Monetary Policy and Household Net Worth*

Martín Harding[†] Mathias Klein[‡]

October 29, 2019

Latest version: click here

Abstract

This paper investigates the interrelation between household balance sheets, collateral constraints and monetary policy. Using data on the U.S. economy, we estimate a monetary DSGE model with financial frictions and occasionally binding borrowing constraints. The model implies stronger effects of monetary policy interventions when the borrowing constraint is binding compared to situations when it turns slack. In a prediction analysis we find that, out of a set of alternative plausible endogenous model variables, the level of household net worth is the single best predictor of the tightness of the borrowing constraint, which implies that monetary policy is more effective when household net worth is low. We test this model prediction on aggregate data and provide robust empirical evidence on asymmetric effects of monetary policy across the household net worth cycle that validates the model predictions. A contractionary monetary policy shock leads to a large and significant fall in economic activity during periods of low household net worth. In contrast, monetary policy shocks have only small and mostly insignificant effects when net worth is high.

JEL Codes: E32, E52.

Keywords: Monetary policy, household net worth, occasionally binding constraints.

*A previous version of this paper was titled "Monetary Policy and Household Deleveraging". We thank the editor Vincenzo Quadrini and two anonymous referees for their helpful comments and suggestions. Special thanks to Mathias Trabandt for detailed feedback and support. David Andolfatto, Dario Caldara, Cristiano Cantore, Efrem Castelnuovo, Martin Eichenbaum, Michael Ehrmann, Philipp Engler, Carlo Favero, Marcel Fratzscher, Jordi Galí, Volker Grossmann, Alexander Haas, Matteo Iacoviello, Alejandro Justiniano, Peter Karadi, Michael Krause, Jesper Lindé, Ludger Linnemann, Michael McMahon, John Muellbauer, Gert Peersman, Michele Piffer, Marco Pinchetti, Frank Smets, Thomas Steger, Gregory Thwaites, Peter Tillmann, Lutz Weinke, Roland Winkler, as well as seminar participants at the Berlin International Macroeconomics Workshop, 2018 RES Annual Conference, 2018 IAAE Annual Conference, 2018 CEF International Conference, 2018 EEA-ESEM Annual Congress, Norges Bank, University of Helsinki, Bundesbank, University of Cologne, Sveriges Riksbank, Trinity Collegue Dublin, University of Melbourne, De Nederlandsche Bank, University of Antwerp, University of Hamburg, HU Berlin, University of Leipzig, Ghent University, Charles University Prague, TU Dortmund University, Vienna University of Technology, and DIW Berlin also provided useful suggestions. The opinions expressed in this article are the sole responsibility of the authors and should not be interpreted as reflecting the views of Sveriges Riksbank.

[†]DIW Berlin, Mohrenstrasse 58, 10117 Berlin, Germany, and Freie Universität Berlin, email: mharding@diw.de.

[‡]Sveriges Riksbank, Monetary Policy Department - Research, SE-103 37 Stockholm, Sweden, email: mathias.klein@riksbank.se.

1 Introduction

Since the beginning of the 2000s, private household net worth has fluctuated substantially in the U.S. economy. As a fraction of disposable personal income, household net worth increased from 550% in 2002 to almost 680% at the outbreak of the 2008 financial crisis. Due to the massive collapse in house prices, the ratio fell back to 560% in 2011.[1] A growing number of mostly theoretical studies interprets this significant adjustment in household balance sheets as the central element to understand the boom and bust period that ended with the Great Recession (Eggertsson and Krugman 2012, Guerrieri and Iacoviello 2017, (GI, henceforth)). Moreover, empirical contributions show that the evolution of households' financial position is crucial for understanding the propagation and amplification of economic shocks and policy interventions (see, e.g., Klein 2017, Mian et al. 2013, Schularick and Taylor 2012). In this paper, we show that shifts in the financial position of households significantly affect the transmission mechanism of monetary policy.

Despite the important role of household balance sheets in shaping macroeconomic outcomes, little is known about whether the effectiveness of monetary policy depends on household net worth dynamics. This issue is of particular interest because unconventional monetary policy interventions and massive changes in household net worth evolved in parallel since the financial crisis. If borrowing constraints play an important role for households' saving-consumption decisions and the tightness of collateral constraints varies considerably with the households' net worth position, monetary policy may indeed have asymmetric effects across the household net worth cycle.

Against this background, our contribution in this paper is twofold: first, we estimate a New Keynesian model with financial frictions on U.S. data, in which household balance sheets influence the monetary transmission mechanism, to characterize monetary policy effectiveness. Specifically, the model illustrates that monetary policy is more effective when borrowing constraints bind and household net worth is low. Second, we test this result on U.S. macro data and find robust empirical evidence supporting the model predictions.

We rely on the DSGE model by GI, which on top of the standard New Keynesian ingredients features financial frictions on the household side. We use the estimated DSGE model to study the determinants of when borrowing constraints bind. Specifically, we simulate data from the model and conduct a prediction analysis to shed light on which endogenous model variable best predicts the tightness of the borrowing constraint. We look at several possible candidates commonly highlighted in the literature (see, e.g., Drehmann and Tsatsaronis 2014, Iacoviello 2015) as measures of financial excess, such as household leverage, debt, net worth, house prices, and credit-to-GDP gaps. We find that the level of household net worth is the single best predictor of the borrowing constraint being binding

[1] These numbers are based on official data published by the FRED database (series ID: HNONWPDPI).

or becoming slack. This result implies that monetary policy is significantly more effective in periods where household net worth is low. More specifically, the responses of output and aggregate consumption are amplified by more than 50% in periods where net worth is low compared to periods where it is high.

The model provides us with a framework in which the interrelation between household balance sheets, borrowing constraints, and monetary policy can be investigated in great detail. The model features two types of households with heterogeneous saving-consumption preferences, which generates borrowing and lending. Borrowing households face a housing collateral constraint that limits borrowing to a maximum fraction of housing wealth. Importantly, this constraint binds only occasionally rather than at all times, implying that the propagation and amplification of economic shocks in general and exogenous monetary policy interventions in particular depend on the endogenous degree of financial frictions. In the model, the effect of a monetary policy shock is significantly larger when the borrowing constraint is binding compared to a situation in which it turns slack. The magnitude of this amplification depends chiefly on households' expectations about the duration of slack borrowing constraints: the longer the expected slack duration, the larger the amplification effects.

The intuition for these asymmetric effects can be summarized as follows: When the constraint is slack, standard adjustments common to New Keynesian DSGE models occur. Because nominal prices are sticky, the central bank - controlling the short-term interest rate - influences the ex-ante real interest rate. An increase in the nominal rate leads to an increase in the real rate, which in turn reduces aggregate demand and puts pressure on firms to gradually adjust prices to a lower level. Thus, when borrowing constraints are turned off, a monetary tightening has mild contractionary effects. However, there are two additional channels that gain importance when the constraint is binding: debt-deflation and redistribution. The fall in prices induced by the monetary policy shock raises the cost of debt services for constrained households, which induces a redistribution of resources from borrowers to savers. Because borrowers have a higher marginal propensity to consume, aggregate demand falls more strongly compared to the slack constraint case, when they can smoothen the shock out by taking on more debt. In sum, asymmetric responses following a monetary policy shock are driven by financially constrained households, which are forced to cut back consumption when an adverse shock hits the economy.

In the second part of the paper, we test this model prediction of asymmetric effects of monetary policy across the household net worth cycle on empirical data. To investigate the effects of monetary policy shocks conditional on the household net worth cycle, we estimate state-dependent impulse responses of aggregate variables to exogenous monetary policy interventions using local projections as proposed by Jordà (2005). The estimated responses are allowed to depend on whether household net worth is high or low. To measure the stance of monetary policy during the zero lower bound period, we use the shadow federal funds rate constructed by Wu and Xia (2016). Thereby, we take the significant adjustment in household balance sheets that occurred after the Great Recession explicitly into account. In our baseline estimation, we rely on a timing restriction to identify monetary policy shocks.

The empirical results strongly support the theoretical predictions. When private household net worth is low, an increase in the short-term interest rate leads to large and significant decreases in GDP, private consumption, and investment. In contrast, monetary policy shocks have mostly insignificant effects on economic activity during a high household net worth state. In our baseline estimation, the maximum GDP response is twice as large in a low household net worth state than the corresponding GDP response in a high net worth state.

These results are robust to alternative definitions of low and high household net worth periods, different ways of identifying monetary policy shocks, and changes in the sample. Moreover, we show that positive and negative monetary policy shocks are fairly evenly distributed across low and high household net worth states, which implies that our findings are not driven by the nature of the shocks.

Our paper contributes to the growing literature on the role of household balance sheets for understanding the impact of macroeconomic shocks. Mian and Sufi 2011, 2012 show that those U.S. counties that experienced the largest increase in housing leverage before the financial crisis, suffered from more pronounced economic slack in the post-crisis period. Jordà et al. (2016) find that more mortgage-intensive credit expansions tend to be followed by deeper recessions and slower recoveries, while this effect is not present for non-mortgage credit booms. Di Maggio et al. (2017) and Wong (2019) show how households' heterogeneous financial profiles affect the transmission of monetary policy. We contribute to this literature, first, by showing how borrowing constraints matter for the transmission channel of monetary policy in the context of a standard New Keynesian model of the business cycle and, second, by providing extensive empirical evidence that households' financial position is key to understand the effects of monetary policy when looking at U.S. macro data. Our work is complementary to the papers by Cloyne et al. (2019) and Gelos et al. (2019), who consider household-level survey data to assess the role of households' balance sheets for the the effectiveness of monetary policy. In addition, our paper provides guidance for empirical work on which data to focus on to characterize borrowing constraints.

The remainder of the paper is organized as follows. Section 2 gives an overview of the structure of the DSGE model and presents results of the model estimation. Moreover, we investigate the transmission mechanism of monetary policy depending on the tightness of the borrowing constraints and discuss the findings of our prediction analysis. In Section 3, we conduct an empirical analysis based on aggregate data and find strong empirical support for the theoretical predictions. Finally, Section 4 concludes.

2 The DSGE model and monetary policy transmission

We consider the model by GI, which is a standard New Keynesian model with financial frictions on the household side.[2] The model features two types of households with heterogeneous saving-consumption preferences, which generates borrowing and lending. Borrowing households face a housing collateral constraint that limits borrowing to a maximum fraction of housing wealth. Importantly, this constraint binds only occasionally rather than at all times, implying that the propagation and amplification of economic shocks in general and exogenous monetary policy interventions in particular depend on the endogenous degree of financial frictions. This feature allows us to study how the tightness of borrowing constraints affect the transmission channel of monetary policy. The model also allows us to take the effective lower bound on interest rates into account, which was in place for several years recently in the U.S.

2.1 Model overview

There are two types of households which only differ in that one has a lower discount factor than the other: impatient (borrowers) and patient (lenders). The supply of housing is fixed, but house prices evolve endogenously as a function of demand for housing. Housing enters the utility function as a durable good separately from non-durable consumption and labor, and it is also used as collateral by the impatient households such that newly issued debt is restricted to a maximum of housing wealth. Most importantly, this borrowing constraint is only occasionally binding such that the degree of financial frictions is endogenously determined in the model.

Both types of households work, consume, and accumulate housing. Patient households own the productive capital of the economy, they supply funds to firms and to the impatient households. Impatient households accumulate just enough net worth to meet the down payment on their home and are subject to a binding borrowing constraint in equilibrium. Each group (patient and impatient) is a continuum of measure 1 of agents, while the economic size of each group is given by their wage share, which is constant due to a constant elasticity of substitution production function. The household utility functions read

$$E_0 \sum_{t=0}^{\infty} \mathsf{z}_t \left(\beta^i\right)^t \left(\Gamma_c^i \log(c_t^i - \varepsilon_c c_{t-1}^i) + \Gamma_h^i \mathsf{j}_t \log(h_t^i - \varepsilon_h h_{t-1}^i) - \frac{1}{1+\eta}(n_t^i)^{1+\eta}\right) \quad (1)$$

[2]Here we discuss the model features that are central to our analysis, while additional model equations are provided in Appendix A1.

for $i = \{P, I\}$, where P refers to patient households and I to impatient ones and the discount factors satisfy $\beta^I < \beta^P$. In what follows, to simplify notation, we denote the impatient household with the I superscript, while the variables with no superscript refer to the patient household. c_t, h_t, and n_t stand for consumption, housing, and hours worked in period t, respectively. z_t is an AR(1) intertemporal preference shock and j_t is an AR(1) housing preference shock that shifts preferences from consumption and leisure to housing. ε_c and ε_h measure the degree of habit formation in both consumption goods, while the Γ_c and Γ_h are scaling factors to ensure that marginal utility of consumption and housing are independent of habits in the non-stochastic steady state.

Impatient households neither accumulate capital nor own final good firms. Therefore, their budget constraint is given by

$$c_t^I + q_t h_t^I + \frac{R_{t-1} b_{t-1}}{\pi_t} = \frac{w_t^I n_t^I}{x_{w,t}^I} + q_t h_{t-1}^I + b_t, \tag{2}$$

that is, the value of durable and non-durable consumption plus loan payments (left hand side) must equal income from labor, housing wealth, and new loans. Here, q_t is the price of housing, w_t^I is the real wage, $x_{w,t}^I$ is a markup due to monopolistic competition in the labor market, R_t is the nominal risk-free interest rate, and $\pi_t = \frac{P_t}{P_{t-1}}$ is the gross inflation rate. In addition, they face the following borrowing constraint

$$b_t \leq \gamma \frac{b_{t-1}}{\pi_t} + (1-\gamma) M q_t h_t^I, \tag{3}$$

where $\gamma > 0$ is the degree of debt inertia[3] and M is the loan-to-value (LTV) ratio limit.

The firm sector follows the standard New Keynesian model, where competitive (wholesale) firms produce intermediate goods that are later differentiated at no cost and sold at a markup $x_{p,t}$ over marginal cost by monopolistically competitive final good firms. Wholesale firms hire capital from the patient households and labor from both types of households to produce intermediate goods y_t.

Final good firms face Calvo-style price rigidities: Each period, a fraction $(1 - \theta_\pi)$ of firms set their price optimally and a fraction θ_π have to index their price to the steady state inflation $\bar{\pi}$. The linearized forward-looking Phillips curve takes the standard form:

$$\log(\pi_t/\bar{\pi}) = \beta E_t \log(\pi_{t+1}/\bar{\pi}) - \varepsilon_\pi \log(x_{p,t}/\bar{x}_p) + u_{p,t}, \tag{4}$$

where $\varepsilon_\pi = (1-\theta_\pi)(1-\beta\theta_\pi)/\theta_\pi$, and $u_{p,t}$ is a normally distributed i.i.d. price markup shock.

The labor market is also subject to Calvo-style rigidities, with a fraction $(1 - \theta_w)$ of wages being set optimally each period, and θ_w being indexed with $\bar{\pi}$. As in Smets and

[3] This is the formulation of GI, capturing the idea that borrowing constraints are only fully reset when households refinance their mortgages and the empirical observation that aggregate debt lags house price movements.

Wouters (2007) labor unions differentiate labor services that are then combined into the homogeneous labor composites n_t and n_t^I by labor packers. This framework implies the following linearized wage Phillips curves:

$$\log(\omega_t/\bar{\pi}) = \beta E_t \log(\omega_{t+1}/\bar{\pi}) - \varepsilon_w \log(x_{w,t}/\bar{x}_w) + u_{w,t}, \tag{5}$$

$$\log(\omega_t^I/\bar{\pi}) = \beta^I E_t \log(\omega_{t+1}^I/\bar{\pi}) - \varepsilon_w^I \log(x_{w,t}^I/\bar{x}_w^I) + u_{w,t}, \tag{6}$$

where $\varepsilon_w = (1-\theta_w)(1-\beta\theta_w)/\theta_w$, $\varepsilon_w^I = (1-\theta_w)(1-\beta^I\theta_w)/\theta_w$, $\omega_t = \frac{w_t \pi_t}{w_{t-1}}$, $\omega_t^I = \frac{w_t^I \pi_t}{w_{t-1}^I}$, and $u_{w,t}$ is a normally distributed i.i.d. wage markup shock.

Monetary policy follows a Taylor rule that responds to year-on-year inflation and GDP in deviations from their steady state values, allows for interest rate smoothing with smoothing parameter r_R, and is subject to the ZLB constraint:

$$R_t = \max\left[1, R_{t-1}^{r_R}\left(\frac{\pi_t}{\pi}\right)^{(1-r_R)r_\pi}\left(\frac{y_t}{y}\right)^{(1-r_R)r_Y}\bar{R}^{(1-r_R)}\mathsf{e}_t\right]. \tag{7}$$

$\bar{R}$ stands for the nominal gross interest rate and e_t is a monetary policy shock that follows an AR(1) process.

We approximate the model around the non-stochastic steady state, where all the optimality conditions are satisfied, the borrowing constraint binds, and the economy is not constrained by the ZLB. The model dynamics are due to the following six innovations: housing preference, investment specific, price markup, monetary policy, wage markup, and intertemporal preference shocks. The key feature of the model is that, for certain realizations of shocks, the borrowing constraint becomes slack when impatient households have enough collateral to pledge for their desired level of borrowing. This typically happens during economics expansions, especially during housing booms, when positive housing demand shocks put upward pressure on house prices and housing wealth increases.

2.2 Estimation of the DSGE model

We use Bayesian techniques to estimate the model parameters and shocks. As we have mentioned before, a key element of the model is that borrowing constraints fluctuate endogenously with the state of the economy. In order to take this nonlinearity into account, as well as the nonnegativity constraint on the policy rate, we solve the model using Guerrieri and Iacoviello (2015)'s OccBin toolbox and use the filter proposed by GI to evaluate the likelihood.[4] Depending on whether each of the two constraints binds or not, the model features four different regimes. The solution is based on a first order approximation around the same point - the model's steady state - for each regime. However,

[4]We provide the main equations and implementation details in Appendix A2.

the model dynamics depend on the agents' expectations about how long a certain regime will remain in place and hence can be highly nonlinear. While the focus of our analysis is on the nonlinear dynamics arising from the borrowing constraint, we model the ZLB constraint explicitly in order to make the model consistent with U.S. interest rates data when estimating it.

One caveat is that the filter cannot extract shocks that enter occasionally binding constraints in regimes where those shocks become irrelevant for model dynamics. One such case is when the ZLB binds, where a monetary policy shock is inconsequential given that the interest rate is stuck at zero. We follow GI and set monetary policy shocks to zero when the ZLB binds.[5] The estimation provides us with a full characterization of the periods when the borrowing constraint is filtered to be binding or slack, given the model parameters and empirical data.

2.2.1 Data

We fit the model to six macro time series: real household consumption, price inflation (GDP deflator), wage inflation, real investment, real house prices, and the Federal Funds Rate. Our sample covers quarterly data from 1960q1-2018q1.[6] A detailed description of the data and the transformation undertaken to make it consistent with model variables is provided in Appendix A3. While we use the same model and macro time series as in GI, our sample spans a much larger time period. For this reason, our parameter estimates differ from those obtained by GI.

2.2.2 Calibration and priors and posteriors

We calibrate some of the parameters as described in Table 1. This calibration follows GI and is fairly standard in the literature. In our baseline estimation we also fix the debt inertia and the discount factor of impatient households to the estimated values by GI, which makes our results more easily comparable to theirs.[7]

The estimated parameters are shown in Table 2. As in GI, the Calvo prices and wages parameters imply a relatively flat Phillips curve, while habit parameters for housing and consumption suggest an important degree of smoothing, especially for housing. When looking at the parameters concerning monetary policy, the response of the policy rate to prices is not too strong and persistence of the monetary policy shocks is relatively low. The standard deviation of the monetary policy shock is larger than in GI, given that our

[5]This is implemented by making the set of observables time-varying. When the ZLB binds, we drop the nominal rate from the set of observables and the monetary policy shock is set to zero. When the model implied notional rate is above zero, that rate is the observed rate and the monetary policy shock is reinstated.

[6]We use the first 20 quarters as a training sample for the filter, so that the data that enters the evaluation of the likelihood is from quarters 21 onward.

[7]We try different values for these parameters and the key results are robust to different specifications.

sample includes the pre Great Moderation period, where inflation and interest rates were relatively high and volatile. Overall, our estimated parameters are fairly similar to the ones obtained by GI and are within the range of values considered standard in the New Keynesian DSGE literature.

These estimated parameters are robust to several alternative specifications. In particular, the estimates are robust to excluding the ZLB period from our sample and to applying an alternative de-trending filter to the data. Our estimates are also robust to including a neutral technology shock in the model.

2.3 Collateral constraints and monetary policy transmission

How important are borrowing constraints for the transmission of monetary policy shocks? Figure 1 shows the responses of output and consumption to an annualized 100 basis points monetary policy shock in when the borrowing constraint binds and when it is slack. We compute these responses by simulating the model, feeding a monetary policy shock in states where the constraint is binding and slack, and computing the average response in each case. For the average slack response we focus on states where the constraint is expected to remain slack at least one year after the shock hits. The two upper panels show that the maximum responses of output and consumption (2 quarters after the shock) are amplified by about 45% and 50%, respectively.

What explains this state-dependent impact of monetary policy shocks? When the constraint is slack, the model produces dynamics that are common across a wide range of New Keynesian DSGE models. Because prices are sticky, an increase in the nominal interest rate also leads to an increase in the real interest rate, which depresses private consumption and investment, and thus aggregate demand and output. This induces pressure on firms to lower prices. Thus, in a slack constraint regime the model implies modest declines in output, consumption, and inflation following an unexpected monetary tightening. When the constraint binds, two additional channels are responsible for the stronger contractionary effects. First, the lower price level induced by a higher interest rate implies a rise in real debt service costs. Constrained households have to use a higher share of their income stream to meet their debt payments. Second, this debt-deflation implies a redistribution of resources from borrowers to savers. Because savers have a lower marginal propensity to consume, they do not compensate for the lower consumption expenditures by borrowing households. Overall, financially constrained households, which are forced to cut back consumption strongly when an adverse shock hits the economy, are responsible for the asymmetric responses to a monetary policy shock. The lower panels of Figure 1 illustrate these dynamics. The peak consumption response of borrowers is amplified by 90%. In contrast, the consumption response of savers is not amplified at all. To illustrate the relative importance of the different channels at play, the figure also presents results of a model version with indexed debt contracts such that debt-deflation effects are shut down. The responses of this model are given by the black crossed lines. In line with Iacoviello (2005), without debt-deflation the contractionary effects of a monetary policy shock are clearly reduced. Still, the figure highlights that binding borrowing constraints play a quantitatively sizable role over and above that of debt-deflation effects for the transmission of monetary policy shocks.

The key state-dependent amplification mechanism of monetary policy shocks in our model is the degree by which credit constraints bind. The higher the steady state loan-to-value ratio limit, the higher the steady state level of household debt and the larger the decline in economic activity in response to a contractionary monetary policy shock. Thus, the tighter financial frictions become, the more important the interplay between falling prices, higher debt service costs, and redistribution from borrowers to lenders becomes for the monetary policy transmission mechanism. For instance, for a steady state loan-to-value ratio limit of 80%, the amplification in output and consumption reduces to 33% and 37%, respectively.[8]

Likewise, the expected duration of slack borrowing constraints when a monetary policy shock hits determines the size of these amplification effects. We document the relation between the expected duration of slack constraints and amplification effects of monetary policy shocks in Figure 2. The figure shows the amplification in the maximum response of consumption and GDP after a monetary policy shock, as a function of the minimum expected duration of a slack borrowing constraint after the shock. The black vertical line indicates the 4-quarter minimum expected duration of our baseline scenario depicted in Figure 1. The figure illustrates that amplification in aggregate consumption (orange dashed line) and GDP (blue solid line) can be mild if the constraint is predicted to be slack for only one or two quarters, while it can go well over 50% when the constraint is expected to be slack for 2 or more years.

It is also worth noting that the relation between amplification effects and expected duration of the constraint is nonlinear. It increases quickly for lower expected duration, until the constraint is expected to remain slack for about at least 4 quarters. But when the constraint is already expected to remain slack for very long, the extra periods of expected slackness add less and less to the amplification effects of monetary policy. This is because of two reasons. First, once the constraint is expected to be slack for a long time, impatient agents start behaving more and more as if they were fully unconstrained and their consumption choices start approaching the unconstrained optimal choice. Second, when impatient households expect to be unconstrained for very long, they borrow and consume more, as indicated by the increasing yellow dotted line. These extra funds come from patient households, who start cutting their consumption in order to meet the increasing demand for loans, which somewhat counteracts the amplification effects

[8]See Figure A1 for the full impulse response functions for this model specification.

on aggregate consumption and output triggered by the increase and consumption from impatient households.

2.3.1 Determinants of collateral constraints

In the previous section we show that binding borrowing constraints amplify the effects of monetary policy. A direct implication of this result is that characterizing the state of borrowing constraints - binding or slack - is crucial to understand the effectiveness of monetary policy. To this end, we use the estimated DSGE model to investigate which macro aggregates are the best predictors of binding borrowing constraints. We proceed as follows: first, we simulate data from the model to obtain artificial time series for the macro variables of interest, including the Lagrange multiplier on the constraint. We then create a slack variable Y_t that takes values of zero or one for periods of slack and binding constraints, respectively. Subsequently, we estimate a set of probit regressions with Y_t as dependent variable and different predictor candidate variables on the right-hand-side. Finally, we look for the right-hand-side variable with the best predictive performance for the Lagrange multiplier slack variable.[9]

Formally, we run regressions

$$\Pr(Y_t = 1 \mid X_{k,t}) = \Phi(X_{k,t}^T \beta_k), \quad k = 1 \ldots K \tag{8}$$

where Y_t is the slack variable, Φ is the CDF of a standard normal distribution and $X_{k,t}$ includes a constant and one of the predictor candidates $x_{k,t}$. That is, we run K independent regressions for K predictor candidates. The variables that we include in $X_{k,t}$ are commonly regarded as relevant measures of "financial excess". In particular, we focus on household net worth, leverage, credit, house prices and credit-to-GDP gaps.[10] We consider variables separately in levels, growth rates, and detrended with a one-sided HP filter. In order to assess the predictive performance of variable $x_{k,t}$ we simply compute the share of correctly predicted slack and binding states of the constraint for each variable.[11]

Table 3 shows the predictive performance for a number of predictor candidates. Overall, the best predictors are within the variables in levels. Among those, it turns out that the best predictor of binding borrowing constraints is net worth of the impatient house-

[9] We thank the associate editor for this suggestion.

[10] For net worth and leverage we consider two definitions: the aggregate concept and the concept that corresponds to the impatient or constrained household. The model definitions for aggregate net worth, net worth of the impatient household, aggregate leverage, and leverage of the impatient household are: $nw_t = q_t + qk_t k_t$, $nw_t^I = q_t h_t^I - b_t$, $lev_t = \frac{b_t}{q_t}$, and $lev_t^I = \frac{b_t}{q_t h_t^I}$, respectively. Credit-to-GDP gaps are defined as the difference between the credit-to-GDP ratio and its long run trend (extracted from an HP-filter with $\lambda = 400,000$), following the tradition of the BIS (see, e.g., Drehmann and Tsatsaronis 2014).

[11] The predicted regimes are a result of comparing the probability $\hat{P}_t = \Phi(X_{k,t}^T \hat{\beta}_k)$ to the share of periods where constraints bind in the sample, $\bar{B}$. The constraint is then predicted to be binding whenever $\hat{P}_t > \bar{B}$. This is a standard approach in the literature that goes back at least to Jappelli (1990).

hold (henceforth, simply net worth), which on average correctly predicts binding and slack regimes 87% of the time, while leverage of the impatient household ranks closely behind at 83%. This should be expected, since both concepts are closely related in the model. House prices is the third best predictor, followed by credit, aggregate net worth, credit-to-GDP gaps, and aggregate leverage. While the relative rankings of variables changes when looking at variables in growth rates or HP-detrended, the prediction performance is absolute terms is well below the 87% of net worth in levels. These results are robust to several alternative specifications, such as using an alternative simulation approach, computing the prediction statistics in-sample or out-of-sample, and using alternative parameterizations of the model (see Tables A2 and A3 in the Appendix).

Two facts about these results are worth highlighting. First, at 87% of correctly predicted states of the constraint, net worth is very informative about whether the collateral constraint binds or not. Recall that the regression in equation 8 includes only a constant and the variable of interest as regressors. Second, with the exception of leverage, the predictive performance of net worth is quantitatively much higher than that of other variables. These facts combined suggest that the effects of monetary policy should be amplified when net worth is low, because the borrowing constraint will generally be binding in those states.

To investigate the interaction between borrowing constraints and net worth further, Figure 3 shows the distribution of net worth across binding and slack states. In fact, the distribution differs starkly across states: the mean (median) of the distribution is 0.37 (0.37) in binding states, 0.59 (0.57) in slack states, and 0.46 (0.44) overall. Further, we conduct a Kolmogorov-Smirnov test to formally test the hypothesis that both sub-samples are drawn from the same distribution. The test strongly rejects the null hypothesis that the distribution of net worth in binding states and net worth in slacks states are drawn from the same distribution. 90% of the slack periods correspond with realizations of net worth above the median, while 80% of the binding periods correspond with net worth realizations below the median. The figure also shows that below the 15th percentile and above the 85th percentile of the net worth distribution there is essentially no overlap between binding and slack states.

In order to illustrate the role of the net worth cycle for monetary transmission we re-compute the impulse responses of Figure 1, but instead of focusing on the state of the borrowing constraint directly, we compute the response to a monetary policy shock across the net worth distribution. Specifically, we simulate data from the model and compute the average response of output and consumption to a monetary policy shock in states where net worth is below the 15th percentile and above the 85th percentile of the simulated net worth time series before the shock hits. The resulting maximum responses of output and consumption are amplified by 37% and 41%, respectively, when net worth is low.[12] Using this simple definition of low and high net worth states, every low net worth state in the artificial time series coincides with a binding borrowing constraint. On the other hand, the high net worth states correspond with states in which the constraint is slack for an average of 11 quarters after the shock hits.

All told, the model suggests that household net worth is a strong and significant indicator of the tightness of borrowing constraints. In the next section we start from this premise and test for asymmetric effects of monetary policy across the household net worth cycle in the empirical data.

3 Empirical Evidence

In this section, we test the models' predictions using aggregate data. In particular, we investigate whether the effects of a monetary policy shock depend on the level of household net worth. We first describe our empirical strategy and data and then present our baseline empirical findings. Our empirical results strongly support the theoretical predictions. In particular, we find that a contractionary monetary policy shock leads to a large and significant fall in economic activity during periods of low household net worth. In contrast, monetary policy shocks have only small and mostly insignificant effects when net worth is high. We show that these findings are robust to several modifications of the baseline model.

3.1 Empirical Model

To investigate the effects of monetary policy shocks depending on the state of the household net worth cycle, we follow Tenreyro and Thwaites (2016) and Ramey (2016) in estimating state-dependent impulse responses to exogenous monetary policy innovations using local projections as proposed by Jordà (2005). This method has become a popular tool to estimate state-dependent models and calculate impulse responses.[13] The main advantages compared to VARs are that local projections are more robust to model misspecifications and do not impose the implicit dynamic restrictions involved in VARs. Moreover, local projections offer a very convenient way to account for state dependence.[14]

[12]The shape of these impulse responses is almost identical to those in Figure 1. We report these responses in Figure A2 in the Appendix.

[13]See, for example, Auerbach and Gorodnichenko (2012a) and Ramey and Zubairy (2018).

[14]The Jordà method does not uniformly dominate the standard VAR approach for calculating impulse responses. In particular, because it does not impose any restrictions that link the impulse responses across different horizons, the estimates are often erratic because of the loss of efficiency. Moreover, it sometimes display oscillations at longer horizons. For a more detailed discussion, we refer to Ramey and Zubairy (2018).

The Jordà method simply requires estimation of a series of regressions for each horizon, h, and for each variable. The linear model takes the following form:

$$y_{t+h} = \alpha_h + \tau t + \psi_h(L)x_t + \beta_h \epsilon_t + u_{t+h}, \text{for } h = 0, 1, 2, ..., \tag{9}$$

where y is a specific variable of interest (e.g. GDP), τ is a linear time trend, x is a vector of control variables, $\psi_h(L)$ is a polynomial in the lag operator, and ϵ measures the identified monetary policy shock. The coefficient β_h measures the response of y at time $t+h$ to the monetary policy shock at time t. Thus, the impulse responses are constructed as a sequence of β_hs estimated in a series of separate regressions for each horizon. The state-dependent model is easily adapted. More specifically, we estimate a set of regressions for each horizon h as follows:

$$\begin{aligned} y_{t+h} = \tau t + I_{t-1} \left[\alpha_{A,h} + \psi_{A,h}(L)x_t + \beta_{A,h}\epsilon_t\right] \\ + (1 - I_{t-1}) \left[\alpha_{B,h} + \psi_{B,h}(L)x_t + \beta_{B,h}\epsilon_t\right] + \nu_{t+h}, \end{aligned} \tag{10}$$

where τ is the linear time trend and $I_{t-1} \in \{0, 1\}$ is a dummy variable that captures the state of the economy before the monetary policy shock hits. In particular, I_{t-1} takes the value of one when household net worth is low and zero otherwise. Following the literature on state-dependent effects of fiscal policy (see, for example, Auerbach and Gorodnichenko 2012b, Ramey and Zubairy 2018), we include a one-period lag of I_t in the estimation to minimize the contemporaneous correlation between the shock series and changes in the indicator variable. The coefficients of the model (other than the deterministic trend) are allowed to vary according to the household net worth state of the economy. Thus, the collection of $\beta_{A,h}$ and $\beta_{B,h}$ coefficients directly provide the state-dependent responses of variable y_{t+h} at time $t+h$ to the shock at time t. Given our specification, $\beta_{A,h}$ indicates the response of y_{t+h} to the monetary policy shock in low household net worth states whereas $\beta_{B,h}$ shows the effect in high household net worth states.

We measure household net worth by the aggregate series on net worth held by households and nonprofit organizations provided by the Flow of Funds tables.[15] Because this series measures nominal household net wort, we first deflate it by the CPI price index. To differentiate between low and high household net worth states, the real net worth series is filtered by a smooth Hodrick-Prescott (HP) trend, where the smoothing parameter, λ, is set to $100,000$. The relatively high smoothing parameter ensures that the filter removes even the lowest frequency variations in the net worth series. As shown by Borio (2014) and Drehmann et al. (2012), the household credit cycle is significantly longer and has a much greater amplitude than the standard business cycle. Therefore, Drehmann et al.

[15] Details on data construction and sources are given in the Appendix.

(2012) propose the use of a very smooth HP-trend to capture the low frequency of financial cycles. GI apply the same value of the smoothing parameter to extract the trend in household borrowing and leverage. Given these considerations, applying an HP-filter with a smoothing parameter $\lambda = 100.000$ to construct the trending and cyclical component of household net worth seems appropriate for our analysis. High household net worth states are defined as periods with positive deviations of the net worth series from trend, whereas low net worth states indicate periods when net worth was below its long-run trend. This procedure implies that out of the 234 periods included in the sample, 125 or 53% are detected as low household net worth periods, while the remaining 109 episodes or 47% indicate periods of high household net worth.

As shown in Figure 4, we detect six distinct episodes of persistently low household net worth: 1960q1-1964q3, 1974q2-1978q4, 1980q1-1985q4, 1990q3-1997q4, 2001q3-2003q3 and 2008q2-2013q3. These low household net worth states correspond with specific events in the history of the U.S. economy. The first period of low household net worth, indicates the preceding of the so-called Credit Crunch in 1966. The second low household net worth episode, which lasts with some minor break from the mid 1970s until the mid of the 1980s, coincides with the surge in interest rates toward the end of the Great Inflation. Around the 2000s, the Asian and Dot-com crises are associated with two more short-lived low net worth periods. Finally, the Great Recession caused a significant drop in households net worth, especially housing values, which corresponds with our sixth low net worth period at the end of the sample. Importantly, Figure 4 also shows the difference between the traditional business cycle and the household net worth cycle. Official NBER recessions, indicated by the dashed lines, are in general much shorter than low household net worth periods. In line with Borio (2014) and Drehmann et al. (2012), we find that the the U.S. financial cycle is significantly longer than the real economic cycle.[16]

In our baseline specification, we estimate the responses to monetary policy shocks using a recursive identification strategy which is commonly used in the traditional VAR literature (see for example Christiano, Eichenbaum, and Evans 2005). As shown by Barnichon and Brownlees (2016), when estimating local projections such a timing restriction correspond to a specific choice of control variables. We include the following control variables: the log-level of GDP, the log-level of the CPI deflator, the log-level of real household net worth and the difference between the 10-year Baa corporate yield and the 10-year Treasury bond yield. The stance of monetary policy is measured by the effective federal funds rate and the shadow federal funds rate constructed by Wu and Xia (2016). In particular, we use the observed federal funds rate from 1960q1 to 2008q4 and from 2015q4 until the end of the sample. For the zero lower bound episodes between 2009q1

[16]We study the interrelation between the state of the business cycle and the household net worth cycle in a latter section in more detail. Moreover, it is shown that our empirical results are robust to an alternative definitions of low and high household net worth.

to 2015q3 we use the shadow federal funds rate to measure the monetary policy stance. By measuring the actual stance of monetary policy between 2009q1 and 2015q3 by the shadow federal funds rate, we are able to include the significant decline in household net worth that occurred after the Great Recession in our estimations. Moreover, in contrast to the effective federal funds that is constrained by the ZLB, the Wu and Xia (2016) series allows to identify the effects of unconventional monetary policy interventions.

We assume that the monetary authority reacts contemporaneously to changes in GDP, the CPI deflator, and household net worth, while it reacts only with a one-period lag to changes in the corporate spread. Thus, we assume that a monetary policy shock has no contemporaneous effects on the first three control variables. Note that this identification assumption is equivalent to using the contemporaneous policy rate as the shock ϵ_t in Equations (9) and (10), and ensuring that the contemporaneous and lagged values of the log-level of GDP, the log-level of the CPI deflator, the log-level of real household net worth, along with the lagged values of the corporate spread and the policy rate, are part of x_t in Equations (9) and (10). By including household net worth into the vector of control variables, we allow the central bank to take the state of the household net worth cycle into account when setting the short-term interest rate. We include two lags of the endogenous variables in all our estimations. The sample we use for the empirical analysis is the same as the one used for the estimation of the theoretical model in the previous section (1960q1-2018q1).

3.2 Baseline Results

In this section, we present our baseline empirical findings. Figure 5 shows the impulse responses of GDP, inflation, private consumption, and investment to a contractionary shock to the policy rate for our baseline specification. The first column presents the results of the linear model whereas the second and third columns show the responses in a low and high household net worth state, respectively. The solid lines show the response to a monetary policy shock, where 0 indicates the quarter in which the shock occurs. Shaded areas indicate 90% confidence bands based on Newey and West (1987) standard errors.

We first discuss the results of the linear model. In response to an increase in the federal funds rate, GDP, private consumption, and investment decline significantly, where the responses peak between 10 and 12 quarters after impact. The inflation response is more muted and mostly insignificant. Just at the end of the forecast horizon, we observe a significant fall in prices. This contractionary effects to an increase in the policy rate are in line with previous empirical work (e.g., Christiano et al. 2005, Gertler and Karadi 2015).

As columns 2 and 3 reveal, the effect of monetary policy shocks differs substantially across the household net worth cycle. When household net worth is low, GDP falls significantly in response to a contractionary monetary policy innovation. GDP responds in a hump-shaped manner with a peak response around two years after the shock occurred. In contrast, the GPD response is mostly insignificant when household net worth is high. It oscillates around zero 2 years after the shock as well as towards the end of the forecast horizon, and estimation uncertainty is relatively large.

When taking a closer look at the expenditure components, it turns out that a substantial fraction of the state-dependent GDP response is driven by private consumption. In a low household net worth state, consumption decreases significantly, whereas in a high household net worth state the consumption response is mostly insignificant. In addition, investment reacts differently in both net worth states: when household net worth is below its long run trend, investment decreases significantly whereas in high household net worth episodes, the monetary policy shock induces a mostly insignificant investment response. The inflation response also depends on the state of the household net worth cycle. While inflation increases slightly in a high household net worth state, it declines in a delayed manner when household net worth is low.

The state dependent responses reveal differences in the propagation and amplification of monetary policy shocks under low and high household net worth at different horizons. In order to further assess the total effectiveness of monetary policy in each state, we also compute the cumulative impulse responses. Figure 6 shows the cumulative effects of each variable in both household net worth states. The cumulative responses are computed using the integral of the corresponding impulse response function. The figure illustrates that for all variables, the effects in a low household net worth state are estimated to be statistically significant while the responses are mostly statistically insignificant in a high household net worth state. Moreover, the cumulative declines in response to a contractionary monetary policy shock are also larger in magnitude. For example, the cumulative loss in GDP and consumption 15 quarters after the increase in the interest rate is more than twice as large in a low household net worth state compared to a high net worth state.

Overall, these results support our theoretical findings and confirm that the effectiveness of monetary policy interventions depends on the state of the household net worth cycle. When private household net worth is low, an increase in the short-term interest rate has large and significant effects on aggregate economic activity and inflation. In contrast, monetary policy only has a small and mostly insignificant impact on the economy when household net worth is above its long run trend.

3.3 Robustness

In the following, we consider various robustness checks on our baseline specification. We show that our findings are robust to alternative ways of identifying monetary policy shocks, different definitions of high and low household net worth states and changes in the sample. Moreover, we present evidence that our results are not driven by a different distribution of monetary policy shocks across household net worth states. For easier visual comparison, we focus in this section solely on GDP responses.

Alternative Identification: In our baseline specification, we identify exogenous monetary policy innovations by relying on a timing restriction. Now, we conduct the same analysis as in the previous section, but consider the Romer and Romer (2004) narrative measure. We use the extended series by Miranda-Agrippino and Rey (2015), which is available for the period 1969q1-2012q4.[17] The first row of Figure 7 shows that our empirical findings are robust to this alternative identification approach. In particular, we find that an exogenous increase in the policy rate induces a strong and persistent decline in GDP when household net worth is low. In high net worth states, in contrast, the GDP response is only of limited magnitude and estimated to be insignificant for most periods of the forecast horizon.

In addition, we check whether our results depend on the specific series to measure the stance of monetary policy. In our baseline, we use the shadow federal funds rate as proposed by Wu and Xia (2016) to control for unconventional monetary policy interventions. Gertler and Karadi (2015) argue to rely on treasury rates with a longer maturity to capture the effect of unconventional monetary policy. We follow this suggestion and use the 5-year treasury rate. Thus, we identify a monetary policy shock by using the same set of control variables as in our baseline specification but replace the short term interest rate with the 5-year treasury rate in equation (10). As shown in the second row of Figure 7, our main empirical results are robust to using this long-term interest rate to measure the stance of monetary policy.

Alternative State Definition: We now make use of an alternative way to differentiate between high and low household net worth periods. For this purpose, we make use the approach proposed by Hamilton (2018) instead of the HP-filter to calculate the cyclical component of household net worth. As the third row of Figure 7 indicates, estimation uncertainty generally declines when using this alternative filter. However, when comparing the point estimates across both states, the contractionary effect is clearly amplified when household net worth is low which implies that our findings prevail when using this alternative state definition.[18]

Changes in the Sample: We further check whether our results are driven by specific time periods. In doing so, we first, drop the period of the Great Recession and the subsequent zero lower bound by ending the sample in 2008Q4. Second, we follow Gertler

[17] This series is available at: `http://silviamirandaagrippino.com/research/`.

[18] Our results are also robust to assigning different values to the smoothing parameter of the HP filter. The corresponding results are available from the authors upon request.

and Karadi (2015) and start the sample in 1979 which coincides with the beginning of Paul Volcker's tenure as Federal Reserve chair. As pointed out by other studies, there might be a regime shift in monetary policy pre- and post-Volcker (e.g., Clarida et al. 2000).[19] As the fourth and fifth row of Figure 7 show our results are robust to both changes in the sample.

Distribution of Monetary Policy Shocks: One possible explanation for our findings could be that the effects of monetary policy shocks are indeed nonlinear, but are not directly a function of the household net worth state. Rather, it is possible that policy interventions of different kinds are more common at certain times and that this generates the apparent dependence of the responses on the household net worth cycle. If, for instance, contractionary policy interventions have a larger effect on the economy than expansionary shocks and if contractionary shocks are more common in a low net worth state, then the distribution of shocks could be responsible for our results. Indeed, Angrist et al. (2017) and Barnichon and Matthes (2014) provide empirical evidence for this narrative as they show that contractionary monetary policy shocks have significantly larger effects on the economy than expansionary ones. Thus, if we observe proportionally more interest rate increases in a low net worth state than in a high net worth state, the sign of the shocks may well be explaining our results.

It turns out that monetary policy shocks are fairly evenly distributed across the high and low household net worth states: For both states, the relative proportion of positive shocks is similar to the relative proportion of negative shocks. This confirms that our main finding of household net worth-dependent effects of monetary policy cannot be attributed to different shock distributions between both states of the net worth cycle. Of all monetary policy shocks that happened during a high household net worth state, 50% are positive innovations and the remaining 50% are negative innovations. The respective numbers in a low household net worth are 46% (positive shocks) and 54% (negative shocks). Of all positive monetary policy shocks, 52% happened during a low household net worth state and of all negative innovations, 55% occurred during a low net worth state. Figure A3 in the Appendix shows the distribution of shocks across states.

4 Conclusion

This paper shows that the household net worth cycle significantly determines the effects of monetary policy shocks. We investigate this issue both from a theoretical and an empirical perspective. First, we estimate a standard New Keynesian DSGE model with financial frictions and an occasionally binding borrowing constraint on aggregate U.S. data. The

[19]We thank an anonymous referee for pointing this out.

model implies stronger effects of monetary policy interventions when the borrowing constraint is binding compared to situations when it turns slack. In a prediction analysis, we find that, out of a set of alternative plausible endogenous model variables, the single best predictor of the tightness of the borrowing constraint is the level of household net worth. As a result, the model implies that monetary policy is more effective when household net worth is low. When testing this theoretical prediction on aggregate data, we find strong support for it. We provide robust empirical evidence that monetary policy interventions in a low household net worth state have a sizeable and significant impact on the economy. In contrast, in a high household net worth state monetary policy has only small and mostly insignificant effects. Our paper shows that the state of household net worth cycle plays an important role in understanding the transmission of monetary policy.

References

Angrist Joshua D., Jordà Òscar, and Kuersteiner Guido M. (2017) "Semiparametric Estimates of Monetary Policy Effects: String Theory Revisited". *Journal of Business & Economic Statistics forthcoming.*

Auerbach Alan J and Gorodnichenko Yuriy. (2012a) "Fiscal multipliers in recession and expansion". In: *Fiscal Policy after the Financial crisis*. University of Chicago press, 63–98.

Auerbach Alan J. and Gorodnichenko Yuriy. (2012b) "Measuring the Output Responses to Fiscal Policy". *American Economic Journal: Economic Policy 4* (2), 1–27.

Barnichon Regis and Brownlees Christian. (2016) "Impulse Response Estimation By Smooth Local Projections". CEPR Discussion Papers 11726.

Barnichon Regis and Matthes Christian. (2014) "Gaussian Mixture Approximations of Impulse Responses and the Nonlinear Effects of Monetary Shocks". Working Paper 16-8. Federal Reserve Bank of Richmond.

Borio Claudio. (2014) "The financial cycle and macroeconomics: What have we learnt?" *Journal of Banking & Finance 45* (C), 182–198.

Christiano Lawrence J., Eichenbaum Martin, and Evans Charles L. (2005) "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy". *Journal of Political Economy 113* (1), 1–45.

Clarida Richard, Galí Jordi, and Gertler Mark. (2000) "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory*". *The Quarterly Journal of Economics 115* (1), 147–180.

Cloyne James, Ferreira Clodomiro, and Surico Paolo. (2019) "Monetary policy when households have debt: new evidence on the transmission mechanism". *Review of Economic Studies forthcoming.*

Di Maggio Marco, Kermani Amir, Keys Benjamin J., Piskorski Tomasz, Ramcharan Rodney, Seru Amit, and Yao Vincent. (2017) "Interest Rate Pass-Through: Mortgage Rates, Household Consumption, and Voluntary Deleveraging". *American Economic Review 107* (11), 3550–88.

Drehmann Mathias and Tsatsaronis Kostas. (2014) "The credit-to-GDP gap and counter-cyclical capital buffers: questions and answers". *BIS Quarterly Review*, 55–73.

Drehmann Mathias, Borio Claudio, and Tsatsaronis Kostas. (2012) "Characterising the financial cycle: don't lose sight of the medium term!" BIS Working Papers. Bank for International Settlements.

Eggertsson Gauti B. and Krugman Paul. (2012) "Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach". *The Quarterly Journal of Economics 127* (3), 1469–1513.

Fair Ray and Taylor John. (1983) "Solution and Maximum Likelihood Estimation of Dynamic Nonlinear Rational Expectations Models". *Econometrica 51* (4), 1169–85.

Gelos R. G, Griffoli Tommaso Mancini, Narita Machiko, Grinberg Federico, Rawat Umang, and Khan Shujaat. (2019) "Has Higher Household Indebtedness Weakened Monetary Policy Transmission?" IMF Working Papers 19/11. International Monetary Fund.

Gertler Mark and Karadi Peter. (2015) "Monetary Policy Surprises, Credit Costs, and Economic Activity". *American Economic Journal: Macroeconomics 7* (1), 44–76.

Guerrieri Luca and Iacoviello Matteo. (2015) "OccBin: A toolkit for solving dynamic models with occasionally binding constraints easily". *Journal of Monetary Economics 70* (C), 22–38.

——— (2017) "Collateral constraints and macroeconomic asymmetries". *Journal of Monetary Economics 90*, 28 –49.

Hamilton James D. (2018) "Why you should never use the Hodrick-Prescott filter". *Review of Economics and Statistics 100* (5), 831–843.

Iacoviello Matteo. (2005) "House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle". *American Economic Review 95* (3), 739–764.

——— (2015) "Financial Business Cycles". *Review of Economic Dynamics 18* (1), 140–164. DOI: 10.1016/j.red.2014.09.003.

Jappelli Tullio. (1990) "Who Is Credit Constrained in the U.S. Economy?" *The Quarterly Journal of Economics 105* (1), 219–34.

Jordà Òscar. (2005) "Estimation and Inference of Impulse Responses by Local Projections". *American Economic Review 95* (1), 161–182.

Jordà Òscar, Schularick Moritz, and Taylor Alan M. (2016) "The Great Mortgaging: Housing Finance, Crises, and Business Cycles". *Economic Policy 131*, 107–152.

Klein Mathias. (2017) "Austerity and Private Debt". *Journal of Money, Credit, and Banking, 49*, 1555–1585.

Mian Atif R. and Sufi Amir. (2011) "House Prices, Home Equity-Based Borrowing, and the US Household Leverage Crisis". *American Economic Review 101* (5), 2132–56.

——— (2012) "What explains high unemployment? The aggregate demand channel". NBER Working Papers 17830. National Bureau of Economic Research, Inc.

Mian Atif R., Rao Kamalesh, and Sufi Amir. (2013) "Household Balance Sheets, Consumption, and the Economic Slump". *The Quarterly Journal of Economics 128* (4), 1687–1726.

Miranda-Agrippino Silvia and Rey Hélene. (2015) "US monetary policy and the global financial cycle". *NBER working paper 21722.*

Newey Whitney K and West Kenneth D. (1987) "A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix". *Econometrica 55* (3), 703–708.

Ramey V.A. (2016) “Macroeconomic Shocks and Their Propagation”. In: vol. 2. Handbook of Macroeconomics. Elsevier, 71–162.

Ramey Valerie A and Zubairy Sarah. (2018) “Government spending multipliers in good times and in bad: evidence from US historical data”. *Journal of Political Economy 126* (2), 850–901.

Romer Christina D. and Romer David H. (2004) “A New Measure of Monetary Shocks: Derivation and Implications”. *American Economic Review 94* (4), 1055–1084.

Schularick Moritz and Taylor Alan M. (2012) “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008”. *American Economic Review 102* (2), 1029–61.

Smets Frank and Wouters Rafael. (2007) “Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach”. *American Economic Review 97* (3), 586–606.

Tenreyro Silvana and Thwaites Gregory. (2016) “Pushing on a String: US Monetary Policy Is Less Powerful in Recessions”. *American Economic Journal: Macroeconomics 8* (4), 43–74.

Wong Arlene. (2019) “Refinancing and the Transmission of Monetary Policy to Consumption”. *working paper.*

Wu Jing Cynthia and Xia Fan Dora. (2016) “Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound”. *Journal of Money, Credit and Banking 48* (2-3), 253–291.

Tables

Table 1: Calibrated Parameters

	parameter	
β	patient discount factor	0.995
α	capital share in production	0.3
δ	capital depreciation rate	0.025
$\bar{j}$	housing weight in utility	0.04
η	labor disutility	1
$\bar{x}_p$	price markup	1.2
$\bar{x}_w$	wage markup	1.2
$\bar{\pi}$	steady state inflation	1.0075
r_Y	weight of GDP in Taylor rule	0.1
M	steady state LTV limit	0.9
β^I	impatient discount factor	0.9922
γ	inertia, borrowing const.	0.6945

Table 2: Estimated Parameters

	parameter	prior	posterior			
			mode	5%	median	95%
ε_c	habit in consumption	BETA 0.70(0.10)	0.4295	0.3804	0.4559	0.5270
ε_h	habit in housing	BETA 0.70(0.10)	0.9208	0.8888	0.9223	0.9415
ϕ	invest. adjustment cost	GAMMA 5.00(2.00)	11.0144	8.5145	11.2128	14.3330
σ	wage share impatient HH.	BETA 0.50(0.05)	0.4324	0.4046	0.4320	0.4705
r_π	Taylor Rule, inflation	NORMAL 1.50(0.10)	1.4427	1.3901	1.6175	1.7673
r_R	Taylor Rule, inertia	BETA 0.75(0.10)	0.2506	0.1419	0.2248	0.3284
θ_p	Calvo, prices	BETA 0.50(0.07)	0.9294	0.7960	0.8655	0.9374
θ_w	Calvo, wages	BETA 0.50(0.07)	0.9011	0.8764	0.8975	0.9154
ρ_J	AR(1) housing shock	BETA 0.75(0.10)	0.9876	0.9553	0.9763	0.9909
ρ_K	AR(1) investment shock	BETA 0.75(0.10)	0.5804	0.5289	0.5839	0.6373
ρ_R	AR(1) monetary shock	BETA 0.25(0.10)	0.4223	0.3371	0.4864	0.6035
ρ_Z	AR(1) preference shock	BETA 0.75(0.10)	0.8573	0.7559	0.8035	0.8675
σ_J	stdv. housing shock	INVGAMMA 0.01(1.00)	0.0470	0.0394	0.0686	0.0971
σ_K	stdv. investment shock	INVGAMMA 0.01(1.00)	0.0944	0.0702	0.0955	0.1222
σ_P	stdv. price markup shock	INVGAMMA 0.01(1.00)	0.0061	0.0059	0.0068	0.0078
σ_R	stdv. monetary shock	INVGAMMA 0.01(1.00)	0.0051	0.0048	0.0053	0.0058
σ_W	stdv. wage markup shock	INVGAMMA 0.01(1.00)	0.0084	0.0077	0.0084	0.0092
σ_Z	stdv. preference shock	INVGAMMA 0.01(1.00)	0.0154	0.0138	0.0155	0.0175

Notes: Posterior statistics based on one chain of 55,000 MCMC replications, where the first 5,000 are discarded. The prior column indicates the prior shape, mean and standard deviation in parenthesis.

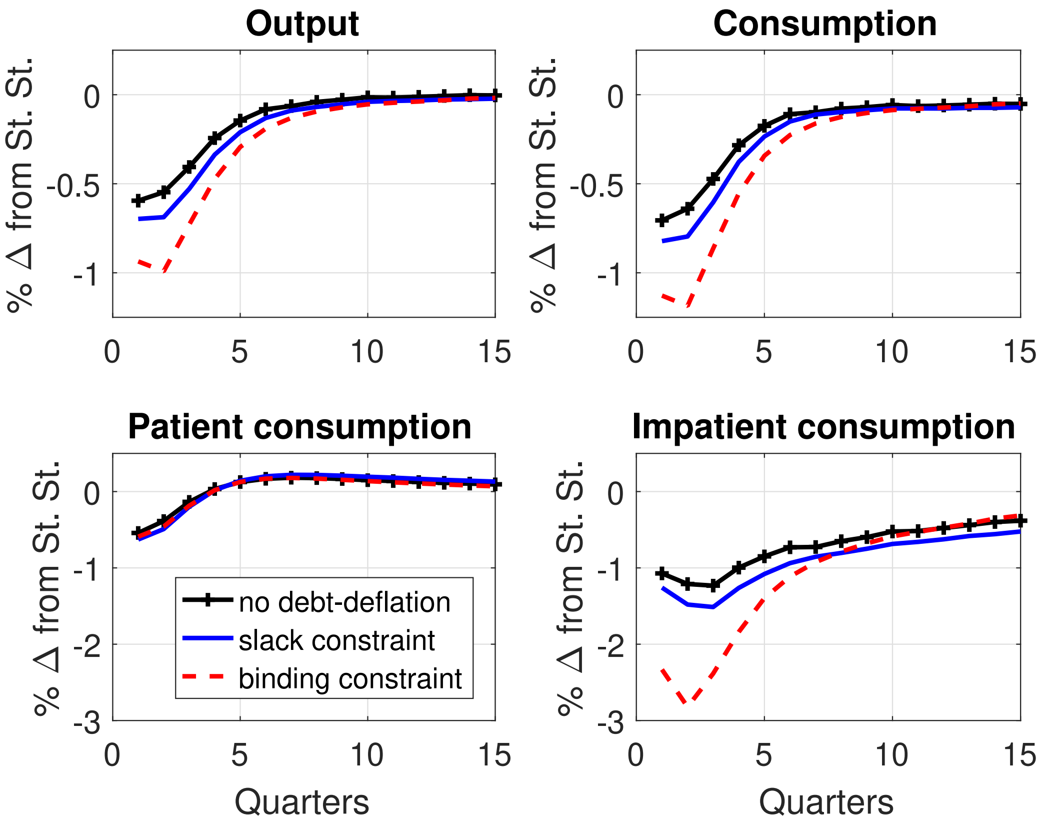
Table 3: Prediction of binding collateral constraints

predictor candidate x_k	levels	growth rates	HP-cycle
net worth (impatient)	0.87	0.55	0.69
net worth (aggregate)	0.59	0.50	0.54
leverage (impatient)	0.83	0.54	0.65
leverage (aggregate)	0.56	0.55	0.57
credit	0.62	0.66	0.66
house prices	0.66	0.54	0.69
credit gaps	0.57	0.49	0.49

Notes: We simulate 100 artificial samples of size $N = 233$, which corresponds to the sample size used to estimate the DSGE model. The share of correctly predicted regimes is calculated computing the probability $\hat{P}$ that the constraint binds from equation 8 and comparing it to the share of periods where the constraint binds in the simulated sample, $\bar{B}$. We define $\bar{P} = 1$ if $\hat{P} > \bar{B}$, and $\bar{P} = 0$ otherwise. The share of correctly predicted regimes is then $[\sum I(\bar{P} = 1|Y = 1) + \sum I(\bar{P} = 0|Y = 0)]/N$. The table reports the averages over these simulations.

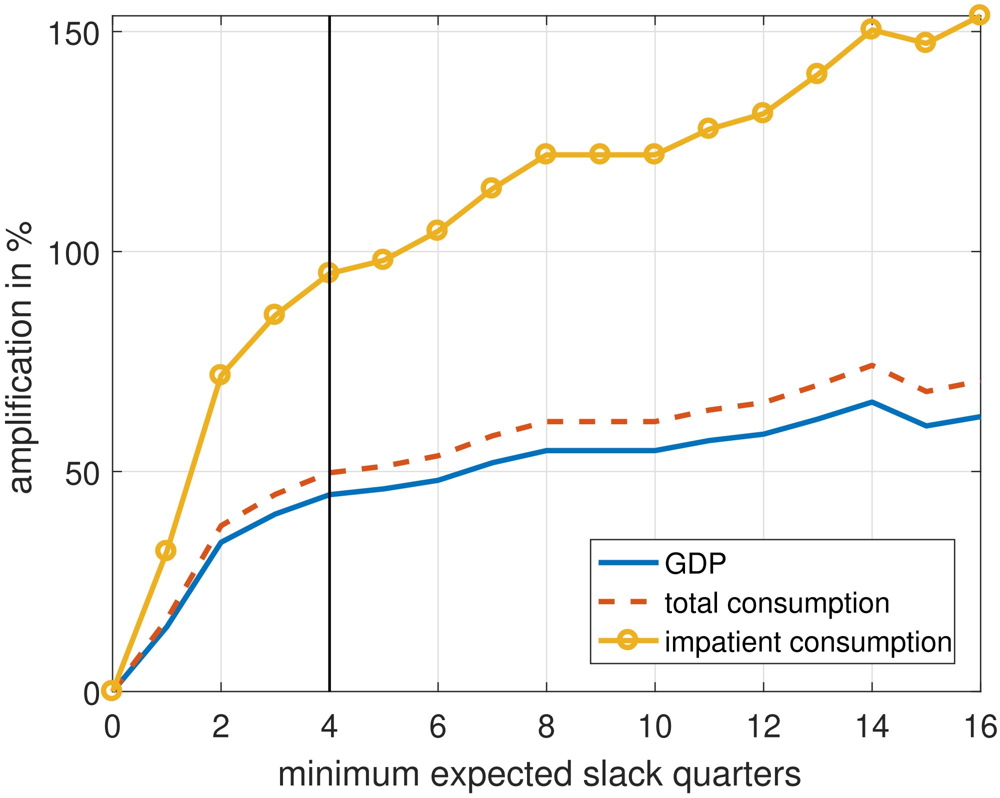
Figures

Figure 1: IRFs to a Contractionary Monetary Policy Shock



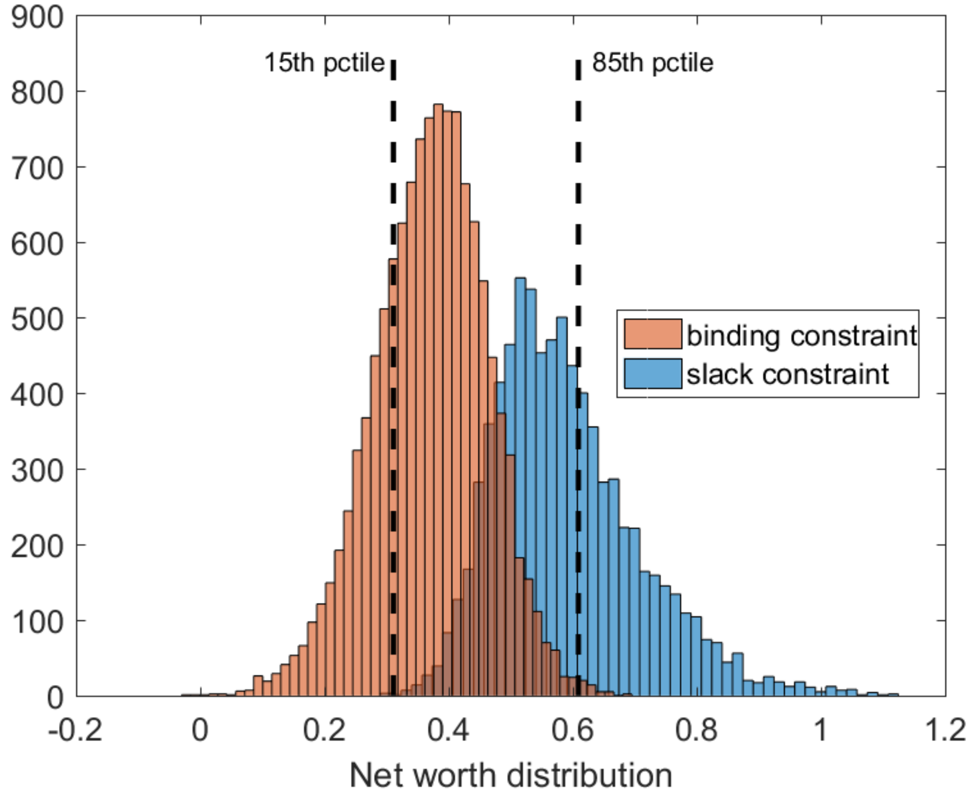
Notes: Generalized IRFs to an (annualized) 100 basis points monetary policy shock under binding and slack collateral constraints. GIRFs are computed by simulating the model for 600 periods, once with all shocks evaluated at their estimated standard deviations and a second time where, on top of that, an (annualized) 100 basis points monetary policy shock is added in period 501. Each IRF is computed as the difference between these two paths, dropping the first 500 periods of the simulation. The figure reports the average response to a monetary policy shock in period t over 100 simulations for two cases: when the constraint binds in $t-1$ (red dashed line) and when it is slack in $t-1$ (blue solid line). The black crossed lines show the same exercise for slack states states under indexed debt contracts, i.e., when there is no debt-deflation effect. The y-axis shows the responses in percentage deviations from the steady state. The x-axis shows quarters after the monetary policy shock hits.

Figure 2: Amplification Effects After a Monetary Policy Shock



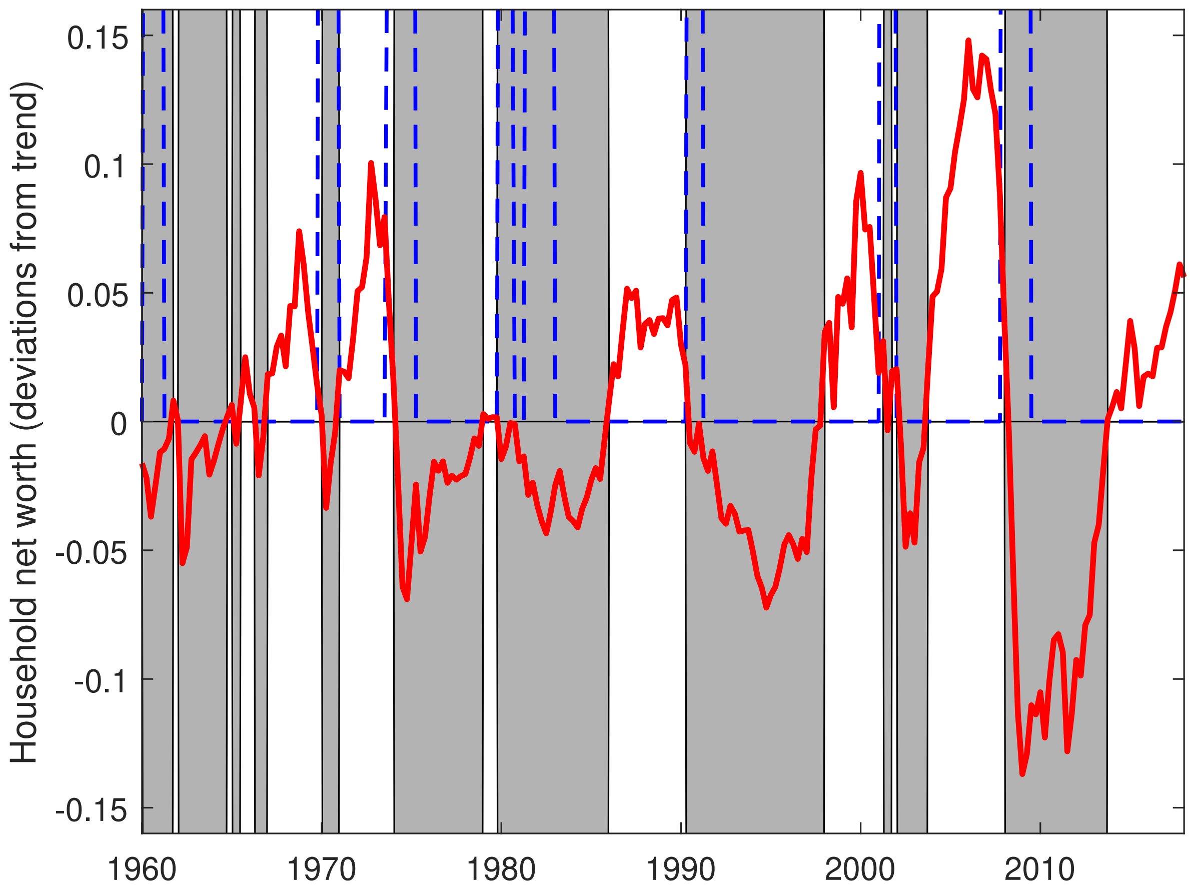
Notes: Amplification of the maximum response of GDP, aggregate consumption and consumption of the impatient household is computed as the average amplification of the maximum response for each horizon of expected slack constraints in the x axis. Impulse responses are calculated as described in Figure 1. The black vertical line indicates the baseline scenario from Figure 1, where the constraint is expected to remain slack for at least 4 quarters after the shock hits.

Figure 3: Net worth distribution across states of the borrowing constraint



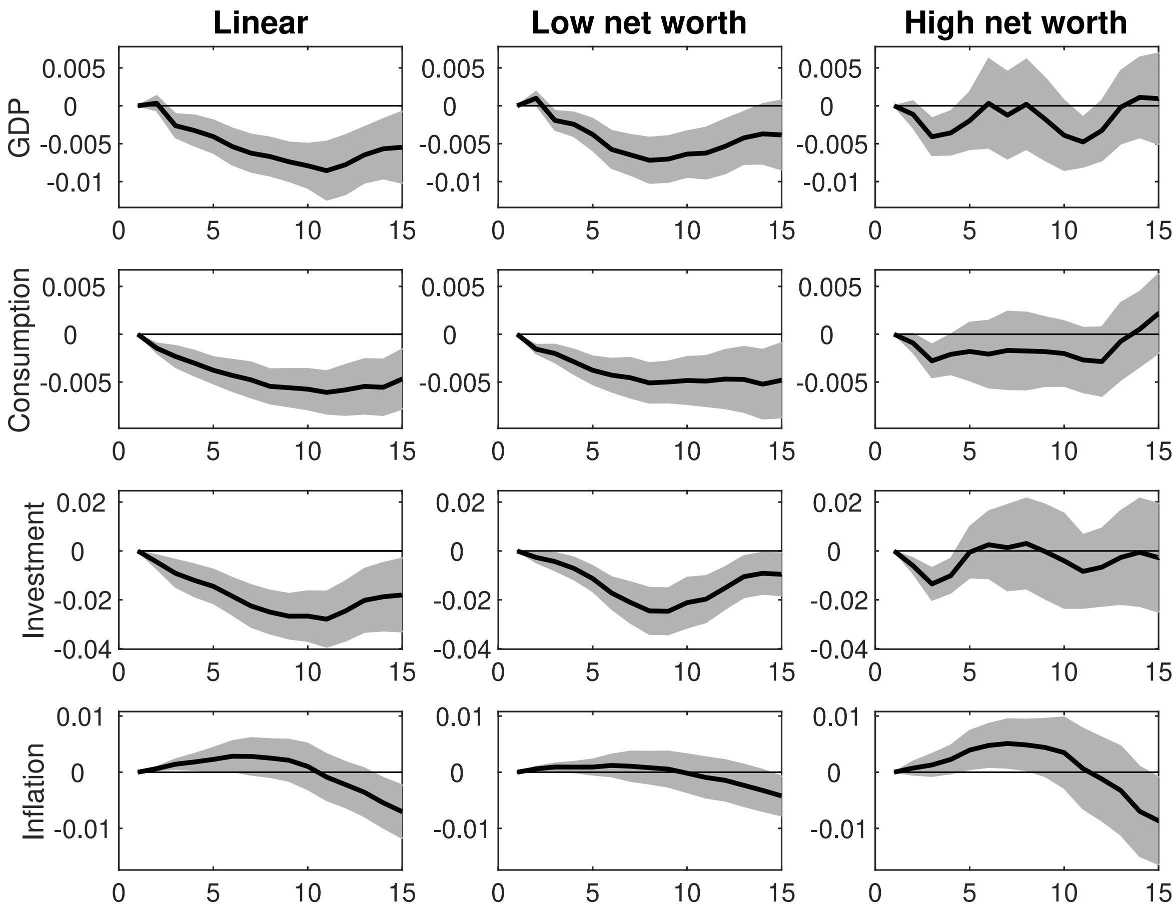
Notes: Net worth distribution across binding and slack states of the borrowing constraint. The distributions correspond to a simulation of 22,000 periods, where the first 2,000 are discarded.

Figure 4: Household net worth



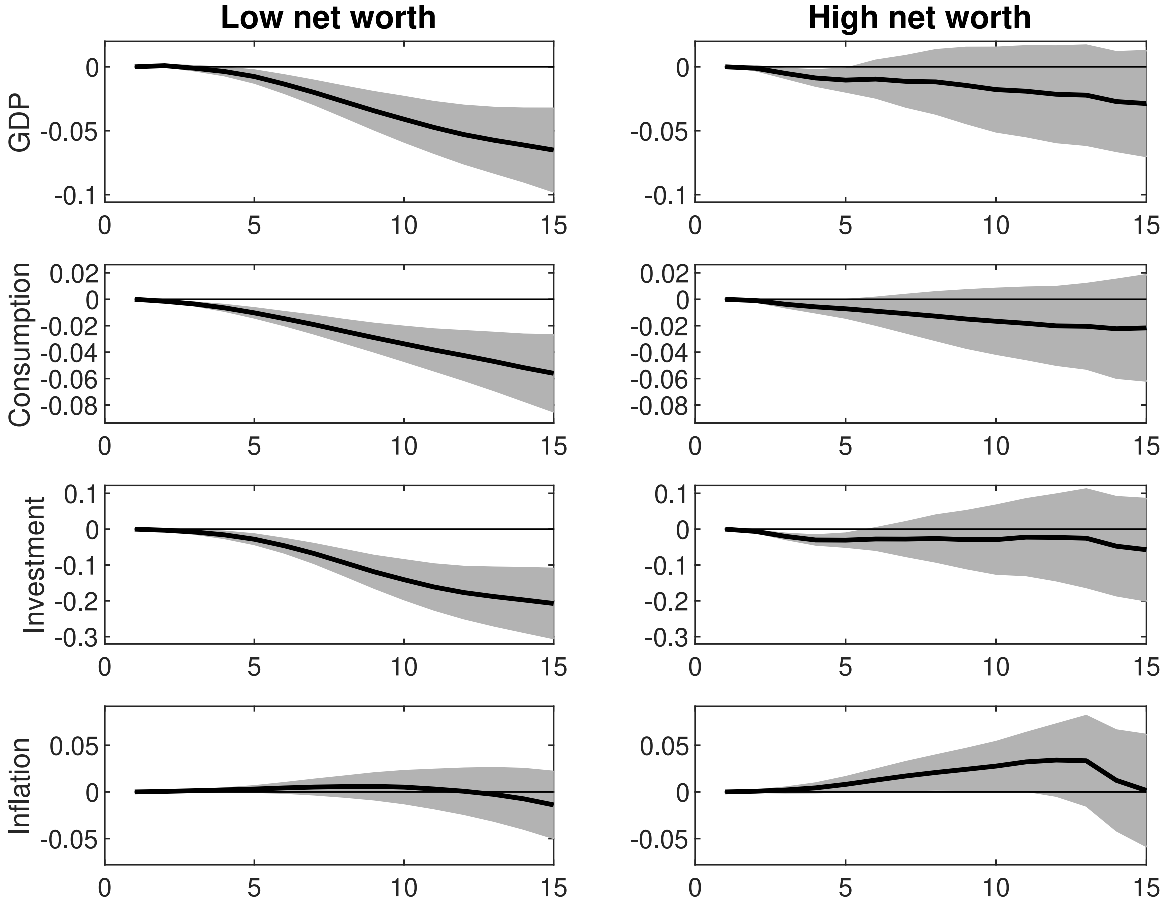
Notes: Household net worth is measured as the net worth held by households and nonprofit organization provided by the Flow of Funds tables and deflated by the CPI price index. To calculate the cyclical component, the real household net worth series is filtered by a smooth HP trend, where the smoothing parameter, λ, is set to $100,000$. The shaded areas indicate our baseline deleveraging identified periods. Dashed lines show official NBER recessions.

Figure 5: Baseline: Impulse Responses



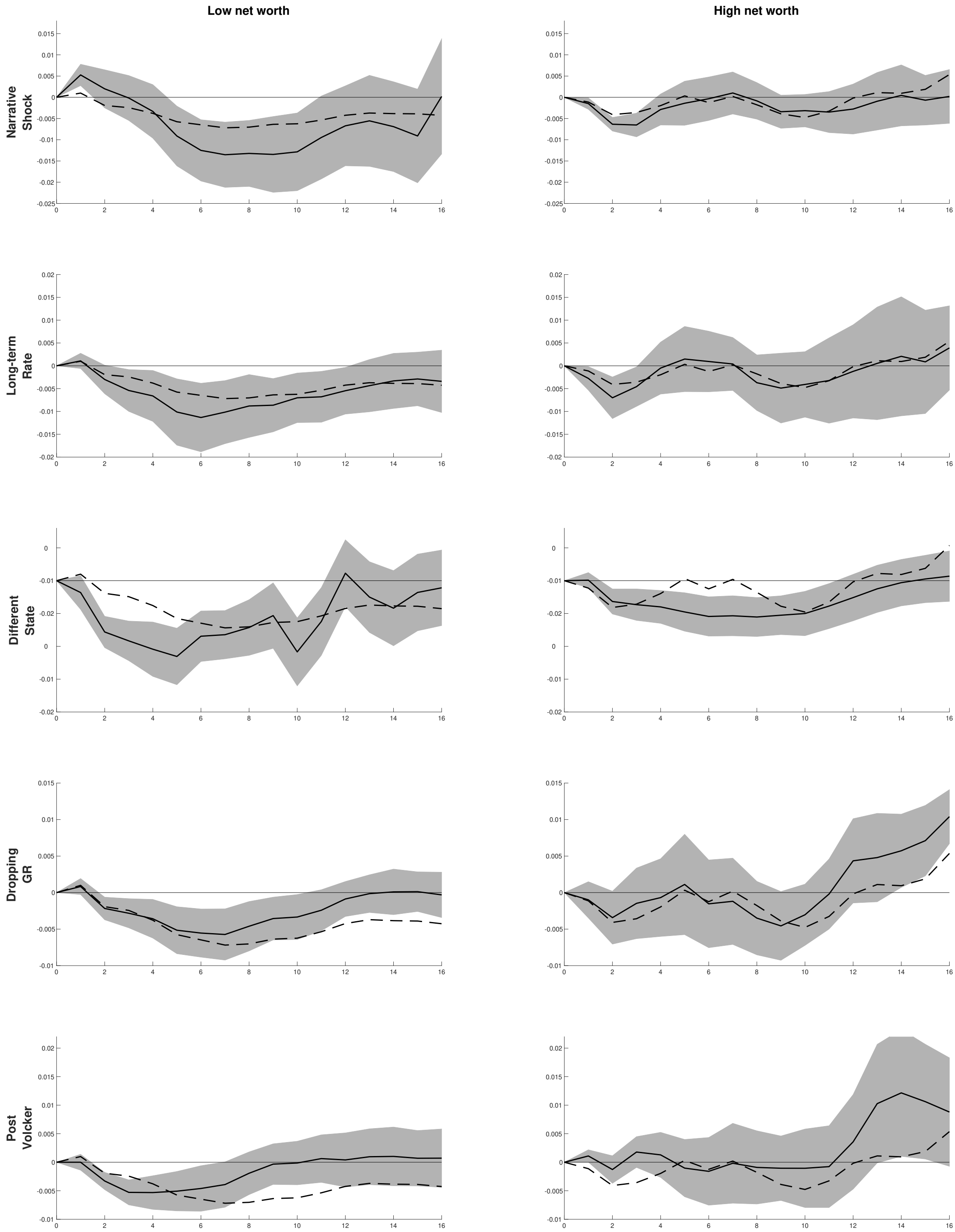
Notes: The first column shows the impulse responses of a monetary policy shock on a variable in the linear model. The second and third column show impulse responses of a monetary policy shocks on a variable in a low household net worth (second column) and high household net worth (third column) state. The shaded areas indicate 90% confidence bands based on Newey and West (1987) standard errors.

Figure 6: Baseline: Cumulative Effects



Notes: The first column shows the cumulative effects of a monetary policy shock on a variable in a low household net worth state. The second column shows the cumulative effects of a monetary policy shocks on a variable in a high household net worth state. The shaded areas indicate 90% confidence bands based on Newey and West (1987) standard errors.

Figure 7: Robustness (GDP responses)



Notes: The first column shows the impulse responses of a monetary policy shock on GDP in a low household net worth state. The second column shows the impulse responses of a monetary policy shocks on GDP in a high household net worth state. The shaded areas indicate 90% confidence bands based on Newey and West (1987) standard errors. The dashed line shows the impulse responses from the baseline estimation.

Appendix to Monetary Policy and Household Deleveraging by Martin Harding and Mathias Klein

A1 DSGE Model Equation Details

This section provides additional details on the model equations.

A1.1 Patient households

The patient household budget constraint is given by

$$c_t + q_t h_t + b_t + i_t = \frac{w_t n_t}{x_{w,t}} + q_t h_{t-1} + \frac{R_{t-1} b_{t-1}}{\pi_t} + rk_t k_{t-1} + div_t, \tag{A.1}$$

which implies that the value of durable and non-durable consumption, loans to the impatient household, and investment (left hand side) must equal income from labor, housing wealth, the returns on the loans to the impatient households and capital, and dividends from final good producing firms div_t (right hand side). Here, q_t is the price of housing, w_t is the real wage, $x_{w,t}$ is a markup due to monopolistic competition in the labor market, R_t is the nominal risk-free interest rate, $\pi_t = \frac{P_t}{P_{t-1}}$ is the gross inflation rate and rk_t is the return on capital.

The law of motion for capital reads

$$k_t = a_t \left(i_t - \phi \frac{(i_t - i_{t-1})^2}{\bar{i_t}} \right) + (1-\delta) k_{t-1}, \tag{A.2}$$

where a_t is an AR(1) investment specific technology shock and ϕ captures the degree of investment adjustment costs. The patient household chooses consumption c_t, housing h_t, hours n_t, loans b_t, investment i_t, and capital k_t to maximize utility subject to (A.1) and (A.2).

A1.2 Wholesale firms

The firm sector follows the New Keynesian standard, where competitive (wholesale) firms produce intermediate goods that are later differentiated at no cost and sold at a markup $x_{p,t}$ over marginal cost by monopolistically competitive final good firms. Wholesale firms hire capital from the patient households and labor from both types of households to produce intermediate goods y_t. They solve

$$\max \frac{y_t}{x_{p,t}} - w_t n_t - w_t^I n_t^I - rk_t k_{t-1} \tag{A.3}$$

subject to the production technology

$$y_t = n_t^{(1-\sigma)(1-\alpha)} n_t^{I\sigma(1-\alpha)} k_{t-1}^{\alpha}, \tag{A.4}$$

where σ measures the labor income share of impatient households. Note that if this parameter is set to zero, the model collapses to the standard New Keynesian-model without borrowing constraints.

Final good firms then buy these wholesale goods y_t, differentiate it at no cost and sell it at a markup $x_{p,t}$ over the marginal cost. They face Calvo-style price rigidities, which gives rise to the standard forward-looking Phillips curve in equation 4.

A2 DSGE Model Estimation Details

We solve the model using the OccBin toolbox and evaluate the likelihood with deterministic filter proposed by GI. The solution has the form

$$X_t = P(X_{t-1}, \epsilon_t)X_{t-1} + D(X_{t-1}, \epsilon_t) + Q(X_{t-1}, \epsilon_t)\epsilon_t, \tag{A.5}$$

where X_t contains all the variables of the model and ϵ_t is the vector of innovations to the shock processes. The reduced-form coefficient matrices P and Q, and the reduced-form coefficient vector D are all state-dependent: in any given period, they depend on the value of the state in the previous period but also on the contemporaneous realization of ϵ_t.

The model can be taken to the data with the following observation equation

$$Y_t = H_t P(X_{t-1}, \epsilon_t)X_{t-1} + H_t D(X_{t-1}, \epsilon_t) + H_t Q(X_{t-1}, \epsilon_t)\epsilon_t, \tag{A.6}$$

where Y_t is a matrix of observed time series and H_t is a selection matrix that indicates the observed endogenous variables. Following the method proposed by Fair and Taylor (1983), this expression allows filtering the structural shocks of the piecewise-linear model ϵ_t, given the state of the model X_{t-1}, the current realization of the data Y_t, and initial conditions X_0. The matrix H_t has a time index given that the set of observables changes when the model is filtered to be at the ZLB. In those cases, the federal funds rate is dropped from matrix H_t and the monetary policy shock is set to zero. Whenever the notional rate is filtered to be above the ZLB, however, the observed federal funds rate and the monetary policy shocks are reinstated; hence, it is generally not the case that the observed nominal rate and the monetary policy shock are dropped for the entire period where the ZLB binds in the data.

The likelihood of the model takes the form

$$\log(f(Y)) = -\frac{T}{2}\log(\det(\Sigma)) - \frac{1}{2}\sum_{t=1}^{T}\epsilon_t'\left(\Sigma^{-1}\right)\epsilon_t - \sum_{t=1}^{T}\log(|\det H_t Q(X_{t-1}, \epsilon_t)|), \tag{A.7}$$

where Σ is the variance-covariance matrix of the structural shocks. With all this information at hand, we carry out a standard Bayesian estimation combining information from the priors with the likelihood in equation A.7 to obtain the posterior.

A3 Data

A3.1 Local Projections

Table A1: Data Definitions and Sources

Variable	Definition	Source
GDP	Real GDP	BEA
CPI	Price index personal consumption expenditures	BEA
PGDP	GDP deflator	BEA
Wu and Xia shadow rate	Shadow federal funds rate	Atlanta FED website
Consumption	Nominal personal consumption expenditures	BEA
Investment	Nominal fixed private investment	BEA
Romer and Romer shocks	Extended narrative series	Silvia Agrippino website
Household net worth	Households and nonprofit organizations net worth	Flow of Funds
Corporate bond yield	BAA corporate bond yield	FRED
Long-term bond yield	10-year government bond yield	Robert Shiller website
5-year rate	5-Year Treasury Constant Maturity Rate	FRED

A3.2 DSGE model

- Consumption: Real personal consumption expenditures, log transformed and detrended with one-sided HP filter (smoothing parameter set to 1,600). Source: St. Louis FRED (code PCECC96).

- Price inflation: quarterly change in GDP Implicit Price Deflator minus steady state inflation. Source: BEA.

- Wage inflation: Non-farm business sector real compensation, log transformed, detrended with one-sided HP filter (smoothing parameter set to 1,600), first differenced and expressed in nominal terms by adding back price inflation. Source: St. Louis FRED (code COMPRNFB).

- Investment: Real private non-residential fixed investment, log transformed and detrended with one-sided HP filter (smoothing parameter set to 1,600). Source: St. Louis FRED (code PNFI).

- House prices: Robert Shiller's Real Home Price Index, log transformed and detrended with one-sided HP filter (smoothing parameter set to 100,000). Source: Robert J. Shiller, Irrational Exuberance, 3rd. Edition, Princeton University Press, 2015.

- Nominal interest rate: Effective Federal Funds Rate, annualized percent divided by 400. Source: St. Louis FRED (code FEDFUNDS).

A4 Prediction Analysis: robustness

This section presents a series of robustness checks for our main prediction analysis of the determinants of binding collateral constraints from section 2.3.1. Table A2 performs the analysis using an alternative simulation approach. Instead of drawing a number of independent samples of size $N = 233$ and taking the average prediction performance for each predictor candidate (as in our baseline), here we carry out the prediction analysis using one very large sample of $N = 20,000$. The table reports the in-sample (columns labeled IS) and out-of-sample (columns labeled OOS) predictive performance of predictor candidates. The table shows that the best predictors are still net worth (first) and leverage (second) from the impatient household when using this alternative simulation approach. Moreover, this holds true irrespective of whether we conduct the probit prediction analysis using an in-sample or out-of-sample approach.

Table A2: Prediction analysis: alternative simulation approach

	Levels		Growth rates			HP-cycle	
	IS	OOS	IS		OOS	IS	OOS
net worth (impatient)	0.87	0.86	0.55	0.55	0.71	0.68	
net worth (aggregate)	0.59	0.58	0.51	0.50	0.55	0.55	
leverage (impatient)	0.83	0.83	0.54	0.54	0.67	0.64	
leverage (aggregate)	0.55	0.51	0.56	0.56	0.56	0.56	
credit	0.62	0.60	0.66	0.65	0.67	0.66	
house prices	0.63	0.64	0.55	0.54	0.70	0.69	
credit gaps	0.58	0.58	0.61	0.61	0.41	0.41	

Notes: Prediction analysis with simulated sample of size $N = 20,000$. We estimate the probit regressions described in equation 8 on a subsample of size $n = 10,000$. The columns labeled IS report the prediction performance when conducting the prediction exercise on the first $10,000$ observation used to estimate the probit models. The columns labeled OOS report the analogous concept when the prediction exercise is done on the last $10,000$ observations, not used to estimate the probit models.

Table A3 repeats the analysis of table 3 for different values of the debt inertia parameter on the collateral constraint, γ. This parameter plays an important role for debt dynamics in the model, and for this reason it is important to check that our prediction results are not driven by a particular value of this parameter. The table confirms that net worth of the impatient household in levels remains the best predictor of binding collateral constraints for most values of γ. The only exception is for a very low value of debt inertia ($\gamma = 0.2$), where credit in growth rates performs better than net worth in levels. However, such a value γ is rejected by the data. Hence, we conclude that the prediction performance of net worth is not driven by an (unlikely) arbitrary value for debt inertia.

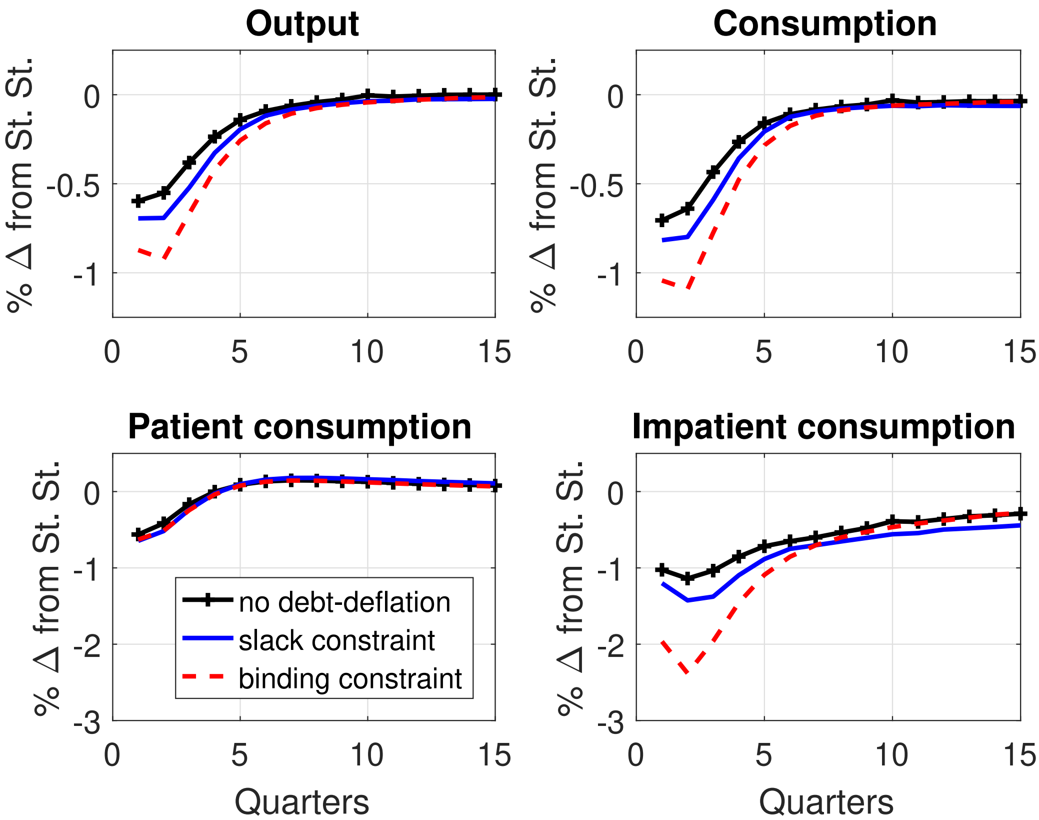
Table A3: Prediction analysis: debt inertia robustness

	Levels				Growth rates				HP-cycle			
debt inertia (γ)	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8
net worth (impatient)	0.88	0.92	0.90	0.85	0.70	0.59	0.56	0.50	0.80	0.75	0.72	0.68
net worth (aggregate)	0.57	0.57	0.58	0.60	0.56	0.54	0.52	0.49	0.57	0.55	0.55	0.55
leverage (impatient)	0.63	0.81	0.86	0.83	0.60	0.59	0.57	0.54	0.64	0.69	0.69	0.65
leverage (aggregate)	0.61	0.59	0.56	0.58	0.87	0.65	0.57	0.53	0.66	0.60	0.56	0.55
credit	0.64	0.64	0.62	0.58	0.93	0.80	0.70	0.59	0.71	0.68	0.65	0.62
house prices	0.73	0.72	0.71	0.70	0.78	0.61	0.56	0.48	0.79	0.73	0.70	0.66
credit gaps	0.63	0.59	0.56	0.55	0.56	0.52	0.52	0.46	0.58	0.54	0.53	0.50

Notes: Prediction analysis for different values of the debt inertia parameter in the collateral constraint, γ. All other parameters evaluated at the posterior mode. We simulate 100 artificial samples of size $N = 233$, which corresponds to the sample size used to estimate the DSGE model. The share of correctly predicted regimes is calculated computing the probability $\hat{P}$ that the constraint binds from equation 8 and comparing it to the share of periods where the constraint binds in the simulated sample, $\bar{B}$. We define $\bar{P} = 1$ if $\hat{P} > \bar{B}$, and $\bar{P} = 0$ otherwise. The share of correctly predicted regimes is then $[\sum I(\bar{P} = 1|Y = 1) + \sum I(\bar{P} = 0|Y = 0)]/N$. The table reports the averages over these simulations.

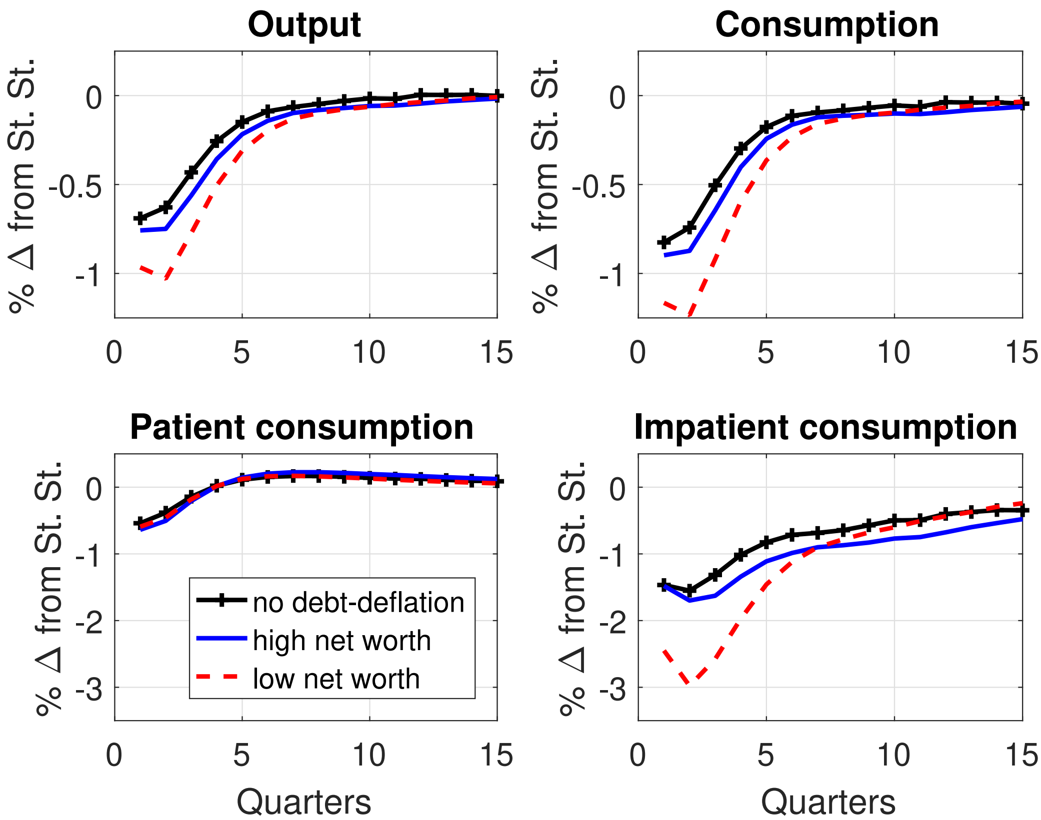
A5 Additional figures

Figure A1: IRFs to a Contractionary Monetary Policy Shock, $M = 0.8$



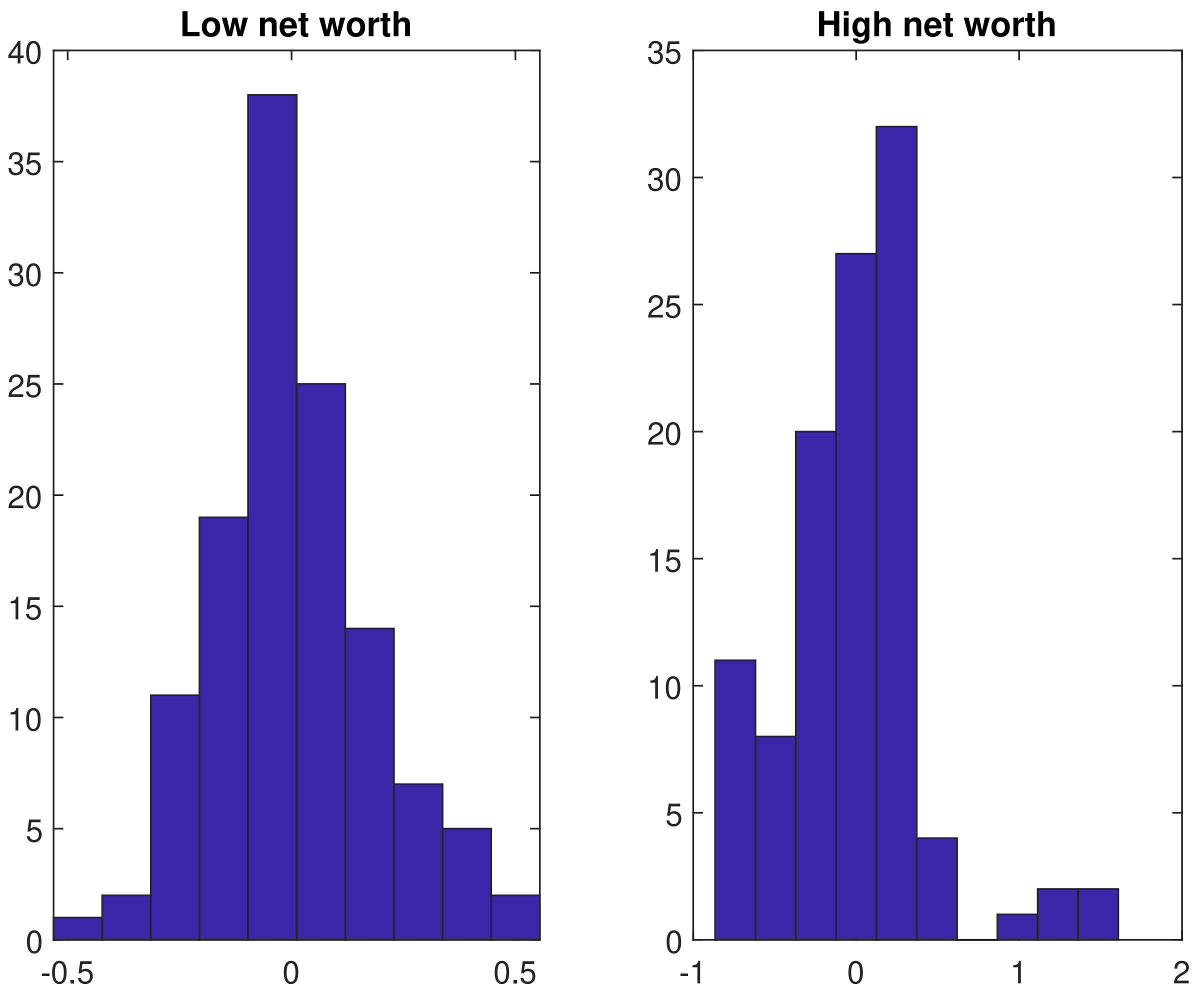
Notes: Generalized IRFs to an (annualized) 100 basis points monetary policy shock under binding and slack collateral constraints. GIRFs are computed by simulating the model for 600 periods, once with all shocks evaluated at their estimated standard deviations and a second time where, on top of that, an (annualized) 100 basis points monetary policy shock is added in period 501. Each IRF is computed as the difference between these two paths, dropping the first 500 periods of the simulation. The figure reports the average response to a monetary policy shock in period t over 100 simulations for two cases: when the constraint binds in $t-1$ (red dashed line) and when it is slack in $t-1$ (blue solid line). The black crossed lines show the same exercise for slack states states under indexed debt contracts, i.e., when there is no debt-deflation effect. The y-axis shows the responses in percentage deviations from the steady state. The x-axis shows quarters after the monetary policy shock hits.

Figure A2: IRFs to a Contractionary Monetary Policy Shock



Notes: Generalized IRFs to an (annualized) 100 basis points monetary policy shock under low and high net worth states, defined as the realizations below the 15th percentile and above the 85th percentile of the net worth distribution, respectively. GIRFs are computed by simulating the model for 600 periods, once with all shocks evaluated at their estimated standard deviations and a second time where, on top of that, an (annualized) 100 basis points monetary policy shock is added in period 501. Each IRF is computed as the difference between these two paths, dropping the first 500 periods of the simulation. The figure reports the average response to a monetary policy shock in period t over 100 simulations for two cases: when net worth is low in $t-1$ (red dashed line) and when it is high in $t-1$ (blue solid line). The black crossed lines show the same exercise for high net worth states under indexed debt contracts, i.e., when there is no debt-deflation effect. The y-axis shows the responses in percentage deviations from the steady state. The x-axis shows quarters after the monetary policy shock hits.

Figure A3: Distribution of Monetary Policy Shocks



Notes: Distribution of monetary policy shocks from baseline specification under high and low household net worth states.