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Mortgage Debt and Time-Varying Monetary Policy Transmission*

David Finck[†] Jörg Schmidt[‡] Peter Tillmann[§]

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Abstract

We study the role of monetary policy for the dynamics of U.S. mortgage debt, which is the largest component of household indebtedness. A time-varying parameter VAR model allows us to study the variation in the mortgage debt sensitivity to monetary policy. We find that an identically-sized policy shock became less effective over time. We use a DSGE model to show that a fall in the share of adjustable-rate mortgages (ARMs) could replicate this finding. Calibrating the model to the drop in the ARM share since the 1980s yields a drop in the sensitivity of housing debt to monetary policy which is quantitatively similar to the VAR results. A sacrifice ratio for mortgage debt reveals that a policy tightening directed towards reducing household debt became more expensive in terms of a loss in employment. Counterfactuals show that this result cannot be attributed to changes in monetary policy itself. The results are consistent with the "mortgage rate conundrum" found by Justiniano et al. (2017) and have strong implications for policy.

Keywords: mortgage debt, monetary policy, deleveraging, time-varying VAR, DSGE

JEL classification: E3, E5, G2

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1 Introduction

The build-up of household debt in the U.S. and other countries is often interpreted as a potential risk to financial stability (see Jordà et al., 2016) and a determinant of the overall credit cycle (see Mian et al., 2016). Since the recent financial crisis originated in the U.S. housing market, the mortgage market receives a lot of attention. Mortgage debt is by far the largest component of household debt, as it reflects the single, most important financial decision of most households. Hence, monetary policy should affect not only the value of houses, but also the dynamics of mortgage debt. A monetary tightening should curb the build-up of mortgage debt. This is a main channel for monetary policy transmission to households.[1]

In this paper, we study the response of U.S. mortgage debt to monetary policy. We believe a model that allows for time-variation in the link between the Fed and the mortgage market is needed. For this purpose, we use a time-varying parameter vector autoregressive (TVP-VAR) model along the lines of Primiceri (2005), thus allowing for drifting coefficients and a time-varying variance covariance matrix.

The choice of this model is based on two observations: first, there is strong evidence that the U.S. economy underwent both structural and institutional changes and also faces structural changes in the world economy, as emphasized by Canova and Gambetti (2009), Boivin (2005) and Mishkin (2009). Second, financial liberalization and deregulation changed the process of financial intermediation in the U.S. economy. We include four variables: civilian unemployment, GDP-deflator inflation and the trend-deviation of real debt of various categories, intended to represent the non-policy block, and a short-term interest rate representing the monetary policy instrument. We assume that the Fed only responds to inflation and employment and restrict all time-varying VAR coefficients in the policy rule other than those related to inflation and employment to zero. Our estimation procedure relies on Markov-Chain-Monte-Carlo (MCMC) methods as in Nakajima (2011).

Our key result is that the reaction of mortgage debt to an identically sized monetary policy shock became much smaller over time. Hence, a monetary policy tightening today reduces household debt much less than the same shock in the 1970s. A 25bp tightening in the 1970s led to a drop in the cyclical component of mortgage debt by about 0.1 percentage points, while the same shock today would result in a drop of only 0.04 percentage points.

We also construct a sacrifice ratio which compares the loss in employment to the size of the deleveraging after a policy tightening. Low negative values correspond to

[1]See Jordà et al. (2015) for historical evidence of the link between loose monetary policy and real estate ending booms.

high costs debt-reduction costs while high negative values express low costs for the Fed to reduce indebtedness. We find that the declining sensitivity in mortgages is more pronounced than for unemployment. Hence, towards the end of the sample, it is particularly costly in terms of employment to use a monetary tightening in order to initiate a reduction in household debt. Our main result is robust to the choice and the ordering of the variables. Counterfactuals in the spirit of Sims and Zha (2006) show that the change in the responsiveness of mortgages does not stem from changes in monetary policy itself. The findings fits to the 'mortgage rate conundrum' put forward by Justiniano et al. (2017). They argue that the link between Treasury yields, which party reflect monetary policy, and rates on mortgages weakened over time. Hence, both papers stress the role of some underlying structural changes in the mortgage market that impair the monetary policy transmission mechanism.

In order to explain our finding, we study the interaction of the interest rate elasticity of mortgages with the share of adjustable mortgages (ARM). The literature points to the ARM share as a key determinant of policy transmission to the housing market (see, among others, Calza et al., 2013). The ARM share in the U.S. exhibits in general a decline since the early 1980s, where the ARM data starts. This encourages us to take a DSGE model of Alpanda and Zubairy (2017) and examine variations in the ARM share. The model features a housing market and an occasionally binding credit constraint along the lines of Iacoviello (2005). The impact of the ARM share is nonlinear: a drop in the ARM share causes a less than proportional decline in the interest rate elasticity of mortgage debt. We calibrate the model to the ARM share in 1982, leaving all other parameters as their sample average, and to the ARM share at the end of the data sample. The resulting responses of mortgage debt to a simulated 25bp tightening shock quantitatively match the empirically observed decline in the mortgage-response to policy shocks.

Our results have important policy implications. First, a weaker transmission of policy impulses to the mortgage market, but not to the real economy, implies that monetary policy is not the right instrument to facilitate a deleveraging of the household sector. A policy tightening at the end of the sample period to curb the build-up of mortgage debt is both ineffective and expensive in terms of forgone employment. Hence, we would advise against using monetary policy to counteract financial risks related to household borrowing. Rather, a macroprudential policy instrument, such as a cap on loan-to-value (LTV) ratios, which could directly target mortgage debt, even on a regional basis, seems preferable.[2]

Second, the results can be interpreted as a case against the 'too low for too low'

[2] This ranking of policy tools is consistent with the results of Alpanda and Zubairy (2017).

argument. If policy is relatively ineffective anyway, even before the financial crisis, keeping interest rate low for an extended period of time does not contribute to inflating a credit boom. Our counterfactuals show that for the past 20 years not only the surprise change to the monetary policy stance, but also the systematic component of monetary policy contributes little to mortgage debt.

Our results are related to several branches of the literature. In the following, we highlight only those papers which we consider most relevant for us. The first field studies structural features of the U.S. mortgage market and relates them to the strength of the transmission process. Calza et al. (2013) present VAR results consistent with the notion that the monetary transmission to housing investment is stronger for a high share of ARMs. We extend this line of research by looking at the U.S. economy over time, not at the cross-section of countries which differ in the average ARM share. Ben Zeev (2016) first presents a partial equilibrium model of the housing market, in which a high share of ARM mortgage contracts amplifies the effect of an interest rate shock. He also presents empirical evidence consistent with this finding. The ARM share is used to interact the economy's response to a credit supply shock. Carriga et al. (2017) build a general equilibrium model with incomplete asset markets in which monetary policy affects housing investment by changing the cost of new mortgages. A high ARM share again intensifies the response of the economy to the monetary policy impulse. Secondly, the result of this paper can be interpreted as an equivalent to Justiniano et al.'s (2017) 'mortgage rate conundrum'. They establish the finding that the connection between mortgage interest rates and Treasury rates broke down in 2003. Hence, the policy tightening of the Fed in 2004 did not lead to higher mortgage rates. Paul (2018) also uses a TVP-VAR model to study the policy transmission to various asset prices. He also finds that the transmission to house prices was particularly weak before the 2008-9 financial crisis.

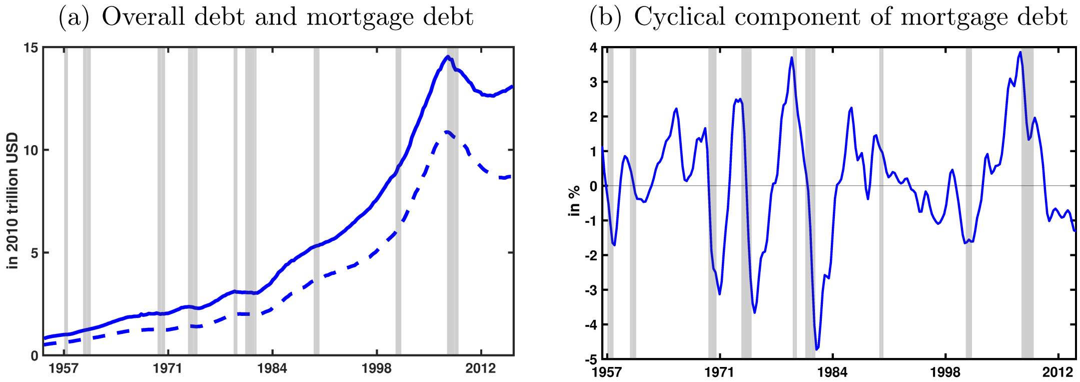
The remainder of this paper is structured as follows: Section two sketches the evolution of mortgage debt. Section three introduces the TVP-VAR model and details about the Bayesian estimation. Section four discusses the main results. Section five focuses on the role of adjustable mortgages for our results and presents results from a DSGE model. Sections six and seven present counterfactual analyses and robustness checks, respectively, and section eight concludes.

2 Mortgage debt

The paper focuses on mortgages held by U.S. private households, which are the main component of overall household debt. Panel (a) in Fig. (1) depicts the development of post-war household debt. There has been a steady increase in real household debt and mortgage debt, respectively, until the eve of the Great Recession.

For the purpose of this paper, we look at the cyclical component of real mortgage debt, which we derive from Baxter and King (1999) filtering the original series. The filter has a band-length of 8 and lets frequencies between four and 64 quarters pass. With this calibration, we account for the average length of financial and debt cycles in the U.S. and take into account that these cycles are about twice as long as the business cycle (Alpanda and Zubairy, 2017). The resulting cyclical series, the mortgage gap, is depicted in panel (b) of Fig. (1).

Figure 1: Household debt in the U.S.



Notes: The solid line in panel (a) is overall real household debt. The dotted line in panel (a) shows real mortgage debt. Panel (b) shows the cyclical component of Baxter-King-filtered mortgage debt (blue-solid). The shaded areas reflect NBER-dated recessions.

We find that the mortgage gap fluctuates between 4% and -5% and peaks before each recession. During a recession, most gaps turn negative. This variable is the key input into our empirical model.

3 The empirical model

The main tool for our empirical analysis is a series of VAR models, whose structure is time-varying. We start with the time-invariant VAR model in order to introduce a few key elements and to fix notation.

3.1 Structural VAR model

A standard time-invariant structural VAR is defined as

$$Ay_t = d + F_1 y_{t-1} + ... + F_s y_{t-s} + \epsilon_t, \qquad t = s+1, ..., T \tag{1}$$

$$\epsilon_t \sim \mathcal{N}(0, \Sigma\Sigma') \tag{2}$$

where y_t is a $k \times 1$ vector of observed variables, ϵ_t a $k \times 1$ vector of structural shocks d is a $k \times 1$ deterministic component, e.g. a constant, and $A, F_1, ..., F_s$ are $k \times k$ matrices of coefficients.

The vector y_t contains four variables. The first is the unemployment rate u_t, which is our measure of real economic activity. The second is inflation, π_t, measured as the year-on-year growth rate of the GDP deflator. The third variable is the cyclical component of real mortgage debt derived before. Our fourth variable is supposed to reflect the Fed's policy instrument. We use the effective federal funds rate, i_t, augmented with the shadow rate during periods characterized by the zero-lower-bound.[3]

Hence, the vector of endogenous variables is given by $y_t = [u_t, \pi_t, d_t, i_t]'$. We refer to the first three variable as the non-policy block of the VAR system, for reasons to become clear below.

The simultaneous relations of structural shocks are specified by recursive identification (i.e. a Cholesky approach), assuming that A is lower-triangular as[4]

$$A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{kk-1} & 1 \end{bmatrix}. \tag{3}$$

Premultiplying both sides by A^{-1}, the model can hence be rewritten as

$$y_t = c + B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1}\Sigma\varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, I_k), \tag{4}$$

[3]We also conduct robustness checks by dropping out the period characterized by the ZLB. The results remain similar, see section (7).

[4]Note that the lower-triangular specification (3) of A (and thus A^{-1}) is widely used and enables us to easily identify structural shocks (as for example monetary policy shocks) by recursive ordering, although the examination of implications for the economic structure may require more complicated identification schemes.

where $c = A^{-1}d$ and $B_j = A^{-1}F_j$ for $j = 1, ..., s$. Σ is the standard deviation of our structural shocks ε_t and specified as

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{bmatrix}. \tag{5}$$

Stacking all elements of c and B_i, we get the $k + (k^2 s) \times 1$ vector B. Defining $X_t = I_k \otimes [1, y'_{t-1}, ..., y'_{t-s}]$, the model can be rewritten in reduced form as

$$y_t = X_t B + A^{-1}\Sigma\varepsilon_t. \tag{6}$$

The ordering of variables in y_t implies that the monetary policy shock, which we are primarily interested in, does not contemporaneously affect the non-policy block. This assumption is standard in the literature (see Christiano et al., 1999). As a matter of fact, our VAR model includes cyclical mortgages, which are not a standard variable in VAR models. However, we believe that the recursive identification remain plausible even if debt is included. Keep in mind that it is unlikely that mortgages, which appear to be an inert variable, contemporaneously respond to monetary policy. Including mortgages also implies that, in principle, the monetary policy reaction function incorporated in the VAR model allows for a feedback from mortgages to monetary policy. Hence, the Fed could respond to real mortgages. Since we want to keep the model as close as possible to the standard VAR model, even when including mortgages, we restrict the response of monetary policy to mortgages to zero across all lags.[5] A detailed description of this approach can be found in the appendix, section (A.1).

Finally, it remains to specify the lag order of the VAR system. Our choice of two lags is the result of two concerns. The first is the fact the we want to maintain our model as parsimonious as possible. This is important as the time-varying model introduced below is heavily parameterized. Second, if we believe the data generating process is affected by structural breaks, which is why we estimate a time-varying model after all, standard lag selection criteria are no longer valid and offer no guidance as

[5]For robustness, we also estimate a TVP-VAR in which this restriction is not imposed, see section (7). The results do not vary in a notable manner.

regards to lag order.[6]
The model is estimated on quarterly data from 1957Q1 to 2014Q3. Below, we will use the VAR model in order to understand policy effects on the U.S. mortgage market, for which the conjecture of constant parameters, and, hence, a stable transmission process, might be too strong an assumption. For this reason, we know allow for time-variation in our modelling framework.

3.2 The TVP-VAR model

Our time-varying parameter VAR is specified as

$$y_t = X_t B_t + A_t^{-1} \Sigma_t \varepsilon_t, \tag{7}$$

where all parameters, i.e. the VAR coefficients captured in B_t, the simultaneous relationships among endogenous variables captured in A_t as well as the stochastic volatility of our structural shocks captured in Σ_t, are time-varying. Thus, the TVP-VAR is able to capture the time-varying nature of the economy. Let $a_t = [a_{21,t}, \cdots, a_{kk-1,t}]'$ be the vector of non-zero and non-one elements of A_t (i.e. the lower-triangular elements of A_t and $h_t = [h_{1,t}, \cdots, h_{k,t}]'$ with $h_{it} = \log \sigma_{it}^2$ for $i = 1, \cdots, k$. Following Primiceri (2005), we assume the following dynamics of the model's parameters

$$\begin{aligned} B_{t+1} &= B_t + \eta_{Bt} && (8)\\ a_{t+1} &= a_t + \eta_{at} && (9)\\ h_{t+1} &= h_t + \eta_{ht}, && (10) \end{aligned}$$

which are jointly normally distributed as

$$V = Var\left(\begin{bmatrix} \varepsilon_t \\ \eta_{Bt} \\ \eta_{at} \\ \eta_{ht} \end{bmatrix}\right) = \begin{bmatrix} I_k & 0 & 0 & 0 \\ 0 & \Sigma_B & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{bmatrix}, \tag{11}$$

where $B_{s+1} \sim \mathcal{N}(\mu_{B0}, \Sigma_{B0})$, $a_{s+1} \sim \mathcal{N}(\mu_{a0}, \Sigma_{a0})$ and $h_{s+1} \sim \mathcal{N}(\mu_{h0}, \Sigma_{h0})$.
Note that the evolution of all parameters is modeled to follow a random walk process. Although the random walk process is non-stationary, its assumption can capture

[6] However, the lag order did not affect our main results qualitatively.

both gradual and sudden structural changes (see, for instance, Nakajima (2011) and Primiceri (2005)). However, the random walk assumption also bears the risk that, besides the true movements, the time-varying coefficients also capture spurious movements as the parameters are allowed to freely move under this non-stationary assumption.

3.3 Estimation

In order to estimate the TVP-VAR, we rely on MCMC methods. Our estimation procedure mainly follows Nakajima (2011) and can be summarized as follows: Given the data $y = \{y_t\}_{t=1}^{T}$, $\omega = (\Sigma_B, \Sigma_a, \Sigma_h)$ and our prior density $\pi(\omega)$, we use the following MCMC algorithm to draw samples from posterior $\pi(B, a, h, \omega|y)$[7]

1. Initialize B, a, h and ω.
2. Sample $B|a, h, \Sigma_B, y$.
3. Sample $\Sigma_B|B$.
4. Sample $a|B, h, \Sigma_a, y$.
5. Sample $\Sigma_a|a$.
6. Sample $h|B, a, \Sigma_h, y$.
7. Sample $\Sigma_h|h$.
8. Go back to 2.

3.4 Priors

Priors need to be specified for the starting values of our MCMC algorithm (i.e. for the initial state of the time-varying parameters) and for the i^{th} diagonals of the covariance matrices. There are mainly two common practices for specifying the initial state. The first approach follows Primiceri (2005) and chooses a prior of normal distribution whose mean and variance are based on a time-invariant VAR model estimated from say the first 10 years. The potential drawback of this approach is the fact that we lose these observations for the estimation of our TVP-VAR, as in a true Bayesian setting, the prior must not contain any information based on the sample. Second, from the standpoint that we do not have any information about the initial state a priori, setting diffuse priors for the initial states is a good idea. In particular, the initial state of our parameters have flat priors, set as

$$B_{s+1} \sim N(0, 10 \cdot I), \qquad a_{s+1} \sim N(0, 50 \cdot I), \qquad h_{s+1} \sim N(0, 50 \cdot I). \tag{12}$$

[7] Accordingly, $B = \{B_{s+1}, ..., B_T\}$, $a = \{a_{s+1}, ..., a_T\}$ and $h = \{h_{s+1}, ..., h_T\}$.

Of course, the prior choice for the hyper-parameters can in fact affect posterior inference, although Σ_B, Σ_a and Σ_h do not parameterize time variation in the first line, but only prior beliefs about the time-variation. However, the priors should be carefully chosen because our model has many parameters to estimate. This holds even more for the coefficients as well as for stochastic volatility, as their process is modeled as a non-stationary random walk process. Thus, tight priors for the covariance matrix of the random walk processes might avoid ill-determined behavior of the parameters. It should be noted that in general the time-varying VAR coefficients require a tighter prior than the time-varying variance-covariance matrix. Therefore, we choose a rather tight prior for Σ_B and rather diffuse priors for Σ_a and Σ_h. More precisely, we set the following priors for $\Sigma_B, \Sigma_a, \Sigma_h$:

$$(\Sigma_B^2)_i \sim G(40, 3 \cdot 10^{-4}), \qquad (\Sigma_a^2)_i \sim G(4, 0.1), \qquad (\Sigma_h^2)_i \sim G(4, 0.01)$$

To compute the posterior estimates, we draw $N = 50,000$ draws and discard the first $45,000$ draws, as samples that have been generated in early iteration steps are likely to be not representative for the true posterior distribution.

4 Results

The advantage of our TVP-VAR model is that we can show time-varying effects of monetary policy shocks. This time-variation is not only driven by the estimated VAR parameters, B_t, but also by the shock-impact matrix, A_t^{-1}, as well as by the stochastic volatility of the covariance matrix, Σ_t. In order to study the results, we first discuss the time-varying impulse response functions generated by our model. We then look at time-variation in the relative responses of mortgage debt and unemployment in order to characterize the trade-off involved in a policy-induced deleveraging.

4.1 Responses to a monetary policy shock

In section we discuss the time-varying effects of monetary policy shocks on the endogenous variables. Fig. (2) shows the mean impact of a monetary policy shock 25bp in size on unemployment and inflation. We are able to show responses for a shock originating at each point in the effective sample period. Panel (a) shows the response of unemployment. We find that unemployment increases after a policy tightening. The main finding is that the sensitivity of unemployment to a monetary policy shock declines over time and reaches a low in the early 2000s. After that, unemployment becomes slightly more responsive to monetary policy. We can also see a slight shift of the timing of the peak response indicating a more inert transmission of monetary policy shocks on unemployment.

Panel (b) reports the response of inflation. For shocks originating in the first decade of the sample, we observe a strong price puzzle, i.e. an increase in inflation. Since the 1970s and early 1980s, the time when Paul Volcker became Fed Chairman and put in place important institutional change in the monetary policy framework, the price puzzle is small and negligible. Most importantly, we also find a decline over time in the response of inflation to monetary policy. This decline, however, is weaker than for unemployment.

The main finding of this paper is shown in Fig. (3), which displays the time-varying reaction of mortgage debt to a monetary policy tightening. The response becomes much smaller over time. Similar to unemployment and prices, mortgage debt exhibits the strongest response at the beginning of our sample. Since then, the impact gradually declines reaching its lowest sensitivity at the sample-end, with a short interruption during the Volcker-period and during the end of the nineties. For most recent dates, the peak response of mortgage debt to monetary policy is a third or a quarter of the response at the beginning of the sample.

To get a full view on the changing nature of monetary policy transmission that accounts for estimation uncertainty, we show selected cross-sections of our model-implied impulse response functions with their respective 16^{th} and 84^{th} percentiles of the posterior distribution of estimated time-varying VAR-parameters. Fig. (4) to Fig. (7) show the time-varying reaction of our endogenous model variables 1, 4, 8 and 16 quarters after the shock. Thus, we slice through Fig. (2) and (3) at a specific horizon of the impulse response. We also add the response of the short-term interest rate itself. The percentiles of the underlying distribution allow us to gauge the magnitude of the responses.

We can observe that the initial significance of our observed price puzzle begins to vanish over time. Unemployment becomes increasingly insensitive to monetary policy since the early 1990s when we take the corresponding percentiles into account. The persistence of the interest rate response to the monetary policy shock does not fluctuate to a large extend over time. For mortgage debt, we see the diminishing significance of the reaction over time quite well, especially in Fig. (5) and Fig. (6).

Finally, we extract the maximum impact of the monetary policy shock on mortgage debt as well as the time at which the maximum response occurs and show both in Fig. (8). This allows us to better describe the shift in sensitivity of mortgage debt to monetary policy over the sample period. We can see the general tendency of diminishing effects of monetary policy shocks with responses becoming non-significant at the end of our sample. We also find that the maximum impact of the policy shock occurs later over time.

The decline in the sensitivity of mortgage debt has strong implications for monetary policy, which we will now study in detail. Keeping in mind that the reduced-form model is not suitable for normative policy analysis, our results suggest that using monetary policy to facilitate a deleveraging of households is difficult. This is because the effectiveness strongly varies over time. This also implies that the costs of such a deleveraging in terms of unemployment also vary over time. We will pick up this thought in the following section.

4.2 The sacrifice ratio of debt reduction

Let us consider a central bank which aims at using an increase of the policy rate in order to foster a deleveraging of households. Since we base this thought experiment on a reduced form model, we should stress that we do not intend to derive normative implications. Rather, we want to shed light on the question when a debt reduction as a result of a monetary tightening is relatively expensive or cheap, respectively. For that purpose we invoke the concept of the sacrifice ratio, which answers the question of how costly a disinflation is in terms of unemployment. We construct a measure that shows how expensive a debt reduction is in terms of unemployment, which fluctuates over the sample period. This measure, Γ_t, is the ratio of the response of mortgage debt, d, and the response of unemployment, u, for horizon h. For each horizon, the nominator and the denominator are the cumulative impulse-responses

$$\Gamma_t = \frac{\sum_{i=1}^{h} IRF_{t+i}^{d}}{\sum_{i=1}^{h} IRF_{t+i}^{u}}, \tag{13}$$

where the horizon h can be interpreted as the relevant horizon over which the costs of deleveraging is observed. Consider a policy shock that leads to a reduction in debt and an increase in unemployment. Hence, the ratio is negative. If for the same reduction in debt the loss in employment falls over time, the deleveraging becomes less costly. In this case, the index falls. We are able to achieve a quite high reduction in mortgage debt per unit increase in unemployment. An increase in Γ_t would thus be consistent with a deleveraging becoming more costly, i.e. for a one unit increase in unemployment we only get a relatively small reduction in debt. We consider two alternative horizons: $h = 8$ and $h = 12$ quarters. Fig. (9) displays the ratio for the two horizons. For both horizons h, we can see an upward trend in both series. Hence, a deleveraging becomes more expensive over time. The trend is broken only during the late 1990s.

The described path of our trade-off-graphs is quite intuitive and mirror-images the time-varying sensitivity of unemployment and debt in Fig. (2) and Fig. (3): deleveraging is (relatively) cheap if either the sensitivity of unemployment to monetary policy shocks is low or the sensitivity of mortgage debt is high.

5 The role of adjustable rate mortgages

There could potentially be many structural forces being responsible for the decline in the sensitivity of mortgages to monetary policy. Calza et al. (2013) highlight key parameters that have an effect on how sensitive mortgages are to the monetary policy stance. Among them, the ARM share plays an important role.

In the U.S. economy, this share declined over time. Fig. (10) plots the ARM share since the early 1980s. While in 1983 the share is about 60 %, it fell to only 10% in 2011.[8]

The share of ARM has some interesting implications for the transmission of monetary policy, as the sensitivity of mortgage debt to short-term interest rates is a key channel of the transmission of monetary policy the housing market and the economy in general. More precisely, given a scenario where mortgages are closely linked to short-term interest rates, unexpected hikes in the policy interest rate quickly shift both cash flows and mortgage payments in particular for existing borrowers. In this scenario, changes in the policy rate also affect the initial cost of new home loans, which in turn affects the demand for housing.

This is however not the case for the U.S. As mentioned before, the share of ARMs has declined in the last three decades, implying that home-buyers mostly preferred fixed-rate-mortgages (FRM) over ARM. We therefore expect that the transmission of monetary policy shocks to the economy is linked to the ARM share. In particular, we expect that the transmission is more powerful in a scenario where the ARM share is high.

This fall in the ARM share since the early 1980s corresponds to the decline in the sensitivity of mortgages to monetary policy documented before. To illustrate this point, Fig. (11) plots the impulse responses following monetary policy shocks originating in 1983Q3 and 2011Q3, respectively.

As we can see, the impact of a 25bp monetary policy shock on mortgages in the early 1980s exceeds by far the non-significant impact of the same shock at the end of our

[8] Moench et al. (2010) discuss the reduction in the ARM share in the U.S. and explain it in terms of financial innovations such as an increase in securitization and a shifting term structure of interest rates.

sample. Thus, in the following, we want to shed light on possible drivers of this sharp decrease in mortgage debt sensitivity with respect to monetary policy shocks and highlight the ARM share as a promising candidate to explain the declining sensitivity.

5.1 Some simple regressions

To obtain a first impression on the determinants of time-variation in the policy-impact on mortgages, we regress the dynamic impulse response functions on the ARM share. We also control for other characteristics of the prevailing contracts in this market. We do so for the peak responses of mortgage debt,

$$IRF_{t,\tau}^{peak} = c + \gamma X_t' + \varepsilon_t,$$

as wells as for impulse responses cumulated up to horizon h,

$$\sum_{\tau=1}^{h} IRF_{t,t+\tau} = c + \gamma X_t' + \varepsilon_t,$$

where t is the timing of the shock and τ is the timing of the response. Possible candidate variables for X_t other than the ARM share are the national average of the loan-to-value ratio (LTV) and the average effective interest rate payed for mortgage contracts (effective rate), both also provided by the Federal Housing Agency's Interest Rate Survey. The vector γ collects the coefficients and ε is a white-noise error term. It should be stressed that such a regression is illustrative only. The explanatory variables are by no means exogenous, structural determinants. Nevertheless, we believe such a regression to be informative. Below, we simulate a structural model to corroborate our findings.

Fig. 12 shows the respective correlation of the these variables with the regressors mentioned above. At a first glance, we can see that the ARM share seems to be negatively correlated with all types of regressors. Thus, for high ARM shares we should find lower impulse responses. The same holds for the loan-to-value ratio and the effective rate on mortgage debt.

To account for possible non-linearities between the impulse responses and the ARM share, we also include the squared ARM share into our regression. This is primarily motivated by the implications of our DSGE model described in the following section and in particular apparent from Fig. (20). Table (1) shows the outcome of regressions. As we can see, our regression analysis underlines the importance of the ARM share in explaining the time-varying negative impact of monetary policy

shocks. When the ARM share increases, the mortgage debt falls stronger after a policy tightening.
This finding holds in most regressions depicted in table (1). In almost all regressions, the control variables show the expected sign. When the LTV ratio is high, refinancing the existing burden of debt is relatively costly and thus incentives to reduce debt are high, respectively. Similar considerations hold for the effective rate. If financing debt is expensive, households tend to deleverage if policy tightens. Summing up, we conclude that the ARM share plays an important role in explaining the time-varying sensitivity of mortgage debt with regard to monetary policy shocks.

5.2 A DSGE-Model with mortgage contracts

While the previous regressions are illustrative only, eventually a structural model is needed to shed light on the impact of a shift in the ARM share on the strength of policy transmission. Therefore, we resort to the DSGE model by Alpanda and Zubairy (2017).
In short, the model builds a closed-economy DSGE with housing and household debt as well as an occasionally binding credit constraint. The model features two types of households, namely patient households (savers) and impatient households (borrowers). Excessive household debt arises due to exuberance shocks on expectations on house prices, thus driving a wedge between actual and fundamental values.
Importantly, the model allows the average duration of the fixed interest rate for loans to be shorter than the full amortization duration of the underlying loan itself. In simple words, the interest rate on new mortgage loans is decomposed into a fraction carrying a fixed mortgage interest rate and a fraction of existing loans that is refinanced each period.
We use the model to simulate impulse responses to monetary policy shocks for different calibrations of the ARM share. We simulate impulse responses for mortgage debt to a 25bp monetary policy shock, which is consistent with the definition of the policy shock in the TVP-VAR. In the first case, the "low share" case, we use the same overall calibration as Alpanda and Zubairy (2017), including the interest rate adjustability of mortgages based on a 10% ARM share, which we can observe at the end of the sample. In the second case, the "high share" case, we recalibrate the interest rate adjustability parameter based on an ARM share of 60% of 1982, keeping anything else similar to the benchmark case.
In Fig. (13), we compare the impulse responses to 25bp monetary policy shock for both the DSGE and the TVP-VAR, as well as for the two states mentioned above, the "low share" state and the "high share" of ARM state, respectively.

Two things stand out. First, similar to our time-varying VAR, there is a weaker reaction of mortgage debt to monetary policy shocks when the ARM share is low. Second, the amplitude of both the DSGE and the TVP-VAR are nearly identical in the high share case with a 0.05% drop in mortgages. For the low share case, the TVP-VAR shows a slightly weaker response. However, this can likely be attributed to the fact that our recalibration was solely based on the different fraction of ARM shares, although the interest rate duration is of course based on different factors, including home equity loans and repayments, among others.
Additionally, we can see that the relationship between the ARM share and the size of the mortgage reaction to a restrictive 25bp monetary policy shock shows a non-linear pattern. Fig. (20) plots a set of peak responses with their corresponding ARM shares. As we can see, this concave, model-implied nexus underpins the appropriateness of our TVP-VAR model as well as the inclusion of the squared ARM share in section (5.1). Summing up, the DSGE model provides further evidence for the important role of ARM shares in the transmission of monetary policy shocks. The empirically observed drop in the ARM share since the early 1980s leads to impulse responses which are quantitatively very similar to the responses derived from the TVP-VAR.

6 Counterfactual analysis

Thus far, our results provide evidence that the transmission of monetary policy shocks may have become weaker over time, based on the drop in the amplitude of impulse responses for the non-policy block, i.e. u, π, d. Moreover, from the standpoint that our model is supposed to uncover the time-varying structure of the economy, relative cumulative responses provide evidence that periods exist in which deleveraging might be less costly than in others. However, this section seeks to isolate Fed's role from the rest of the economy. This section reports results for some counterfactual experiments that might be of interest. Counterfactual analyses have been widely used (see, for instance, Primiceri, 2005, and Sims and Zha, 2006) and are an informative possibility to establish the role of the Fed in the weaker transmission of monetary policy shocks observed in section (4) on the one hand, but also on high volatility episodes of debt on the other. Although there are plenty of interesting experiments in general, we discuss two main results we believe are the most relevant in general and for our purpose in particular.
In a first experiment, we document the path of mortgage debt in a scenario with suppressed monetary policy shocks in an otherwise time-varying fashion, answering

the question what we would have observed if no monetary policy shocks would have hit the economy. This uncovers the time-varying contribution of monetary policy shocks to the fluctuation of household debt that has been observed in reality. In a second experiment, we seek to underpin our finding of a weaker transmission that was reported in section (4). In particular, the question remains whether the weaker impulse responses stem from possible shifts in the policy rule. This is particularly important in episodes where the structure of the economy implies relatively cheap deleveraging on the one hand, but more (costly) fluctuation on the other. From another point of view, given a regime shift occurs that pushes debt into a more volatile direction, there is a conflict in episodes where deleveraging is relatively cheap (based on the sacrifice ratio above). More precisely, if an underlying monetary policy regime leads to systematically higher (lower) fluctuation in debt, intentional deleveraging requires a more (less) aggressive behavior of the central bank to achieve the same outcome. By doing so, we isolate the effect of possible regime switches. In particular, we fix both the average VAR-parameters as well as the simultaneous relationship among variables over the corresponding duration. This is done for the three most recent chairmanships, including the Volcker regime (1979-1987), the Greenspan regime (1987-2006) and the Bernanke regime (2006-2014).
The procedure follows Primiceri (2005) and Sims and Zha (2006) and can be summarized as follows: since we have drawn all parameters from the joint posterior distribution, we are able to reconstruct the independent identically distributed sequence of unit-variance structural shocks. Starting from an arbitrary point, it is possible to simulate counterfactual data series, obtained using the parameters of our TVP-VAR, but with suppressed monetary policy shocks in the first experiment, and with time-invariant policy rules in the second.

Suppressed monetary policy shocks. Fig. (14) shows the simulated path for mortgage debt in a scenario in the absence of monetary policy shocks, keeping anything else similar to the benchmark case (i.e. drawing from the time-varying parameters). Two things stand out. First, there are episodes where the simulated path and the data that has been observed in reality are remarkably different. The red ellipses mark episodes where the simulated paths lie outside the 16^{th} and 84^{th} percentiles. As can be seen, the frequency of such episodes declined just in line with the Great Moderation. Second, the simulated paths are mostly lower (higher) in periods when debt was high (low). Albeit there are episodes of remarkable differences, especially during times of financial turmoil, the simulated path is mostly not too different from the actual path. This shows that there must be mainly sources other than monetary policy shocks in order to explain high episodes of mortgage volatility. This finding is underpinned in Fig. (15), as the difference between simulated and actual path gradually declined over time.

The role of chairmanships. As mentioned above, the second experiment seeks to uncover possible regime shifts that could in fact account for shifting feedback effects in the economy which in turn might contribute to episodes of high fluctuations.[9]
Fig. (16) summarizes the results of our experiment. Focusing on mortgage debt, the upper plot shows the actual data as well as the simulated paths for all different chairmen periods. Clearly, both the simulated paths as well as the actual data cannot be distinguished with the naked eye. This is interesting insofar as that possibly different policy rules cannot account for substantial fluctuations of household debt. The lower plot shows the differences between the actual and simulated paths. Interestingly, there is a well pronounced scheme insofar as the simulated path for a scenario where the Bernanke period (had it persisted from 1957Q1 on) is permanently higher than for the other two cases.

7 Robustness

The results presented in section (4) were derived from a policy rule that contained zero-restrictions. We also assumed a specific ordering of the variables. Therefore, our robustness section aims to underpin our results for several experiments. As it is common in Bayesian literature, we also evaluate our choice of priors.

Unrestricted Policy Rule. Although it is reasonable to assume that the Fed's policy rule does not include a reaction to household debt as depicted in section (3), our first experiment is to relax this assumption for robustness purposes. Therefore, we re-estimate our model without the restriction on the policy rule, keeping all other features of the model constant. The estimated paths for the lagged coefficients in the policy rule as well as the corresponding parameter in the simultaneous relationship matrix are shown in Fig. (17).
Interestingly, the lagged coefficients are different from zero. The variation over time is small, which is clearly attributable to the informative prior on Σ_B. This is not

[9] Of course, to fully account for the role of regime switches, a more complex model is needed, as in Sims and Zha (2006). However, this problem is mitigated for two reasons. First, we are mainly interested in the consequences of possible shifts in the policy rule, saying that uncovering regime switches itself is not of primary interest for us. The second stems from the fact that our results do not provide evidence in favor of remarkable differences among chairmanships.

the case for the covariance between mortgage debt and the short rate, as there is much time-variation observable, even though the estimates mostly fluctuate around zero.
The corresponding impulse responses over time are shown in Fig. (18). It stands out that the impulse responses are not distinguishable from the baseline case with the naked eye. Similarly to the benchmark case, there is a trend towards a weaker transmission of monetary policy shocks.[10] Summarizing our results, we conclude that including mortgage debt in the policy rule leads to very similar results with the estimated parameters not being different from zero. However, it should be noted that this observation could also be the case if we forget to include variables that are strongly correlated to the debt variable.

Sensitivity to priors. As our results presented in section (4) are based on our particular prior choice, this section reports the results for alternative prior specifications as well as alternative orderings of our variables. First, it stands out that the choice of the priors for the initial states of the Gibbs sampler turned out to be innocuous, the prior choice for Σ_B, Σ_a and Σ_h, however, did not. Of course, the prior choice for these hyper-parameters can affect posterior inference, although Σ_B, Σ_a and Σ_h do not parametrize the time variation in the first line, but only prior beliefs about the time-variation. Choosing looser priors for Σ_B, e.g. $(\Sigma_B^2)_i \sim G(30, 1 \cdot 10^{-3})$ results in much more time-variation, although the estimation procedure becomes inefficient as our convergence tests are unsatisfying. This being said, the model seems to misbehave for looser priors than in our benchmark case, saying that our particular prior choice does not penalize time variation in the coefficients (see Primiceri, 2005). Different choices for Σ_a and Σ_h do not affect the results in a significant way. We try both looser and tighter priors, but the results are very much the same as in the baseline model. Summing up, our results are very robust against alternative prior choices, as long as the prior for Σ_B is informative enough.

Sensitivity to an alternative ordering. Choosing an alternative Cholesky-ordering can, in principle, affect our results, as we alter the linear combinations of the reduced form error terms which lie behind the structural shock. For this reason we check whether alternative orderings, i.e. ordering prices before unemployment, affect our main result. It turns out that the alternative ordering results in very similar results, which implies that our results are also robust with regard to the recursive

[10] Also the relative cumulative responses of unemployment and mortgage debt show a similar picture. Other results for the unrestricted policy rule are available upon request.

ordering of the variables.

Alternative variables. Another concern could be related to our choice of variables. For mortgage debt, which we include in deviations from its trend, we also tried different detrending techniques (e.g. the Hodrick-Prescott filter) as well as different settings for our Baxter-King (1999) filter. The results do not change much. This being said, we also try different combinations of variables, replacing unemployment by GDP-growth (annual, seasonally adjusted) or output gap as well as prices by an inflation rate based on the CPI (annual, seasonally adjusted). It stands out that our qualitative results are robust against different variable selections.
For example, using inflation based on the CPI delivers very much the same qualitative results, albeit there is a severe price puzzle, as can be seen in Fig. (19). Other results (e.g. the Γ) show a similar scheme.

8 Conclusions

In this paper, we studied the role of monetary policy for the dynamics of U.S. mortgage debt, the largest and most important component of overall household debt. In the aftermath of the recent financial crisis, which originated in the U.S. housing market, the mortgage market received much attention.
The main tool of our analysis, a time-varying VAR model with stochastic volatility, allowed us to study the sensitivity of mortgage debt to monetary policy over time. We find that since the 1960s the impact of monetary policy on mortgage debt steadily declined. A policy shock in 2014 has a much smaller effect on mortgage debt than a similarly sized shock originating in 1970. This finding, which is new to the literature, is robust to variations of the model and the parameterization and not driven by changes to monetary policy itself.
We also estimate a DSGE model for the U.S. economy in order to replicate our empirical findings. The share of adjustable mortgages, a key parameter in the determination of the model-based impulse responses, is shown to have declined strongly since the early 1980s. Once we calibrate the model to alternative realizations of the ARM share, we are able to replicate the decline in the response of debt to monetary policy quantitatively. To the extent the ARM share could be taken as given, this offers a consistent explanation for our findings.
These findings have several implications for monetary policy and the mortgage market. First, our results suggest that, nowadays, monetary policy is a blunt and

ineffective tool to engineer a deleveraging of households. The decline in the sensitivity to monetary policy implies that a large policy adjustment is needed in order to have a sizable effect on mortgage debt. This, however, would cause a deep recession. Hence, our results speak against using monetary policy as an instrument to prevent the build-up of household debt. Rather, macroprudential instruments such a caps on loan-to-value ratios might be a more effective too to fulfill these roles.

A second interpretation of our results addresses the role of the Fed in the run-up to the recent financial crisis. It is often claimed that the Fed contributed to inflating house prices by keeping the Federal funds target rate too low for too long. Our results put this claim into perspective. If the sensitivity of mortgage debt to monetary policy in the mid-2000s is low, which is our main result, even persistently low levels of the Federal funds rate should contribute little to the rise in mortgage debt before the crisis. Likewise, tightening monetary conditions, as the Fed did after June 2004, should translate into a small decrease in mortgage debt. Of course in the VAR model we focus on the non-systematic part of monetary policy only. However, even counterfactuals in which we replace the systematic part of monetary policy show that the contribution of monetary policy to the dynamics of mortgage debt has been small.

Our results fit together with the "mortgage rate conundrum" diagnosed by Justiniano et al. (2017). These authors argue that the empirical link between mortgage rates and longer-term interest rates broke. Hence, there seem to be strong structural changes in the mortgage market and its link to monetary policy. While this paper focuses on mortgage debt, other aspects of this structural shift are left to future research.

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A Appendix

Convergence diagnostics

This appendix assesses convergence of our MCMC algorithm in the baseline case presented in section (3). We applied different experiments in order to judge how well our chain mixes. Remember that we used 50,000 iterations and discarded the first 45,000. It stands out that choosing different burn-in periods delivered exactly the same results. It is common practice to observe the inefficiency factors for convergence analysis. Simply speaking, the inefficiency factor is the inverse of the relative numerical efficiency measure of Geweke (1992) and defined by $1 + 2\sum_{j=1}^{\infty} \rho_j$, where ρ_j is the autocorrelation of j^{th} order for the underlying parameter. Inefficiency factors of around 20 are regarded as satisfactory. Table A reports the inefficiency factors of our entire parameter space. Except for the hyperparameters, the inefficiency factors are on average far below 20. Not taking single outliers too serious as our parameter space is large, we conclude that our chain mixes quite fast.

	Mean	Median	Max	70^{th} Percentile	90^{th} Percentile
V	23.11	17.21	95.7	24.52	43.93
B	2.91	2.63	10.33	3.31	3.95
A	2.89	1.56	16.89	3.33	7.5
Σ	4.26	2.91	25.8	4.96	9.13

A: Distribution of inefficiency factors for the entire parameter space.

We also applied the Geweke (1992) convergence diagnostic test. The idea can be sketched as follows: for each single parameter, the idea is to compare the first n_0 draws of the chain to the n_1 draws by dropping the corresponding draws in between. The statistics are calculated as $G = (\bar{x}_0 - \bar{x}_1)/\sqrt{\widehat{\sigma}_0^2/n_0 + \widehat{\sigma}_1^2/n_1}$, where $x_j = (1/n_j)\sum_{i=m_j}^{m_j+n_j} x^i$. x^i is the ith draws and $\widehat{\sigma}_j^2/n_j$ is the standard error of $\bar{x}_j$ for $j = 0, 1$. We choose n_0 as the first 10% and n_1 as the last 50%. $\widehat{\sigma}_j^2$ is computed using a Parzen window. Of course, G is below 0.05 if the whole chain is stationary, saying that the means of the first n_0 and the last n_1 values are quite similar.However, it turned out that for V 72.09% , for B 61.97%, for A 60.69% and for Σ 56.55% seemed to converge after the first 5000 draws.
To sum up, the convergence diagnostics seem satisfactory, considering the high parameter space of our model.

A.1 Implementation of the short-run restrictions

As explained in section (3), we include four variables in our model, that is unemployment u, inflation π, mortgage debt d as the non-policy block and a short-term interest rate i intended to represent the policy block. This implies that our TVP-VAR can be written as

$$
\begin{aligned}
\begin{bmatrix} u_t \\ \pi_t \\ d_t \\ i_t \end{bmatrix} = \begin{bmatrix} c_t^u \\ c_t^\pi \\ c_t^d \\ c_t^i \end{bmatrix} + \begin{bmatrix} b_{1,t}^{uu} & b_{1,t}^{\pi u} & b_{1,t}^{du} & b_{1,t}^{iu} \\ b_{1,t}^{u\pi} & b_{1,t}^{\pi\pi} & b_{1,t}^{d\pi} & b_{1,t}^{i\pi} \\ b_{1,t}^{ud} & b_{1,t}^{\pi d} & b_{1,t}^{dd} & b_{1,t}^{id} \\ b_{1,t}^{ui} & b_{1,t}^{\pi i} & b_{1,t}^{di} & b_{1,t}^{ii} \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \pi_{t-1} \\ d_{t-1} \\ i_{t-1} \end{bmatrix} + \cdots \\
... + \begin{bmatrix} b_{s,t}^{uu} & b_{s,t}^{\pi u} & b_{s,t}^{du} & b_{s,t}^{iu} \\ b_{s,t}^{u\pi} & b_{s,t}^{\pi\pi} & b_{s,t}^{d\pi} & b_{s,t}^{i\pi} \\ b_{s,t}^{ud} & b_{s,t}^{\pi d} & b_{s,t}^{dd} & b_{s,t}^{id} \\ b_{s,t}^{ui} & b_{s,t}^{\pi i} & b_{s,t}^{di} & b_{s,t}^{ii} \end{bmatrix} \begin{bmatrix} u_{t-s} \\ \pi_{t-s} \\ d_{t-s} \\ i_{t-s} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ \tilde{a}_t^{u\pi} & 1 & 0 & 0 \\ \tilde{a}_t^{ud} & \tilde{a}_t^{\pi d} & 1 & 0 \\ \tilde{a}_t^{ui} & \tilde{a}_t^{\pi i} & \tilde{a}_t^{di} & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t^u \\ \epsilon_t^\pi \\ \epsilon_t^d \\ \epsilon_t^i \end{bmatrix}.
\end{aligned} \tag{14}
$$

However, considering the Feds' mandate it might be reasonable to assume that d should not appear in the interest rate equation (i.e. the policy rule). This implies that $b_{1,t}^{di}, ..., b_{s,t}^{di}$ as well as $\tilde{a}_t^{di}$ should be restricted to zero. The rationale behind this is that the Fed only responds to unemployment u and price π fluctuations, but not to debt d. Implementing these restrictions implies that policy becomes

$$
\begin{aligned}
i_t =& c_t^i + b_{1,t}^{ui} u_{t-1} + b_{1,t}^{\pi i} \pi_{t-1} + \underbrace{b_{1,t}^{di}}_{\overset{!}{=}0} d_{t-1} + b_{1,t}^{ii} i_{t-1} + ... \\
& ... + b_{s,t}^{ui} u_{t-s} + b_{s,t}^{\pi i} \pi_{t-s} + \underbrace{b_{s,t}^{di}}_{\overset{!}{=}0} d_{t-s} + b_{s,t}^{ii} i_{t-s} + ... \\
& ... + \tilde{a}_t^{ui} \epsilon_t^u + \tilde{a}_t^{\pi i} \epsilon_t^\pi + \underbrace{\tilde{a}_t^{di}}_{\overset{!}{=}0} \epsilon_t^d + \epsilon_t^i,
\end{aligned} \tag{15}
$$

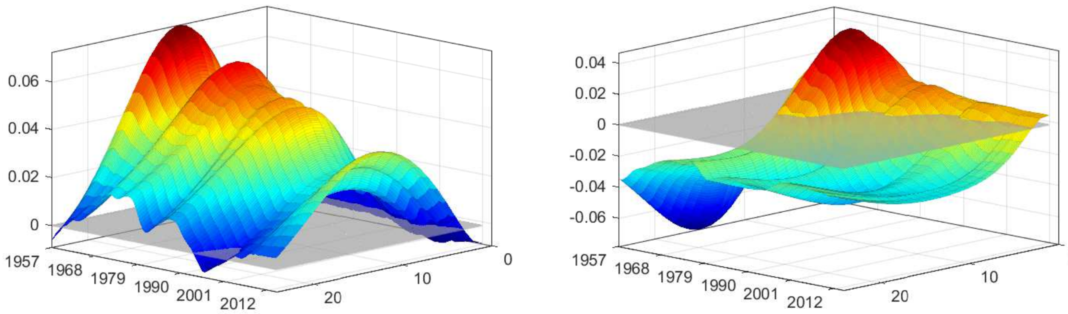
Summing up, restricting $\tilde{a}_t^{\varphi i}$ and $b_{s,t}^{\varphi i}$ for all lags to zero results in

$$
\begin{aligned}
\begin{bmatrix} u_t \\ \pi_t \\ d_t \\ i_t \end{bmatrix} = \begin{bmatrix} c_t^u \\ c_t^\pi \\ c_t^d \\ c_t^i \end{bmatrix} + \begin{bmatrix} b_{1,t}^{uu} & b_{1,t}^{\pi u} & b_{1,t}^{du} & b_{1,t}^{iu} \\ b_{1,t}^{u\pi} & b_{1,t}^{\pi\pi} & b_{1,t}^{d\pi} & b_{1,t}^{i\pi} \\ b_{1,t}^{ud} & b_{1,t}^{\pi d} & b_{1,t}^{dd} & b_{1,t}^{id} \\ b_{1,t}^{ui} & b_{1,t}^{\pi i} & 0 & b_{1,t}^{ii} \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \pi_{t-1} \\ d_{t-1} \\ i_{t-1} \end{bmatrix} + \cdots \\
... + \begin{bmatrix} b_{s,t}^{uu} & b_{s,t}^{\pi u} & b_{s,t}^{du} & b_{s,t}^{iu} \\ b_{s,t}^{u\pi} & b_{s,t}^{\pi\pi} & b_{s,t}^{d\pi} & b_{s,t}^{i\pi} \\ b_{s,t}^{ud} & b_{s,t}^{\pi d} & b_{s,t}^{dd} & b_{s,t}^{id} \\ b_{s,t}^{ui} & b_{s,t}^{\pi i} & 0 & b_{s,t}^{ii} \end{bmatrix} \begin{bmatrix} u_{t-s} \\ \pi_{t-s} \\ d_{t-s} \\ i_{t-s} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ \tilde{a}_t^{u\pi} & 1 & 0 & 0 \\ \tilde{a}_t^{ud} & \tilde{a}_t^{\pi d} & 1 & 0 \\ \tilde{a}_t^{ui} & \tilde{a}_t^{\pi i} & 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t^u \\ \epsilon_t^\pi \\ \epsilon_t^d \\ \epsilon_t^i \end{bmatrix}.
\end{aligned} \tag{16}
$$

B Appendix

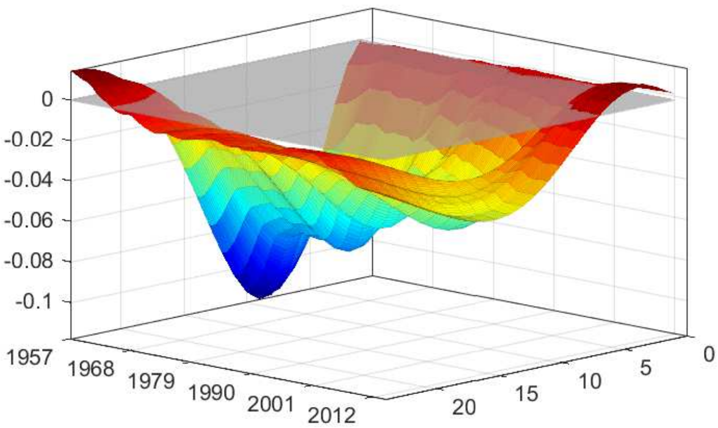
Figure 2: Mean responses to a monetary policy shock

(a) Unemployment (b) Inflation



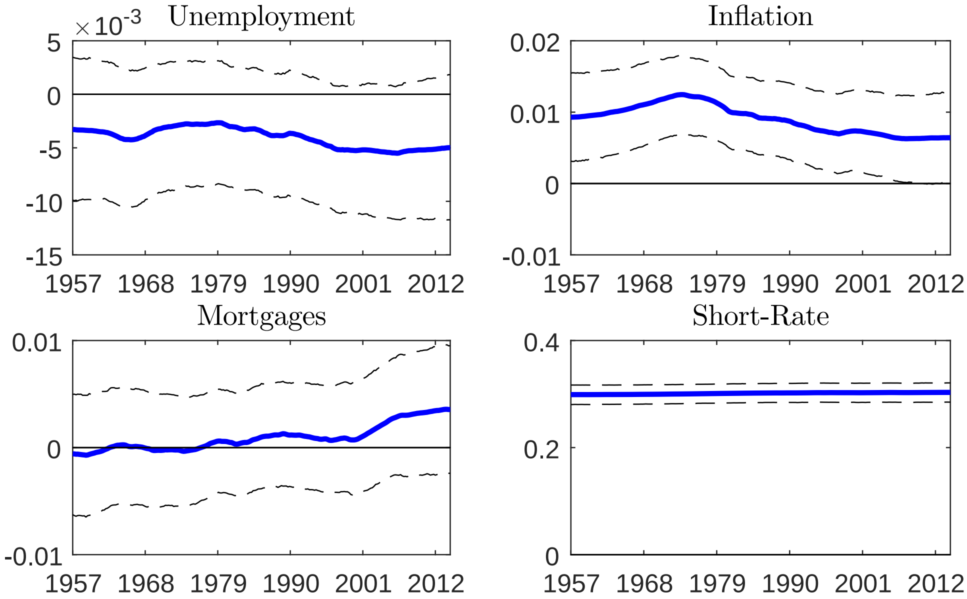
Notes: Results from our baseline TVP-VAR model. The monetary policy shock is 25bp in size.

Figure 3: Mean responses to a monetary policy shock: mortgage debt



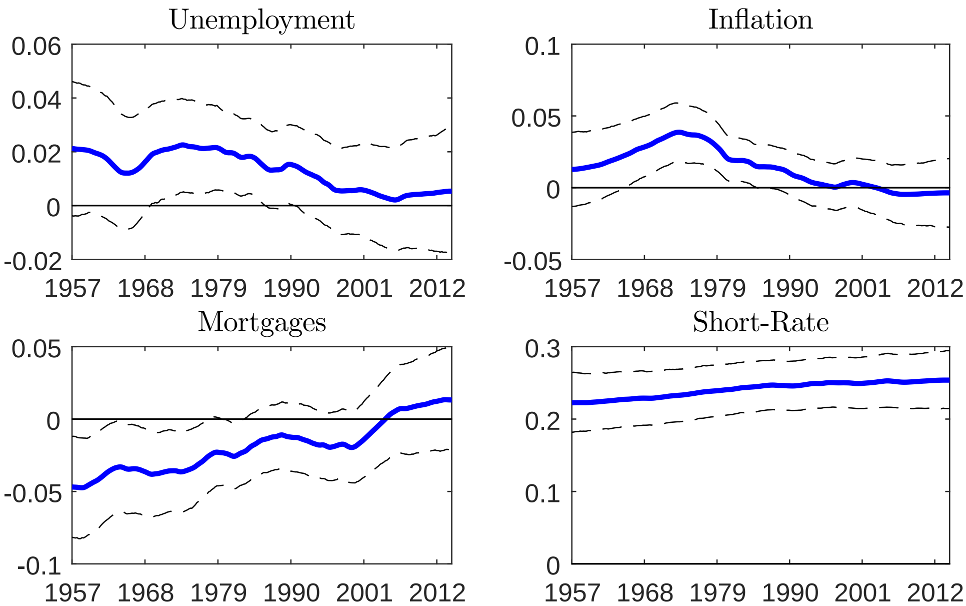
Notes: Results from our baseline TVP-VAR model. The monetary policy shock is 25bp in size.

Figure 4: Responses to a monetary policy shock after 1 quarter



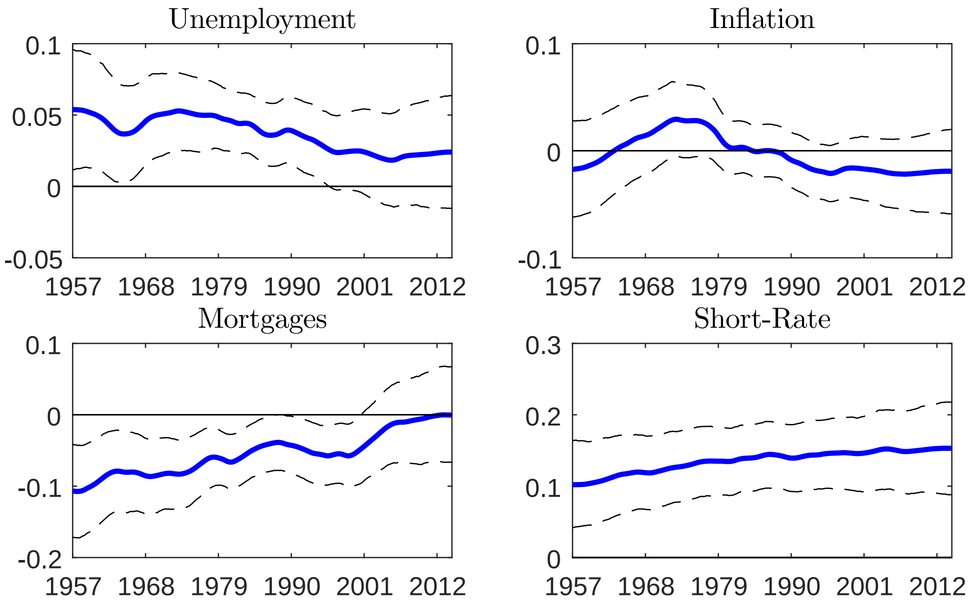
Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (grey-dashed) to an initial monetary policy shock of 25bp after 1 quarter.

Figure 5: Responses to a monetary policy shock after 4 quarters



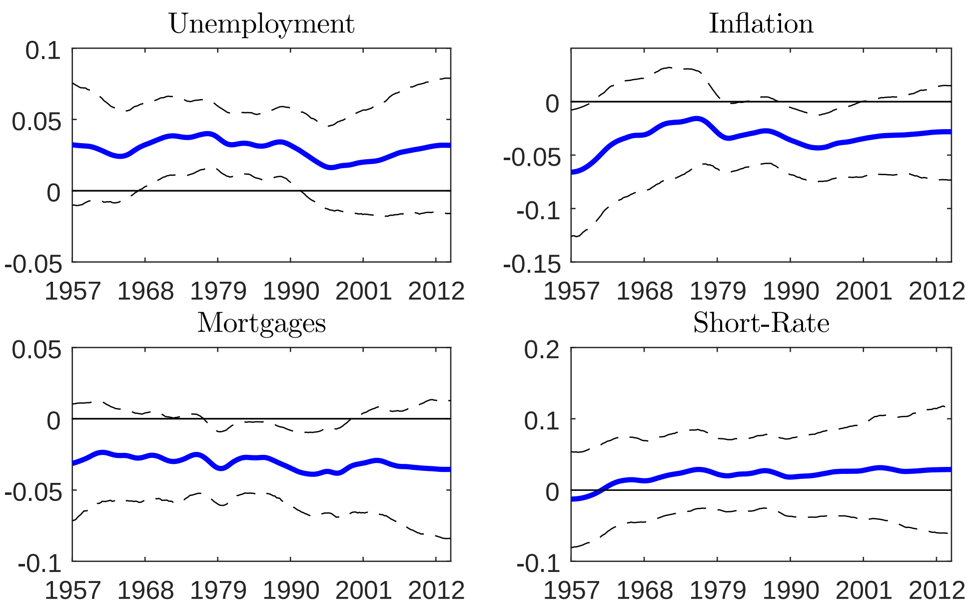
Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (grey-dashed) to an initial monetary policy shock of 25bp after 4 quarters.

Figure 6: Responses to a monetary policy shock after 8 quarters



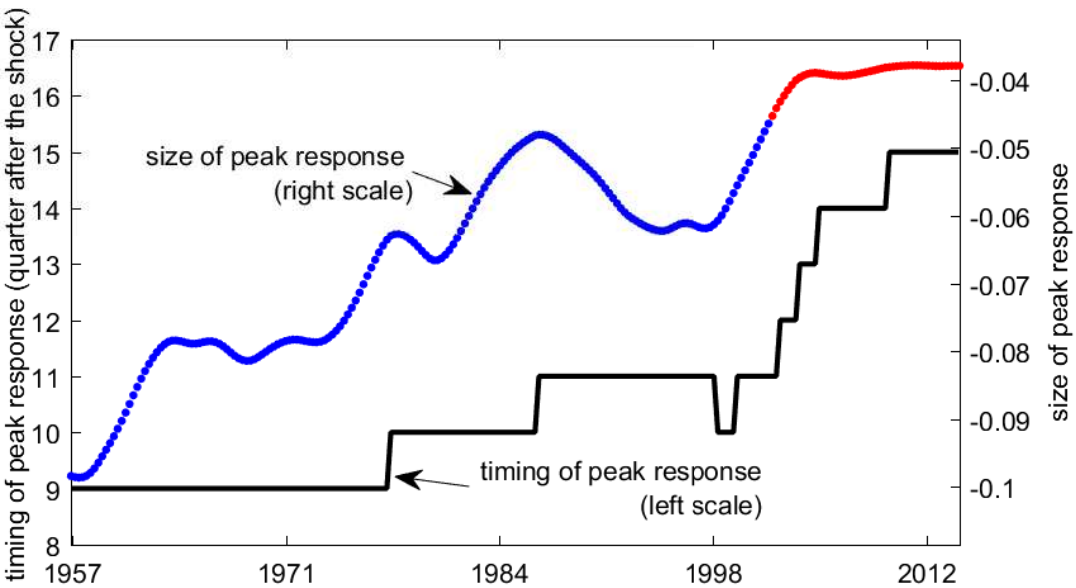
Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (grey-dashed) to an initial monetary policy shock of 25bp after 8 quarters.

Figure 7: Responses to a monetary policy shock after 16 quarters



Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (grey-dashed) to an initial monetary policy shock of 25bp after 16 quarters.

Figure 8: Peak response of mortgage debt

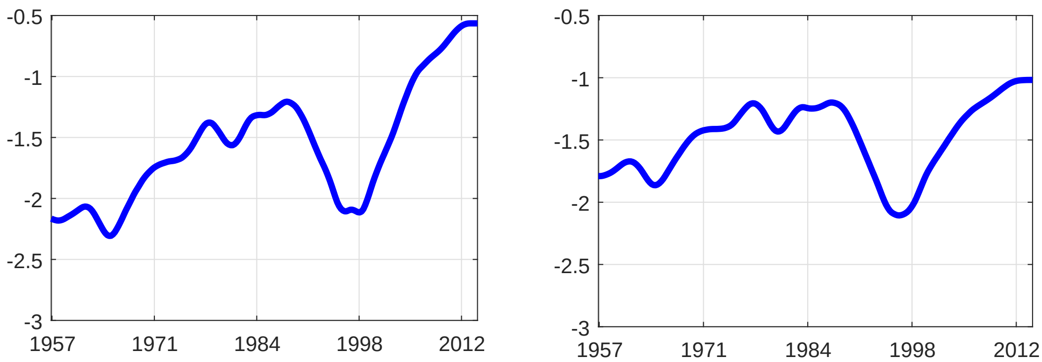


Notes: The peak response of mortgage debt for which the zero line does not lie in the confidence band is shown as a series of blue dots (right axis). The dots turn red when the zero line lies in the confidence band. The black line (left scale) reports the period after the shock in which the peak response occurs.

Figure 9: Costs of debt reduction

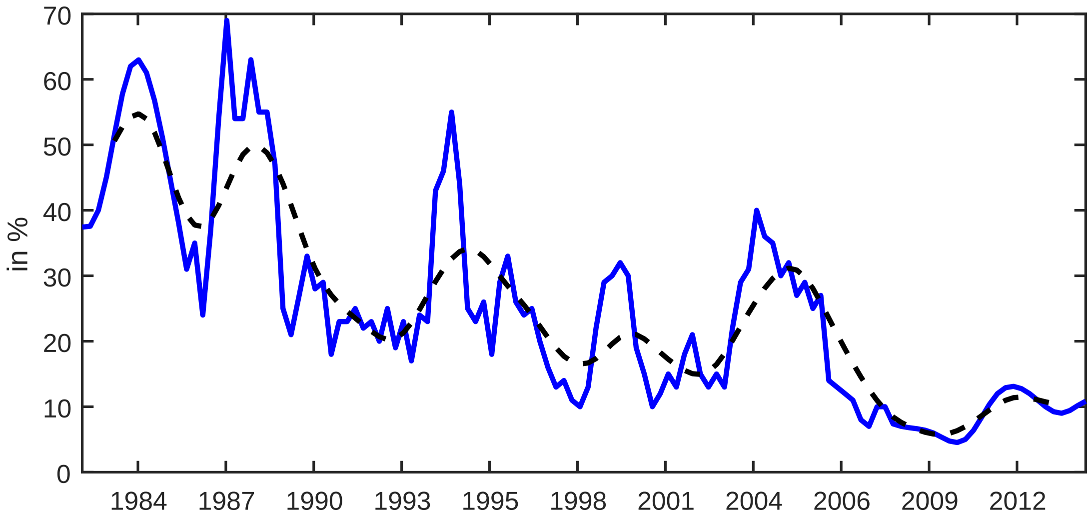
(a) $h = 8$ quarters

(b) $h = 12$ quarters



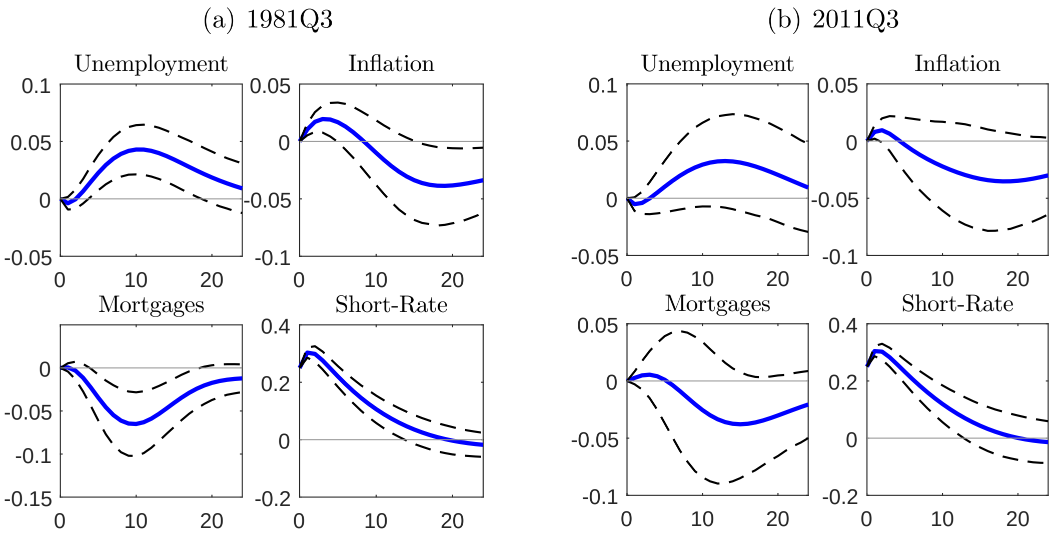
Notes: The graphs plot the ratio Γ_t over time. Γ_t is constructed as the ratio of the cumulative responses of mortgage debt and unemployment for horizon h.

Figure 10: Share of Adjustable Rate Mortgage Contracts



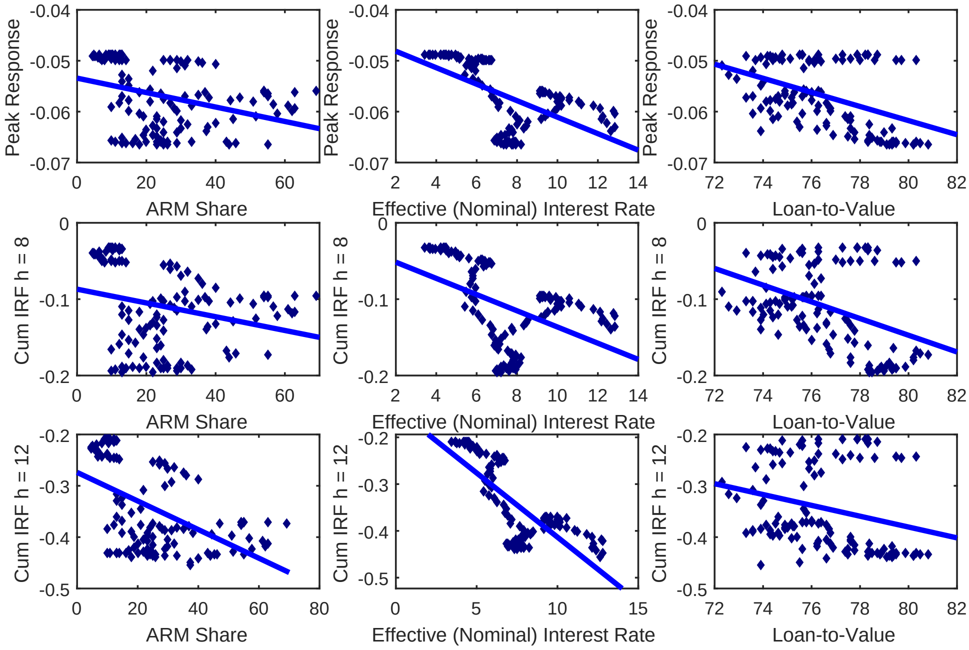
Notes: The data is taken from Federal Housing Agency, Monthly Interest Rate Survey, Table 9 and 17. We use chained data based on data availability, thus we use from 1982Q2 until 1984Q4 and from 2008Q4 until 2014Q3 interpolated data extracted from annual basis and end-of-quarter monthly data else. The blue-solid path corresponds to the quarterly ARM share, the black-dashed to its 2 years moving average, respectively.

Figure 11: Response to a monetary policy shock in 1983Q1 and 2011Q3



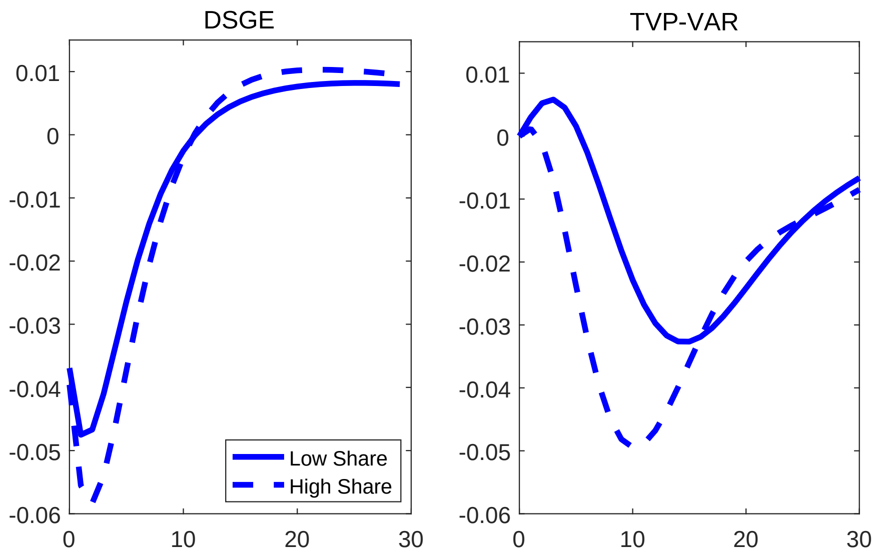
Notes: Mean response to a monetary policy shock in 1983Q1 and 2011Q3 occurring 1983Q3 (a) and 2011Q3 (b) (blue-solid) and 16^{th} and 84^{th} percentiles (grey-dashed).

Figure 12: Scatter plots



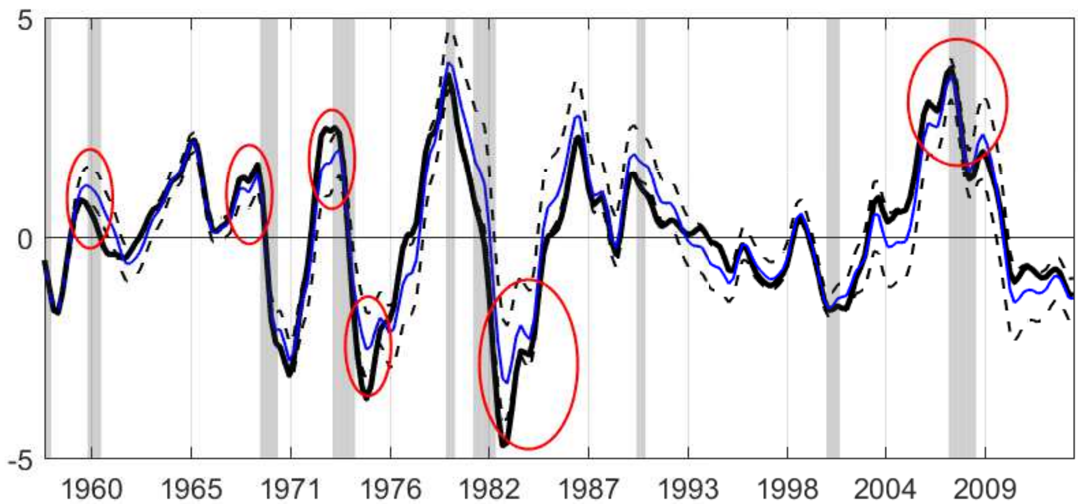
Notes: Correlation between impulse responses and selected variables. The first row plots the peak responses against these variables, the second row plots cumulated responses with h=8 against them and the third row cumulated responses with h=12.

Figure 13: Responses of mortgage debt to a monetary policy shock in the DSGE model and the TVP-VAR



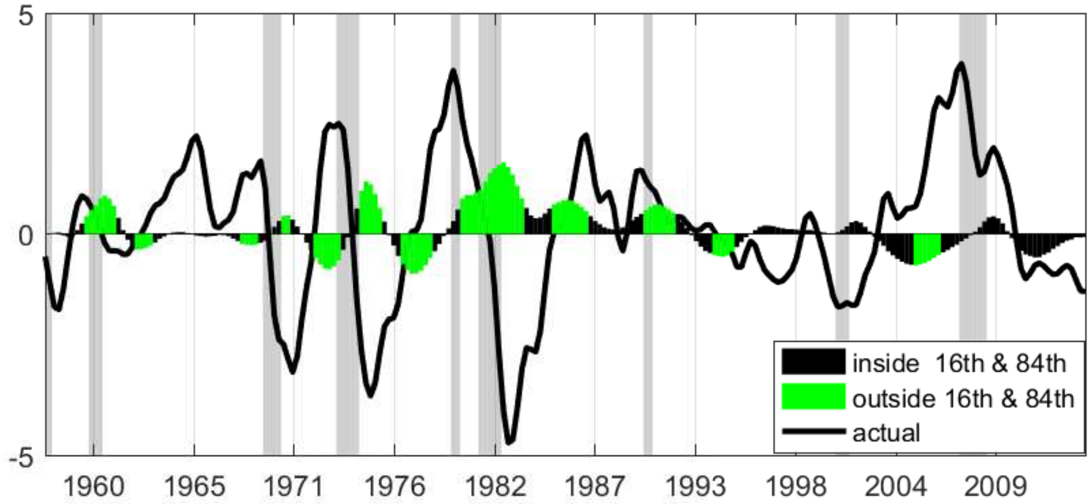
Notes: In both cases, the shock is a surprise increase in the interest rate by 25bp. The DSGE model of Alpanda and Zubairy (2017) is calibrated to a "high share" state with an ARM share of 60% and a "low share" state with a share of 10%.

Figure 14: Counterfactual analysis



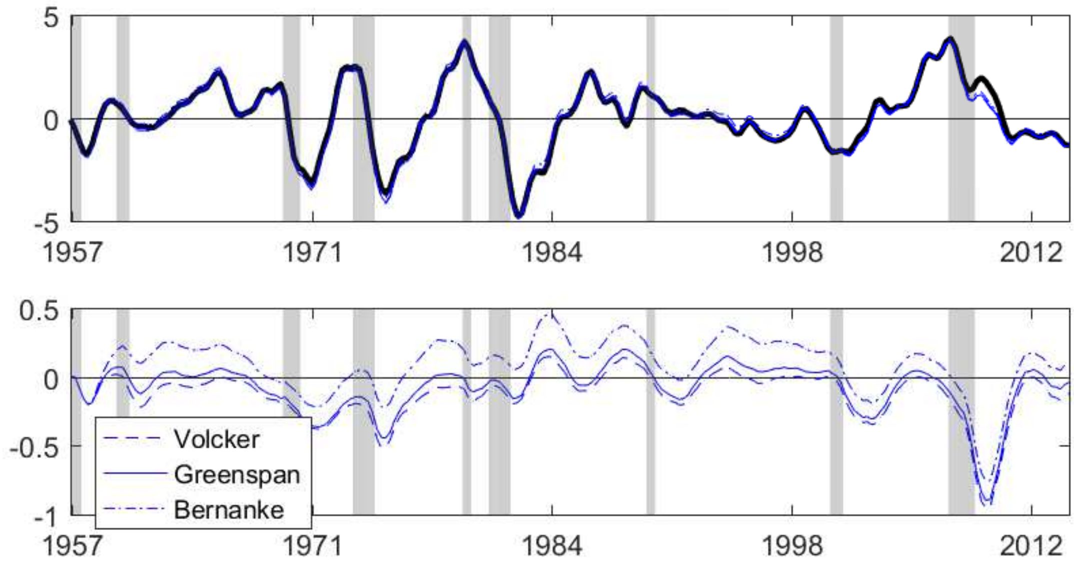
Notes: The blue-solid line corresponds to the simulated paths, the black solid line to the actual (observed) data, the black-dotted paths to the 16^{th} and 84^{th} percentiles.

Figure 15: Explanatory power of monetary policy shocks for mortgage debt



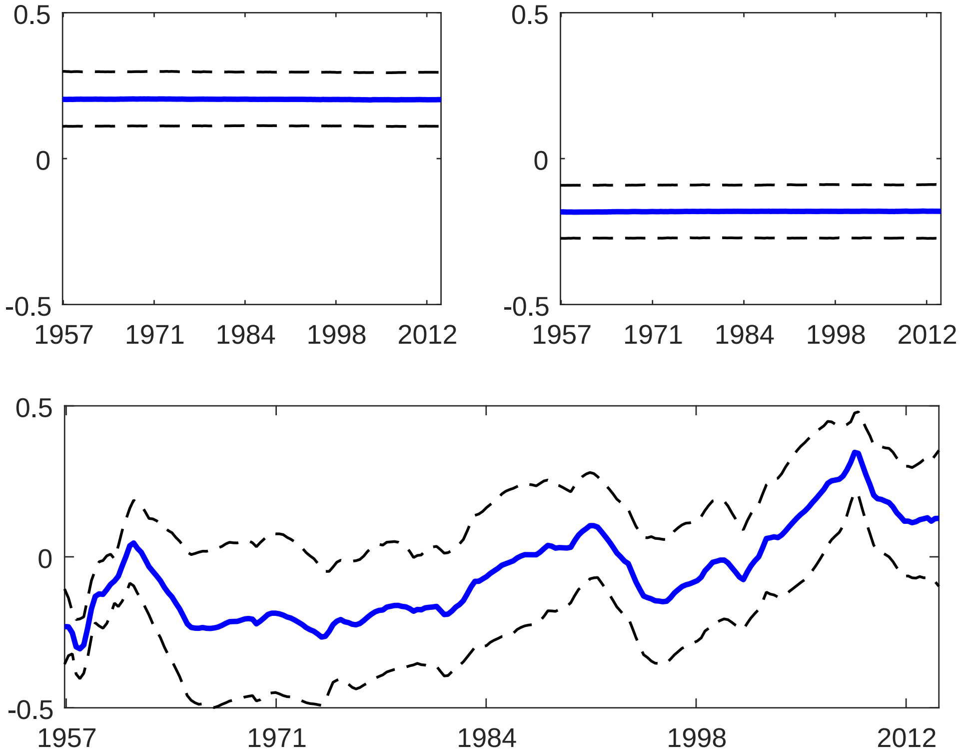
Notes: Difference between the counterfactual and the actual path. Black bars indicate that the observable series lies inside the percentiles around the counterfactuals. Green bars indicate episodes where the observable series lies outside the percentiles.

Figure 16: Counterfactual paths of mortgages for different policy rules



Notes: The upper panel shows counterfactual paths of mortgages for alternative policy rules associated with different Fed chairs. The lower panel shows the differences between the simulated and the actual path.

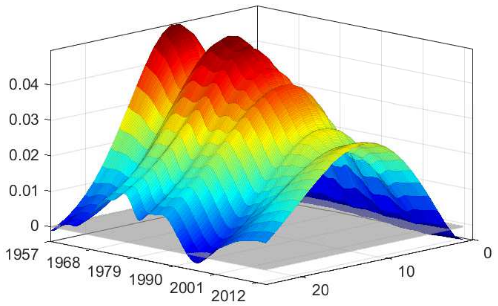
Figure 17: Parameter restrictions



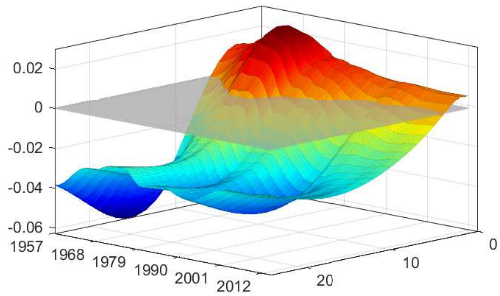
Notes: Restricted parameters (blue-solid line) with 16^{th} and 84^{th} percentiles over time. Panel (a) corresponds to b_1^{di}, panel (b) to b_2^{di} and panel (c) to $\tilde{a}^{di}$.

Figure 18: Response to a monetary policy shock: unrestricted policy rule

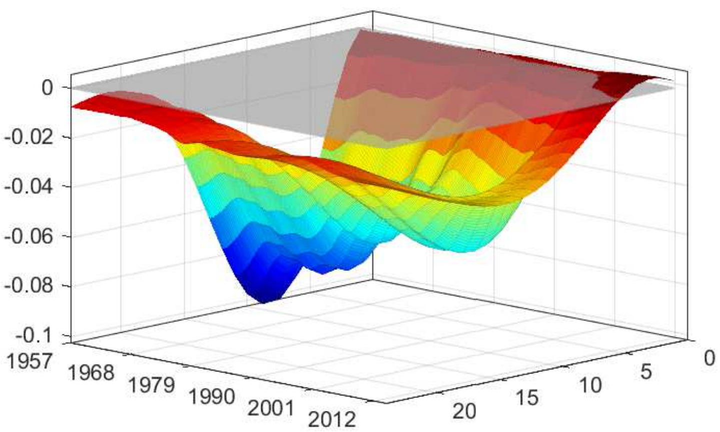
(a) Unemployment



(b) Inflation



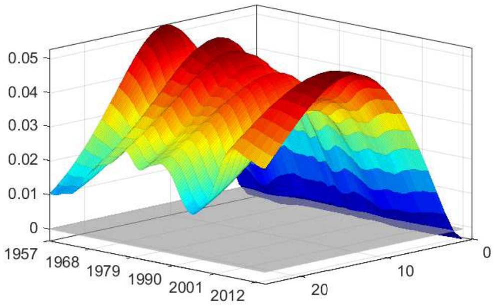
(c) Mortgages



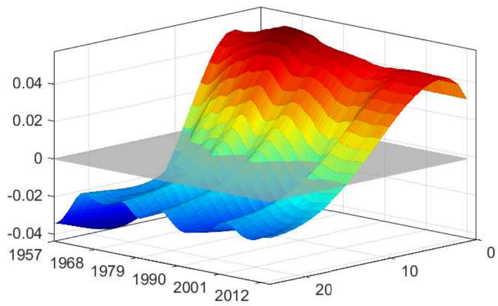
Notes: Impulse response functions following a 25bp monetary policy shock derived from the TVP-VAR model with an unrestricted policy rule.

Figure 19: Response to a monetary policy shock: alternative variables

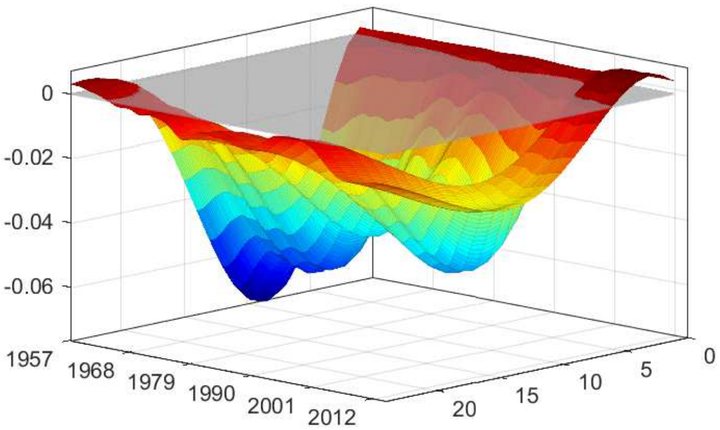
(a) Unemployment



(b) Urban Consumer Price Index Inflation

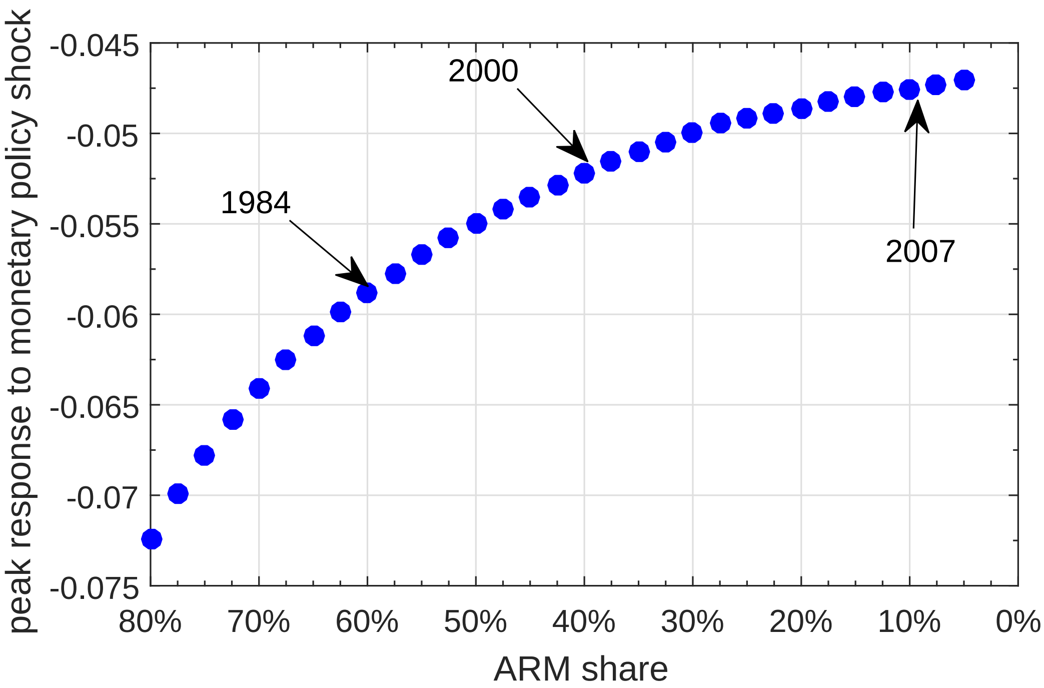


(c) Mortgages



Notes: Impulse response functions following a 25bp monetary policy shock derived from the TVP-VAR model with unemployment and CPI inflation.

Figure 20: DSGE model implied peak responses to monetary policy shocks



Notes: Each point reflects a DSGE model with an altered ARM share and the corresponding peak response to a 25bp monetary policy shock. Additionally, the graphic is augmented with three selected dates characterized by different ARM shares.

Table 1: Regression of time-varying policy impact on ARM share

	peak responses			
constant	-0.035 (0.001)	-0.047 (0.002)	0.063 (0.016)	0.075 (0.013)
ARM share	-0.000 (0.00)	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.000)
ARM share squared		0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
LTV			-0.001 (0.000)	-0.002 (0.000)
effective rate				-0.002 (0.000)
adj. R^2	0.115	0.266	0.457	0.641

	cumulative responses ($h = 8$)			
constant	-0.087 (0.009)	-0.026 (0.014)	0.922 (0.139)	0.981 (0.127)
ARM share	-0.001 (0.000)	0.006 (0.001)	0.008 (0.001)	0.008 (0.001)
ARM share squared		0.000 (0.000)	-0.093 (0.015)	-0.077 (0.014)
LTV			-0.010 (0.002)	-0.011 (0.002)
effective rate				-0.012 (0.002)
adj. R^2	0.057	0.229	0.430	0.528

	cumulative responses ($h = 12$)			
constant	-0.274 (0.012)	-0.188 (0.019)	0.705 (0.207)	0.885 (0.157)
ARM share	-0.003 (0.000)	-0.010 (0.001)	-0.010 (0.001)	-0.005 (0.001)
ARM share squared		0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
LTV			-0.012 (0.003)	-0.013 (0.002)
effective rate				-0.028 (0.003)
adj. R^2	0.264	0.406	0.474	0.701

Notes: The table reports the regression results discussed in section (5.1) for various estimation setups. Standard errors are given in parenthesis.