [11], house prices and real debt responses are conditioned by frictions in the provision of credit, supporting the institutional views (as in HPRLS) that a money tightening impacts house prices and real debts.

The decrease in house prices and real debt may be due to 'accelerator-like' dynamics that involves on one hand an increase in the cost of borrowing, and the opportunity cost of lending vis-à-vis the higher base rate, and on the other hand the households' net worth. This mechanism is captured in theoretical models [Bernanke et al., 1999] and it is self-reinforcing as a contraction depresses current period investments having lasting effects on the future price of capital, further dampening investments and net worth. This puts strains on the availability of external finance beside debt-servicing costs, as households are likely to pledge housing properties as collateral when entering into recourse debt contracts. Hence the fall in house prices leads to a fall in real debt. This amplification mechanism feeds into consumption and output, exacerbating the downturn.

Insolvencies are anti-cyclical, increasing in downturns and tapering in benign periods across the business cycle. Qualitatively, the hump-shaped response I obtain of insolvencies to a recessive shock is consistent with Bernanke et al. [1999]. As per their model, defaults are rising following a decrease in capital, here represented by housing. Capital acquisition is proportional to net worth, so a shock that reduces the return to capital transmits to wealth and raises the default probability. Insolvencies are highly correlated with the unemployment rate (excluded from the baseline VAR) as they are

[11] Piffer [2018] retained a similar approach comparing his VAR findings with general equilibrium models featuring financial market imperfections.

connected to the level of economic activity.

My VAR specification features a decrease in GDP, house prices and debts. Both in the Cholesky specification (Appendix D.1) and in the instrumental variable approach, insolvencies are rising following a monetary policy shock (within a 90% confidence interval). The Cholesky decomposition does not yield any counter-intuitive puzzling response in that case, just a stronger and more persistent positive response in the GDP Deflator, otherwise being qualitatively consistent with the IV-VAR.

Shock's contractionary effects on real GDP and house prices persist after as many as more than 30 quarters. The decline in house prices is somehow comparable to what has been found by Robstad [2018] whereas debt deleverage dynamic is stronger in terms of magnitude and more persistent. It shows the through after 20 quarters with signs of recovery thereafter, but after 40 quarters it is still significantly below zero. The GDP deflator response is somewhat weak in the aftermath of the policy decision and becomes significantly negative after 17 quarters.

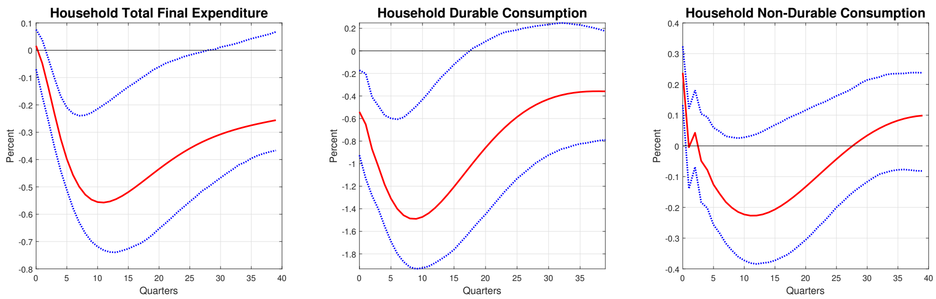
House prices response starts very close to zero, highlighting that even without a strict zero restriction, there is no contemporaneous reaction to a monetary policy shock. Individual Insolvencies show a significant uptick before the tenth quarter, with a peak at 2.2% 8 quarters after the fundamental shock. They fully revert to zero prior to the twentieth quarter after the shock and then are significantly below null at a 90% significance level.

In Figure 3 I plot the effect of a monetary policy shock to key consumption aggregate series, individually substituting them to GDP in the baseline model. Household Total Final Expenditure (consumption) quickly decreases from a near zero response at the time of the shock. Durable consumption (house goods, vehicles) instantaneously falls by -0.5%, when non-durable consumption (food, drinks) spikes at time 0 to decay to nil within the first quarter. This illustration may offer a view on an accelerator-like effect on the transmission mechanism involving household debt and insolvencies appearing in the data. There is a quick and persistent demand side reduction of investment and consumption upon a tightening. Hence insolvency may happen on the back of a reduction in collateral value and tighter borrowing constraints. This finding is consistent the Monacelli's DSGE model, which attributes the slump in durable consumption to collateral constrains becoming tighter after a rate hike.

The policy takeaway is therefore that insolvencies play a role in the monetary transmission mechanism as an exogenous tightening has sizable short run effects on the level of defaults, causing their surge in the immediate wake of the relevant decision. Real debts show a sluggish response, arriving at their lowest level much slower than delinquencies. By the time defaults arrive at their peak in 8 quarters, debt has reduced only by 0.36%. The response on impulse of insolvencies is hump-shaped and becomes significantly negative after its spike, signalling that tight monetary policy can achieve a modicum of financial stabilisation in the longer-run.

**Figure 3:** Structural Impulse Responses of Consumption Aggregates in an IV-VAR(2) model on UK Data.

The figure represents the response of impulse of consumption aggregates when individually substituted to GDP in the baseline VAR. Solid line represents point estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times



### 3.4.1 Policy Relevance and Comparison with papers by HPRLS

My results regarding house prices and debt are broadly comparable with the papers by HPRLS (Table 1), which have made use of the same regressor in spite of the different countries in analysis. It shows however a stronger response of both variables on inpulse. This may be due to the different identification strategy, which here pins down exogenous shocks with the help of an external instrument.

One of the reasons behind the empirical modelling in researching the matter at hand, is the lack of agreement on what the theoretical response of debts is on a shock. Svensson argued through a DSGE example that in Sweden the Debt-to-Income response to a policy tightening can be positive because of the short tenor of loans and the low prepayment rate [Svensson, 2014] and the same applies to Debt-to-GDP. In some cases, DSGE models that are assessing the benefits of a '*leaning against the wind*' policy stance are also ambiguous on stating the costs [Svensson, 2017].

I have controlled other potential policy targets in the VAR by substitution Real Debt (Appendix D.4) with alternative regressors. Tight monetary policy does not result in a meaningful change of the Debt-to-GDP ratio, which appears to raise following a tightening shock but is never significantly different from zero. This result is shared with Robstad [2018] and contradicts Laseen and Strid [2018].

When used in my specification, Debt-to-Income ratio follows an undetermined path up to the sixteenth quarter and then is briefly significantly negative (Appendix D.5). A Granger-causality test highlights that the causality relation goes from house prices to debt and therefore Debt-to-Income as monetary policy target might work indirectly through the steering of real-estate prices.[12]

A specification more similar to Cesa-Bianchi et al. [2020] is presented in Appendix D.6. It includes unemployment as a measure of economic activity and mortgage and corporate rates beside the other variables from the baseline model. This specification is insightful in highlighting the policy rate close to 1-to-1 pass-through on the quoted household mortgage after two quarters since the shock, whereas the corporate rate response is weaker and noisier. In all cases insolvencies respond similarly than the baseline model.

**Table 1:** Comparison with Previous Studies

Peak Response to a standard deviation (or 1%, when marked with an asterisk) monetary policy shock on House Prices and Real Debt. From papers' text body and visual inspection of impulse response charts.

| Authors | Country | Method | Identification | Peak House Prices Response | Peak Debt Response |
|---|---|---|---|---|---|
| Laseen and Strid [2018] | Sweden | Bayesian (Litterman Prior) | Recursive | -0.20% | -0.20% |
| Robstad [2018] | Norway | Bayesian (Inverse Wishart Prior) | Recursive | -3.00%* | -1.00%* |
| Hofmann and Peersman [2017] | Across Panel | OLS | Recursive | -1.70%* | -1.20%* |
| Mario Lupoli | UK | OLS | Daily Frequency | -2.00% | -0.77% |

### 3.4.2 Monetary Policy and Information Shocks [13]

A key consideration for the success of the instrumental identification is that the instrument is uncorrelated with shocks in variables other than the one directly instrumented (Eq. 2 and 3). In this paper the risk of a spurious identification is greater than in the rest of the literature due to the reliance on daily surprises, an indicator sampled at a lower frequency than trading time.

I address this concern through two separate interventions: I sign-identify a pure monetary shock using the Jarociński and Karadi [2020] method and I test the instrument relevance with a Sargan-Hansen over-identification test (see above, in Section 3.3.1).

Jarociński and Karadi [2020] devised an empirical strategy to identify the information shocks and separate it from the pure monetary one. The methodology exploits two high frequency series: monetary surprises and stock prices surprises, but instead of using them as excluded instruments,

[12] Whereas it can be directly impacted by macroprudential policy as in the form of LTV ratios or capital adequacy requirements.

[13] I thank the referees for suggesting me this identification scheme.

they are included as endogenous variables in a Bayesian VAR. The system is then sign-identified by imposing ex-post restrictions on impulse response functions.

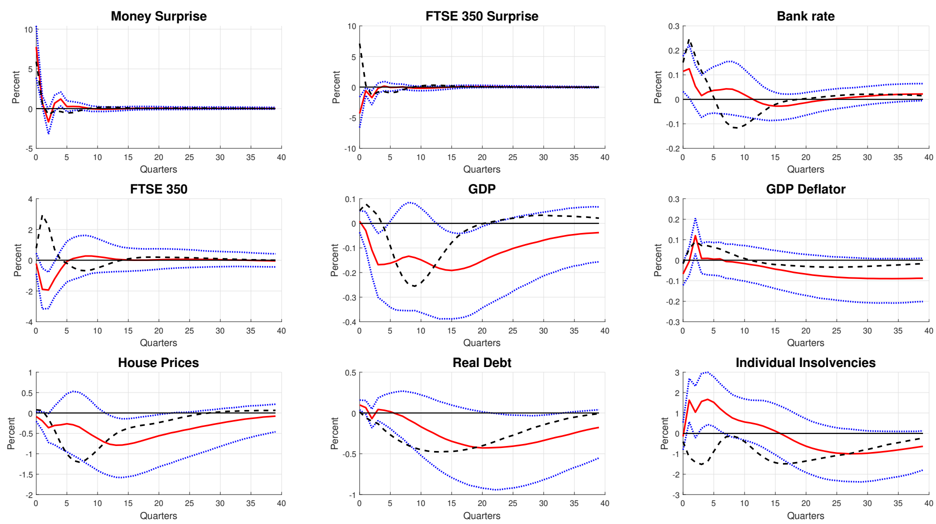
Here, the inclusion of stock market surprises is fundamental to separate two different shocks. Stock market surprises are deemed to move in the same direction of money surprises following an information shock, i.e. when the Central Bank discloses additional positive information about the state of the economy together with a monetary policy decision. In the case of a pure monetary shock, the stock market surprises will move oppositely to money surprise.

In practice, I enforce a sign restriction scheme which allows only the two high-frequency indicators to move simultaneously and I impose zero restrictions to the contemporaneous response of other variables (exactly as in Jarociński and Karadi [2020]). This identification is based on the block recursive scheme presented below in Section 4. I calculated the surprises in the daily FTSE 350 Index around monetary policy decisions in the same way I computed money surprises (Section 3.3).

In Figure 4 I compare the monetary policy shock to the positive information shock. This alternative identification strategy is instrumental to provide a qualitative benchmark to my baseline IV-VAR. A pure monetary shock continues to produce insolvencies even under these stricter identification assumptions. Defaults are more front-loaded than in the baseline instrumental identification, peaking after 5 quarters. This continues to suggest that pure monetary surprises are relevant to households' credit quality.

The caveat here is that this exactly identified scheme is based on stronger identification assumptions than the baseline IV-VAR as it is a mix of sign and zero restrictions. Also, in order to use the derivative high frequency instruments as endogenous variables in the VAR, I throw away their missing values, effectively running this VAR on a subset of 87 observations, making the inference less stable.

**Figure 4:** Structural Impulse Responses of a sign-restricted block recursively-identified VAR(2) model on UK Data identified as in Jarociński and Karadi [2020]. The solid line represents the median response and dotted lines are the 68% percentile bands associated with the Monetary Policy Shock. Dashed line is the median response to the Information Shock.




## 4 Robustness Check: Sign Restrictions

As a robustness check for the instrument identified VAR presented in Section 3, I considered a sign identification, as pioneered by Uhlig [2005] and applied to UK data by Mountford [2005].

This specification can achieve an identification of the monetary policy shock by restricting impulse responses to be either a positive or negative for a number of periods after the shock. This eliminates puzzles by construction producing impulse responses that can be matching the textbook knowledge of what the consequence of a shock qualitative is.

## 4.1 The Bayesian VAR Model

Consider a VAR model as in Eq. 1:

$$y_t = C + A_1 y_{t_1} + A_2 y_{t_2} + ... + A_p y_{t_p} + u_t \tag{10}$$

In which $u_t \sim N(0, \Sigma_u)$. It can be re-written in a compact form of:

$$y = X\beta + U \tag{11}$$

Were $X = (I_n \otimes X)$ and $\beta = vec(A_1, A_2, ..., A_p, C)$. The VAR model is estimated through a Bayesian approach. The Bayes theorem enables us to approximate the posterior density given a sampling distribution and prior beliefs. In particular, the chosen prior is the Inverse-Wishart, the conjugate of the multivariate normal covariance matrix:

$$\beta|\Sigma_u \sim \quad \text{i.i.d.} \quad N(\beta, \Sigma_u \otimes \beta) \tag{12}$$

and

$$\Sigma_u \sim IW(\Psi, \upsilon) \tag{13}$$

The Inverse-Wishart is an informative prior parametrised by a semi-definite $\Psi$ matrix and $\upsilon$ degrees of freedom. The conjugacy implies a posterior distribution of the same family of the prior allowing simpler estimation of the parameters.

## 4.2 The Structural Form

The VAR model in Equation (10) is a reduced form of a model where $A_i = B_0^{-1} B_i$ and the model errors are a weighted average of structural shocks $u_t = B_0^{-1} w_t$, as in the underbrace of Eq. 1.

Differently from the case illustrated above, the Bayesian setting entails embracing a priori beliefs on the parameters of $B_0$ [Miranda-Agrippino and Ricco, 2018] as the selected prior is informative.

I've tried different forms of identification in order to recover the structural monetary shock, belonging to the following categories:

1. Partial Identification;
2. Exact Identification.

The first identification procedure doesn't attempt to identify all structural shocks but only a monetary policy one. Conversely, other identification schemes do by means of exact identification of the system. In both cases a mix of sign and exclusion restrictions is imposed over the parameters of $B_0^{-1}$ to overcome any potential counter-intuitive response to monetary shocks, the 'price puzzle'.

## 4.3 Partial Identification

According to Uhlig [2017] a useful heuristic to verify the reasonableness of restrictions by only imposing restrictions justifiable by textbook economic theory and remain 'agnostic' on the variables which response to a shock is to be investigated.

So the first sign-restiction specification that I've tried is the most parsimonious one, in the spirit of Uhlig [2005]. I only try to retrieve the first vector of the covariance matrix imposing three restrictions to the structural policy shock, which I'm interested in identifying. As a benchmark for using sign restrictions to control a VAR, I've used the recent paper by Cantore et al. [2020], which has the advantage of establishing straightforward sign-identification rules for a monetary policy shock with the aim of imposing as few restrictions as possible and to do so in accordance with known macro-models. I deem a monetary policy shock to:

- interest rate increases upon a monetary shock;
- decrease of GDP upon a monetary shock;
- decrease of the GDP deflator upon a monetary shock;

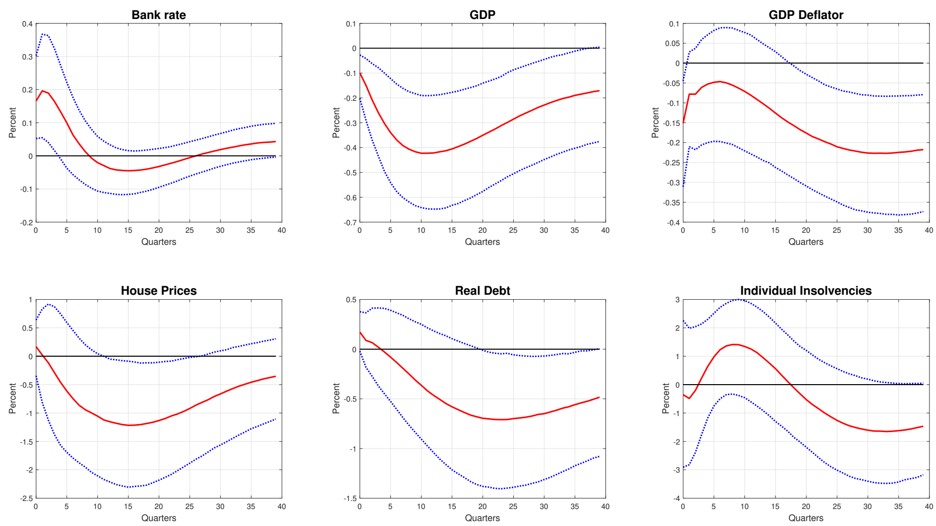
In this case restrictions on the covariance matrix $\Sigma$ have the form:

$$\begin{pmatrix} u^{IR} \\ u^{GDP} \\ u^{Defl} \\ u^{HP} \\ u^{Debts} \\ u^{Ins} \end{pmatrix} = \begin{array}{c} \begin{array}{cccccc} w_m & w_y & w_3 & w_4 & w_5 & w_6 \end{array} \\ \begin{bmatrix} + & * & * & * & * & * \\ - & * & * & * & * & * \\ - & * & * & * & * & * \\ * & * & * & * & * & * \\ * & * & * & * & * & * \\ * & * & * & * & * & * \end{bmatrix} \end{array} \tag{14}$$

where the asterisk denotes unrestricted coefficients and the $+/-$ signs indicate the restricted direction on a shock impact. As a difference with Cantore et al. [2020], I don't impose sign restrictions up to the second time-period, only limiting the contemporaneous responses, hence being more sparing with the number of assumptions. Throughout this section and the next I have used Arias et al. [2014] algorithms rather than the Uhlig [2005]'s ones. The former are based on finding an orthogonal rotation matrix through the QR decomposition of a randomly generated matrix of normal numbers, which have the uniform Haar distribution. The impulse responses are shown in Figure 5.

**Figure 5:** Structural Impulse Responses of a sign-restricted identified VAR(2) model on UK Data.

The solid line represents the median response and dotted lines are the 68% percentile bands.




The impulse response functions are not very informative. Whilst maintaining a similar shape to the IV-VAR they are weaker, displaying very wide posterior density percentile bands. To correct that specification and to improve the shock retrieval, I've used the approach of Arias et al. [2019] in imposing restrictions on the '*systematic component*' of monetary policy.

This identification has the benefit of only restricting the interest rate equation of the VAR system and boils down to two sets of restrictions:

1. The interest rate only contemporaneously responds to GDP and price level;

2. The contemporaneous response of interest rate to GDP and price level is positive.

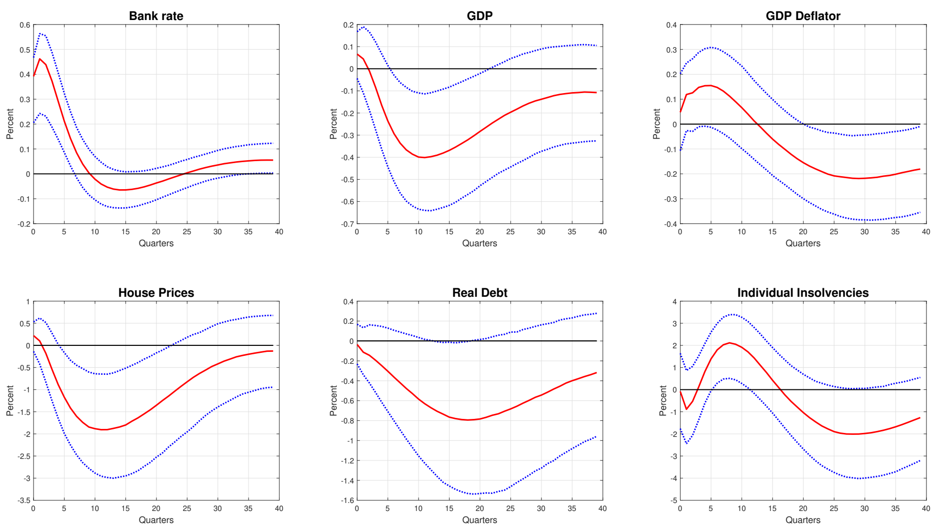
The Restriction (1) allows the interest rate setting process to be consistent with a standard Taylor Rule and Restriction (2) captures the endogenous component of a given policy decision, i.e. the Central Bank hikes the rate simultaneously to an increase of output and prices. An important feature of this approaches is that it does not force GDP and Deflator to be negative at a given horizon, but pins down their response in assuming to what aggregates the Central Bank reacts to.

This identification scheme yields clearer IRFs that are again similar to the baseline IV-VAR model (in Figure 6). GDP, House Prices are immediately declining, whereas the Deflator is significantly negative on the longer term. Insolvencies show a short-term hump, increasing to the 2% on impulse, falling in the same ballpark as in the unrestricted baseline IV-VAR. The covariance matrix presents in this case three zero restrictions (0 in the scheme below - as per restriction 1), as the interest rate is deemed not to react to house prices, debts and insolvencies within the same period.

$$\begin{pmatrix} u^{IR} \\ u^{GDP} \\ u^{Defl} \\ u^{HP} \\ u^{Debts} \\ u^{Ins} \end{pmatrix} = \begin{array}{c} \begin{array}{cccccc} w_m & w_y & w_3 & w_4 & w_5 & w_6 \end{array} \\ \begin{bmatrix} + & + & + & 0 & 0 & 0 \\ * & * & * & * & * & * \\ * & * & * & * & * & * \\ * & * & * & * & * & * \\ * & * & * & * & * & * \\ * & * & * & * & * & * \end{bmatrix} \end{array} \tag{15}$$

**Figure 6:** Structural Impulse Responses of a restricted identified VAR(2) model on UK Data identifying the systematic component of policy.

The solid line represents the median response and dotted lines are the 68% percentile bands.




## 4.4 Exact Identification

The second battery of sign restrictions hinges on exactly identifying the whole model imposing $n \times (n-1)/2$ restrictions on the structural impact matrix in order to recover the structural shocks that are not a linear combination of others.

In the discussion on the Cholesky decomposition above, we have seen that the recursive restriction pattern holds justifiable under an economic standpoint as it is seen as a way to establish a causal chain among variables. In this section I have used the same ordering as in Section 3 to implement sign-restrictions in two different recursive systems.

The first one is a standard Cholesky system, with $\Sigma$ upper triangular. It revolves around the standard assumption that the variables are affected by a monetary policy shock according to their ordering, in this case: GDP, inflation rate, house prices and then follow real debts and insolvencies. Sign restrictions are imposed up to the second period of the impulse response function.[14]

The second identification scheme provides a block-recursive identification, the variables are grouped in two separate blocks. The first $3 \times 3$ block represents the main macroeconomic variables ordered as stated at the beginning of this section. Last three variables constitutes the household debt market. The second block variables' shocks don't feed into the first block macroeconomic aggregates meaning that they don't have a contemporaneous effect on the first block. The relevant impulse responses are shown in Figure 7.

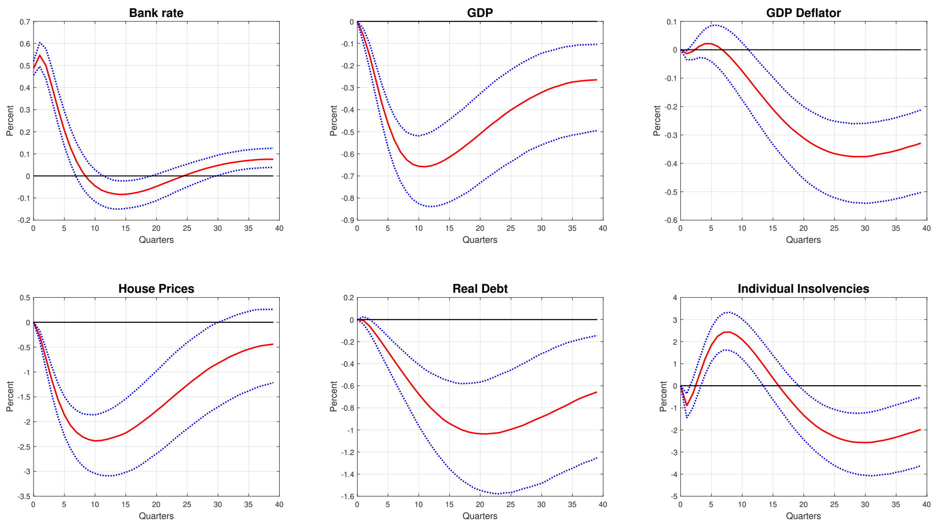
This intuition behind that scheme is that the credit variables react with some lag on monetary impulse and contemporaneously among themselves, being house prices, real debts and insolvencies interrelated. This evidence is also supported by the baseline model, where house prices and Insolvencies responses started very close to 0 without imposing exclusion restrictions on their respective coefficients.

The system is exactly identified as the coefficients associated with the macro variables (represented as dots in the below scheme) are dictated by starting covariance matrix and are not affected by further QR rotations.

$$\begin{pmatrix} u^{IR} \\ u^{Prod} \\ u^{Defl} \\ u^{HP} \\ u^{Debts} \\ u^{Ins} \end{pmatrix} = \begin{array}{c} \begin{array}{cccccc} w_m & w_y & w_3 & w_4 & w_5 & w_6 \end{array} \\ \begin{bmatrix} \bullet & \bullet & \bullet & * & * & * \\ 0 & \bullet & \bullet & * & * & * \\ 0 & 0 & \bullet & * & * & * \\ 0 & 0 & 0 & * & * & * \\ 0 & 0 & 0 & * & * & * \\ 0 & 0 & 0 & * & * & * \end{bmatrix} \end{array} \tag{16}$$

[14] I have omitted the scheme of this identification and its IRFs as they are very similar to the block-recursive ones below.

**Figure 7:** Structural Impulse Responses of a sign-restricted block recursively-identified VAR(2) model on UK Data. The solid line represents the median response and dotted lines are the 68% percentile bands.




# 5 Causal Inference

I test for causality using a Time-Varying Granger-causality test. Granger tests are widely used in the analysis of VAR as they enable the researcher to understand which variable makes a useful predictor of others within the same system. They test $p$ zero constraints to the coefficients matrix. When we fail to reject the null hypothesis of no Granger-causality from a regressor to another, we infer that the former is a good predictor for the latter.

A standard Granger test based on Wald statistics is reported in Lütkepohl [2005] and Shi et al. [2018][15]:

$$\mathrm{W} = [\mathrm{R}\, vec(\hat{A})]'[\mathrm{R}((\mathrm{X}'\mathrm{X})^{-1} \otimes \hat{\Sigma})\mathrm{R}')]^{-1}[\mathrm{R}\, vec(\hat{A})] \tag{17}$$

and

$$\mathrm{W} \sim \chi^2\,(p) \tag{18}$$

Where $\hat{A}$ represent the matrix of reduced form VAR coefficients and $\hat{\Sigma}$ the estimated covariance matrix. X is the matrix of lags and R is a $[n \times (k^2 p + k)]$ constraints selection matrix where $p$ are the lags, $k$ the VAR dimension and $n$ the number of restrictions to be tested.

Shi et al. [2018] have recently proposed an alternative way to carry out the static test in Eq. 17. Computing the Wald statistic over the span of the entire VAR averages the information and potentially produces misleading inference. In particular, such a test would not reveal shifts in Granger-causality relations with the relevant changing points.

They hence base their time-varying testing strategies on a series of nested computation of the Wald statistics on data sub-samples. Starting from the first data point, the Wald statistic is computed on an arbitrary long sub-sample, which is then rolled one period ahead. At each iteration forward, a number of ancillary regressions is calculated expanding the sample backwards until it includes the first observation. The relevant statistic is then a *Supremum Norm* of the set of Wald statistics (SW) calculated for each iteration forward. When the SW exceeds a certain critical value for the first time a changing point in causality relation is identified.

[15] In Shi et al. [2018] the matrix of coefficient is row-vectorised, in Eq. 17 I report a version with column-vectorisation.

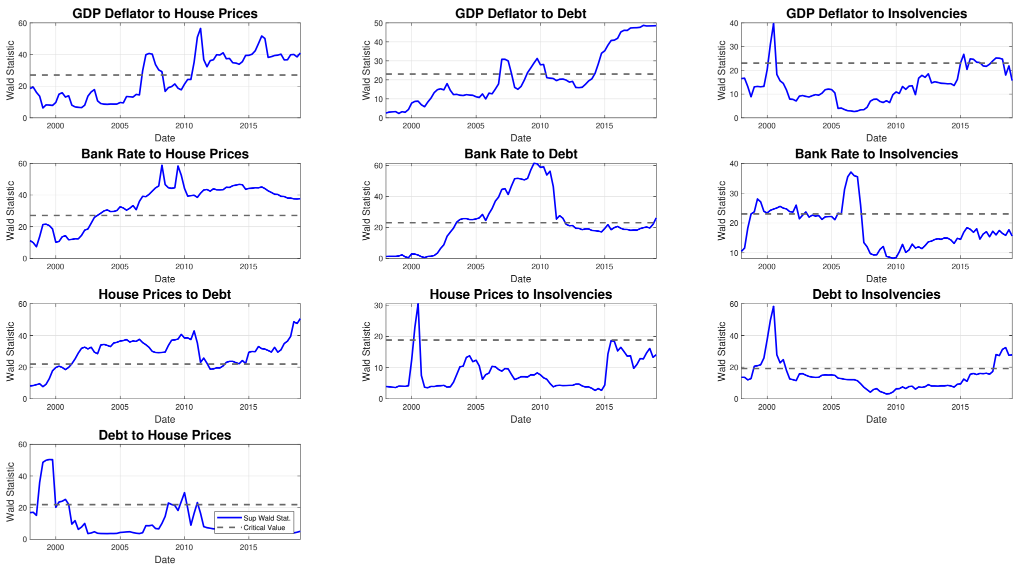
I use this test to address the 2008 Crisis discontinuity in the dataset, during which variables showed extreme behaviour. I also use the Shi et al. [2018] version of the test that is robust to conditional heteroscedasticity (in Eq. 19) given that it is applied to reduced form residuals of Eq. 1, which I've identified as endogenous in the first part of this paper. An implication of the Shi et al. [2018] paper is that the asymptotic distribution of the Wald test should hold when there is not cointegration, given that the VAR is stationary.

$$\mathrm{W} = T_w[\mathrm{R}\, vec(\hat{A})]'[\mathrm{R}((\mathrm{V}^{-1}\hat{\Omega}\mathrm{V}^{-1})\mathrm{R}')]^{-1}[\mathrm{R}\, vec(\hat{A})] \tag{19}$$

Where $\mathrm{V} = \hat{\mathrm{Q}} \otimes \mathrm{I}_n$ and $\hat{Q} = \frac{1}{T_w}\sum_{t=Tf_1}^{Tf_2} x_t x_t'$,and $\hat{\Omega} = \sum_{t=Tf_1}^{Tf_2} \hat{\xi}_t \hat{\xi}_t'$ with $\hat{\xi} = x_t \otimes \hat{\varepsilon}_t$.

**Figure 8:** Time-Varying Heteroscedastic Granger Causality Test

Critical Values are derived from the 95% percentile of the SW statistic on a bootstrapped sample of the VAR




## 5.1 Results the Time-Varying Granger-Causality Test

In Figure 8 I present the results from an evolving recursive heteroscedastic Wald test as in Eq. 19 where coefficients $\hat{A}$ are calculated from a reduced form of the IV-VAR presented above. I use 2 lags in accordance with the Bayesian criterion.

The objective of this exercise is to uncover potential structural changes involving the baseline variables. I find the predictability test in object useful as it enables further inference on the dynamic relations among variables. Some regressors are good predictor of others only for a limited period of the sample and this is not immediately evident from a whole-sample Granger test. This permits to extend the scope of this when it comes to identifying the channels of monetary policy transmission.

There is a data evidence of a debt deflation channel impacting on borrowers. House prices and real household debts are well predicted by the GDP deflator in 2007-2008 and more recently. This is consistent with the view that stable and low inflation with positive GDP developments may be conducive to leverage [Borio and Lowe, 2011]. The GDP deflator Granger-causes the abnormal build up of individual insolvencies from 2016, emphasising the role of the price level on household decisions.

Bank rate Granger-causes house prices almost across the entire sample period and it is a useful predictor of the debt stock from September 1999 to December 2010. Practically, the Bank rate ceases to be relevant to debt once that has reached its peak in late 2010. There is a clear change in the volatility of the SW of interest rate to insolvencies when the rate approaches zero lower bound. The bank rate bears no impact on insolvencies throughout the last decade but it predicts them during the first part of the sample. The Bank rate Granger-causes insolvencies intermittently for two years in 2004-2006, when there are numerous tightening episodes. This seems to suggest that a monetary policy tightening has on defaults a different effect than an easing. An interesting expansion of the present work could be using non-linear VAR models to account for potential differences in how insolvencies respond to either tight or easy monetary policy.

Household debt is endogenous to house prices, supporting the notion of co-movement of these two variables [Borio, 2014]. It is interesting that the causal relation goes from house prices to real debt and not vice versa, this reinforces the understanding of Broadbent [2019] of house prices driving the credit expansion. Inversion of that relation follows on periods of house market decline, maybe due to debt overhang dynamics, e.g. around the financial crisis.

# 6 Conclusions

I present an IV-VAR model with household insolvencies showing that a policy-induced debt deleverage also corresponds to an increase in default levels. This finding is new as insolvencies have not been taken into account by previous papers investigating debt reduction and monetary policy in other countries. I find that households' credit quality acts as a transmission mechanism for monetary policy by deteriorating fast in response to a contractionary monetary shock. This view is consistent with financial frictions DSGE models such as those featuring the '*financial accelerator*'.

This paper has policy implications for both monetary policy and financial stability. Monetary authorities may wish to steer rates attentively in presence of highly levered households. Asset prices rallies and increase in debt in a benign environment can be quickly reversed by a rate hike. Thus there appears to be trade-offs between inflation and household conditions.

Optimal monetary policy and welfare implications of different policy rules in presence of insolvencies and high household debt are outside of the scope of this empirical paper, but their investigation in a canonical DSGE setting represents an interesting and relevant research program for financial stabilisation. Such research could build on the stylised facts regarding deleveraging and default here presented.

Central Banks that deviate from pure inflation targeting to factor in financial stability will wish to be careful that the policy rule is effective. Trying to trigger a debt reduction with monetary policy instruments might be detrimental to households and therefore not achieve its intended objective, adding to imbalances instead of steering the economy clear of a recession.

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# Appendix

## A Data Sources

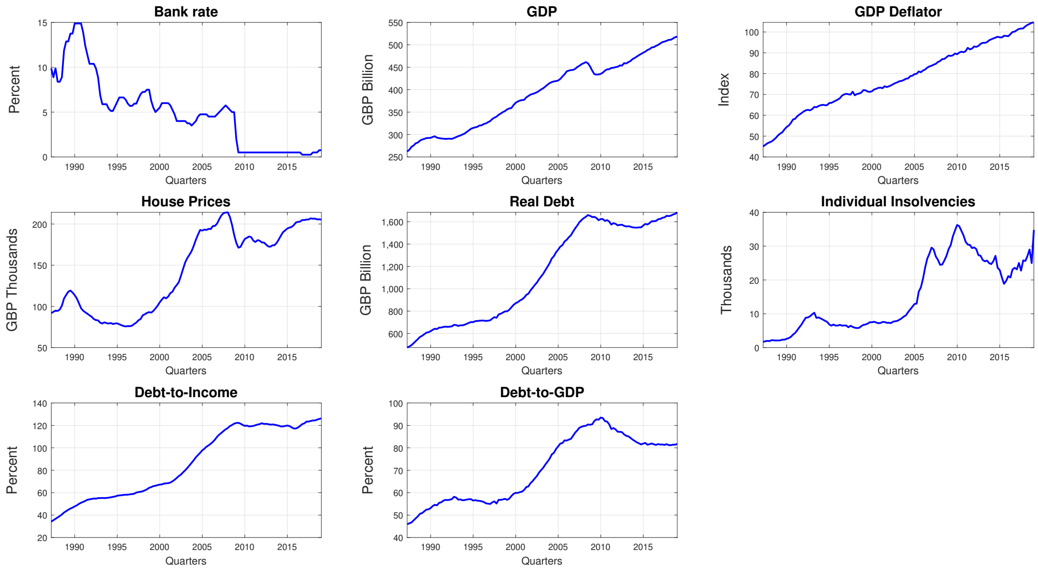
**Table 2:** Data Sources

Time Series that weren't originally adjusted have been seasonally transformed and deflated

| | Variable | Datastream Ticker | Source | Deflated | Deseasoned |
|---|---|---|---|---|---|
| In the VAR | | | | | |
| a | Bank Rate | UKPRATE | BoE | NA | NA |
| b | GDP Chained Volume | UKGDP...D | ONS | NA | Y |
| c | GDP Deflator | NA | g/b | NA | NA |
| d | Average House Price | UKNWALLP | Nationwide | N | N |
| e | Household Debt | UKNIWKQ.A | ONS | N | N |
| f | Individual Insolvencies | UKAIHK..P | Insolvency Service | N | N |
| GDP | | | | | |
| g | GDP at Market Prices | UKGDP...B | ONS | NA | Y |
| Additional Variables | | | | | |
| h | Gross Disposable Income | UKPERDISD | ONS | N | Y |
| i | Annualised Income | NA | Four Quarters Rolling Sum of i | NA | NA |
| j | Unemployment | UKUN%O16Q | ONS | NA | Y |
| k | Debt to Income | NA | e/i | NA | NA |
| l | Debt to GDP | NA | e/Four Quarters Rolling Sum of b | NA | NA |
| m | Mortgage Rate | NA | BoE [16] | NA | NA |
| n | Corporate Rate | NA | BoE [16] | NA | NA |
| o | Household Final Consumption Expenditure | NA | ONS | Y | Y |
| p | Total Durable Goods | NA | ONS | Y | Y |
| q | Total Non Durable Goods | NA | ONS | Y | Y |
| r | FTSE 350 Index | FTSE350 | Refinitiv | NA | NA |
| Z | Instrument | NA | Own Calculations | NA | NA |

[16] Mortgage Rate up to Q4 2016 from 'A millennium of macroeconomic data' dataset, then extrapolated from 'UK Secured Loans,New Advances, Floating Rate' (DS Ticker UKZ6JT..R.). Corporate Rate up to Q4 2016 from 'A millennium of macroeconomic data' dataset, then extrapolated from UK corporate benchmark yields across all maturities and ratings (DS Series TRBC).

**Figure 9:** Baseline Model Time Series and Debt Ratios



# B Summary of Cited Studies

**Table 3:** Cited Studies

| Authors | Country | Time Sample | Research Question/Goal | Identification | Regressors |
|---|---|---|---|---|---|
| Hofmann and Peersman [2017] | Across Panel | 1985 - 2008 | Is there a debt service channel of monetary transmission? | Recursive | Real GDP, G Policy Rate, Servicing Rat |
| Laseen and Strid [2018] | Sweden | 1995 - 2013 | [to investigate] the relation between the shorter-term dynamics of debt and the effects of monetary policy on debt | Recursive | Trade-weighte Foreign Short tic Real GDP and Real Deb |
| Robstad [2018] | Norway | 1994 - 2013 | to quantify the effect of a monetary policy shock on household credit and house prices in Norway | Recursive | GDP, CPI-AT Prices and Re |
| Mountford [2005] | UK | 1974 - 2005 | to investigate the effects of UK monetary policy [shocks] | Sign Restriction | GDP, Bank R Oil Price. |
| Ellis et al. [2014] | UK | 1975 - 2005 | to investigate changes in the transmission mechanism of economic shocks in the UK | Sign Restriction | Bank Rate ar series. |
| Cloyne and Hürtgen [2016] | UK | 1975 - 2007 | estimat[ing] the effects of monetary policy | Narrative | Industrial P Prices, Narra |
| Gerko and Rey [2017] | US and UK | 1982 - 2015 | How does [the importance of financial markets] affect the effectiveness of monetary policy? | Instrumental | 5yr GILT Rat Corporate Sp Rate. |
| Cesa-Bianchi et al. [2020] | UK | 1992 - 2015 | how monetary policy transmits to the broader economy | Instrumental | 1yr GILT rat rate, mortgag |

# C Exogenous Instruments

## C.1 Instrumental Variable Sources

- Bank of England Directory of MPC Minutes: https://www.bankofengland.co.uk/sitemap/minutes;
- Bank of England Directory of Inflation Report publications: https://www.bankofengland.co.uk/sitemap/inflation-report;
- Bank of England 'A millennium of macroeconomic data' dataset: https://www.bankofengland.co.uk/statistics/research-datasets;
- Monetary Policy Committee Voting History Spreadsheet: https://www.bankofengland.co.uk/monetary-policy2.

**Figure 10:** UK Money Surprises Instruments

Monthly and Quarterly Surprises proxies from Gerko and Rey [2017] and Cesa-Bianchi et al. [2020]. Pearson correlation coefficient with my surprises is overlay-ed.

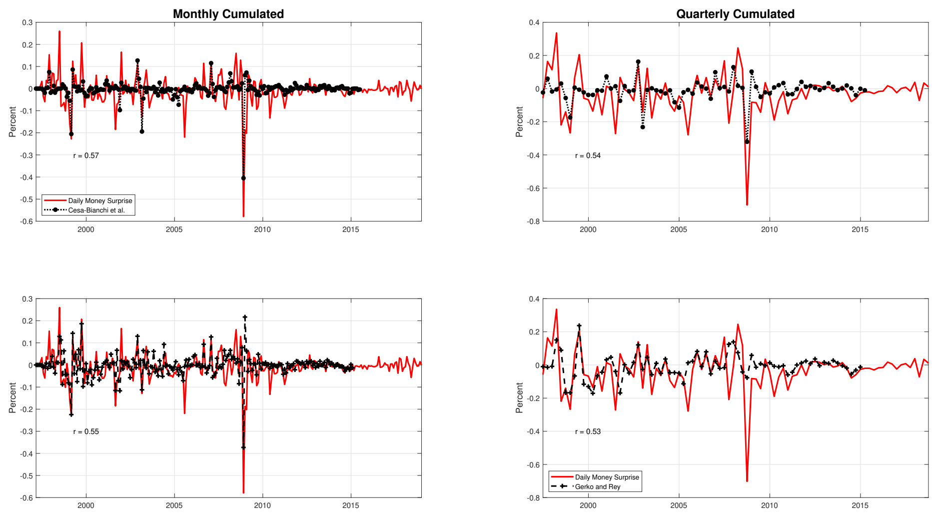
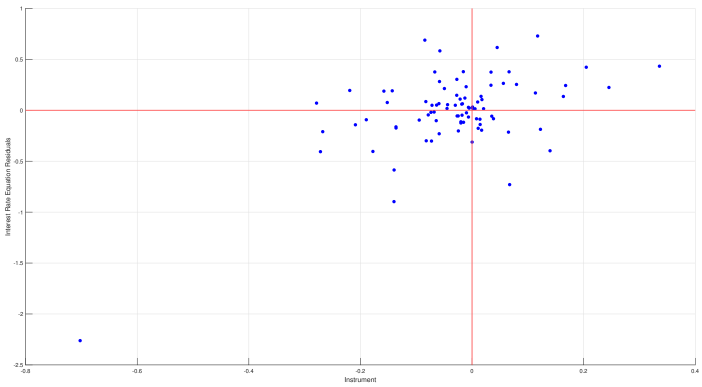



**Table 4:** This Paper First Stage Regression Results

R-Squared = 0.32; F-statistic vs. Constant Model = 41.56

| | Coefficient | Standard Error | t-Stat | p-Value |
|---|---|---|---|---|
| **Intercept** | 0.05 | 0.03 | 1.42 | 0.16 |
| **Money Surprises (Instrument)** | 1.65 | 0.26 | 4.45 | 0.00 |

**Figure 11:** Baseline Model Interest Rate Equation Residuals and Instrumental Surprises



# D Alternative Specifications

## D.1 Cholesky SVAR

**Figure 12:** Structural Impulse Responses of a Cholesky SVAR

Solid line represents point-estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times. The dashed line shows the baseline model IRFs

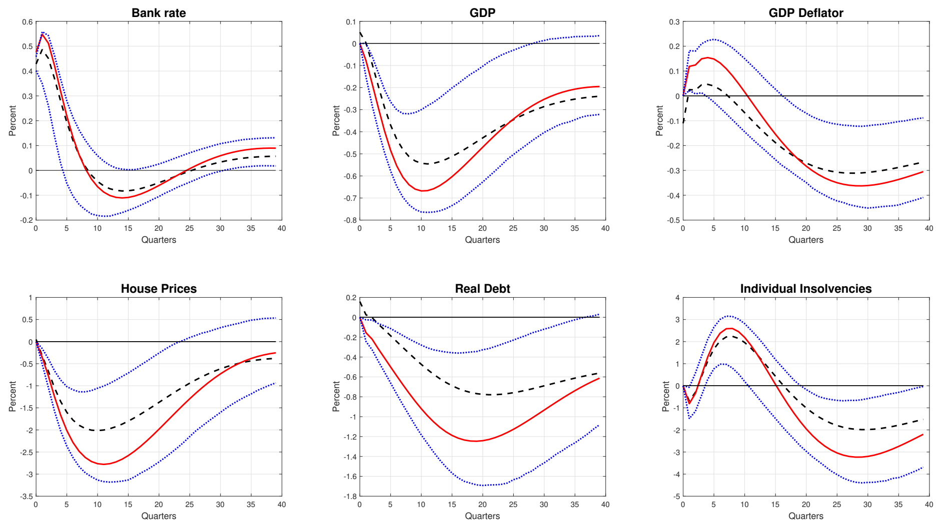
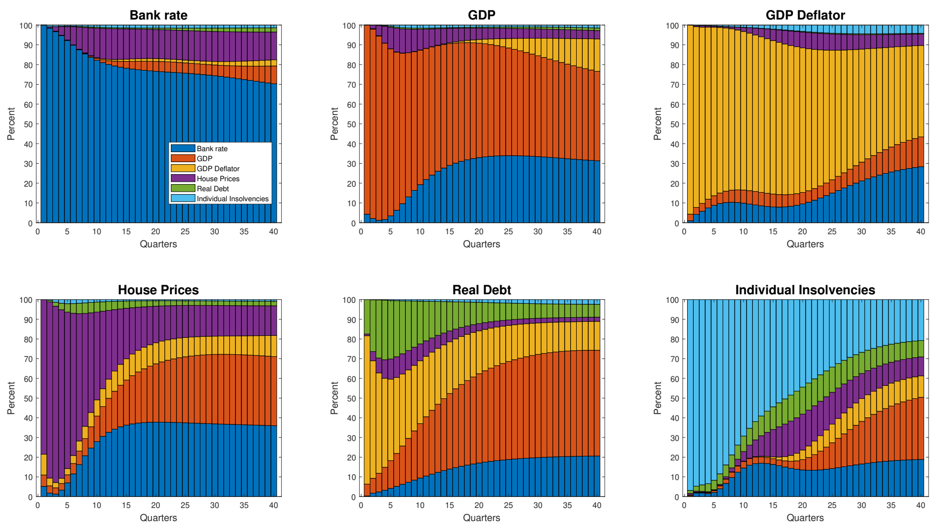



**Figure 13:** Forecast Error Variance Decomposition of a Cholesky SVAR

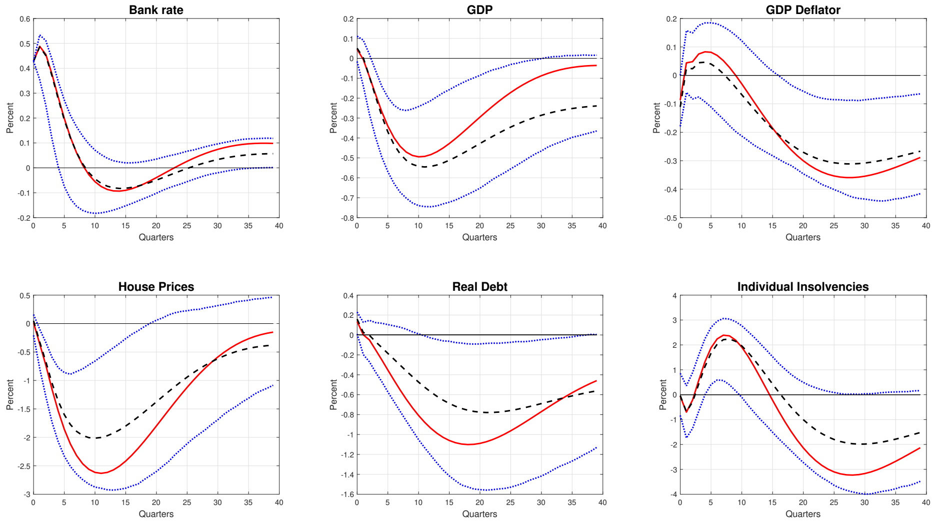
If analysed with a forecast error variance decomposition, in the Cholesky setting, my findings are different from Mountford's as interest rate explains at the least 30% of variation of a GDP shock after 40 quarters and 70% of its own variation, thereby not 'leaning into the wind'.



## D.2 Non-Stationarity Robust

**Figure 14:** Structural Impulse Responses of a IV-VAR(2) model computed with Cheng et al. [2019] GMM estimator and consistent covariance in case of non-stationarity.

Solid line represents point-estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times. The dashed line shows the baseline model IRFs




## D.3 With Consumption Aggregates

**Figure 15:** Structural Impulse Responses of a IV-VAR(2) with Household Total Final Expenditure

Solid line represents point-estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times. The dashed line shows the baseline model IRFs

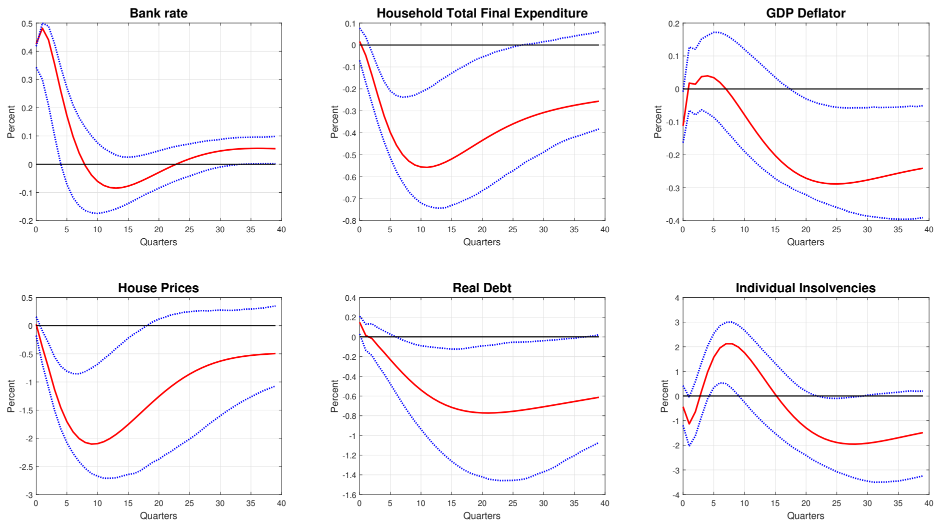


**Figure 16:** Structural Impulse Responses of a IV-VAR(2) with Household Durable Consumption

Solid line represents point-estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times. The dashed line shows the baseline model IRFs

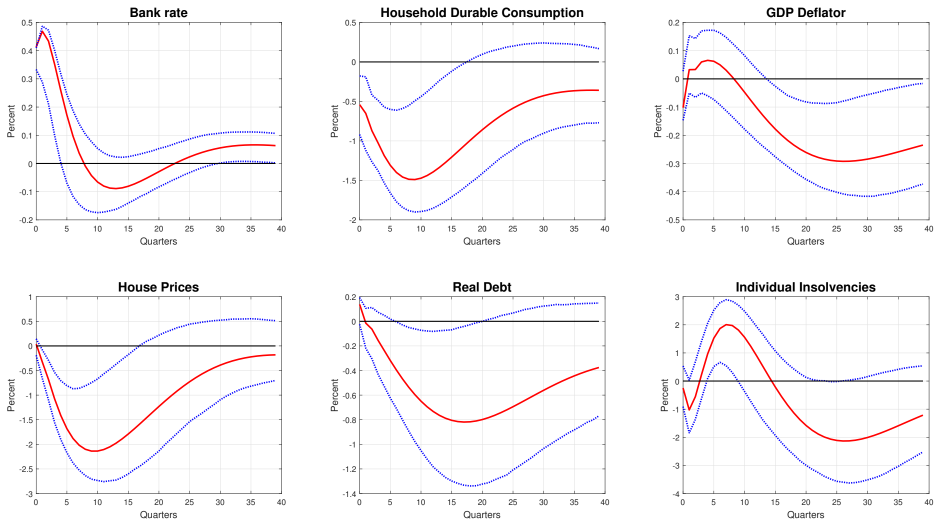
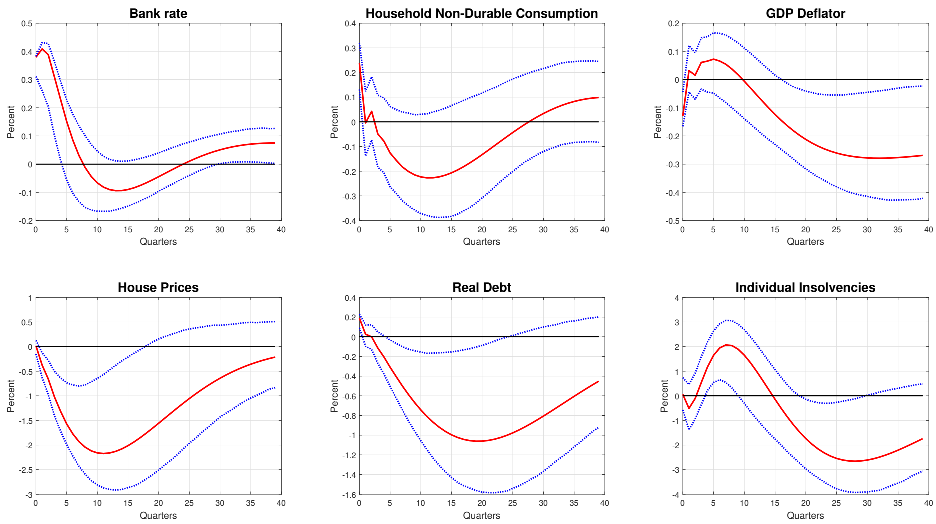



**Figure 17:** Structural Impulse Responses of a IV-VAR(2) with Household Non-Durable Consumption

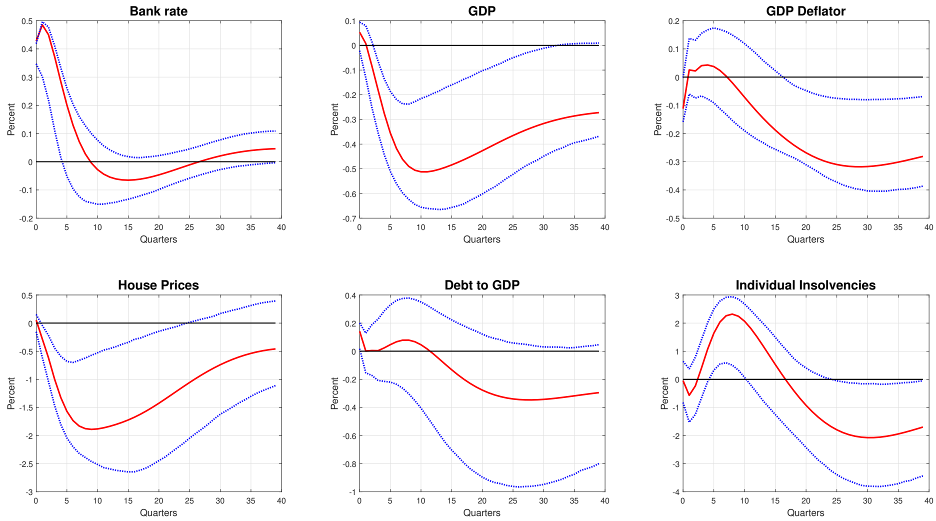
Solid line represents point-estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times. The dashed line shows the baseline model IRFs



## D.4 Debt-to-GDP

**Figure 18:** Structural Impulse Responses of a IV-VAR(2) model with Debt-to-GDP

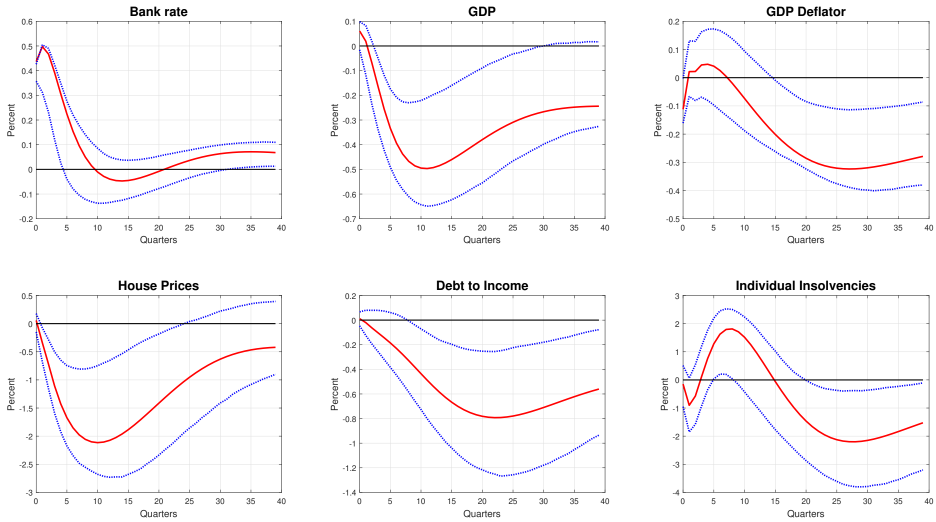
Solid line represents point-estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times. The dashed line shows the baseline model IRFs




## D.5 Debt-to-Income

**Figure 19:** Structural Impulse Responses of a IV-VAR(2) model with Debt-to-Income

Solid line represents point-estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times. The dashed line shows the baseline model IRFs



## D.6 With Lending Rates

**Figure 20:** Structural Impulse Responses of a IV-VAR(2) model with Credit Spreads

Solid line represents point-estimates. 90% confidence bands (dotted lines) are obtained simulating artificial data and re-sampling the residuals 5,000 times. The dashed line shows the baseline model IRFs