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A mis padres

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Declaration of Co-Authorship and Publications

This dissertation consists of three research papers. Two papers were written in collaboration with one co-author. My contribution in conception, implementation and drafting can be summarized as follows:

- Martín Harding and Rafael Wouters:

  Risk and State-Dependent Financial Frictions

  Contribution: 50 percent

- Martín Harding and Mathias Klein:

  Monetary Policy and Household Net Worth

  An earlier version of this chapter was titled *Monetary Policy and Household Deleveraging* and was published as DIW Discussion Papers 1806, 2019.

  Contribution: 50 percent

- Martín Harding:

  Credit Constraints and the Transmission of Monetary Policy to Consumption

  Contribution: 100 percent

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List of Abbreviations

LIST OF ABBREVIATIONS

BGG Bernanke et al. (1999)
CEX Consumer Expenditure Surveys
CMR Christiano et al. (2014)
DGP Data generating process
DSGE Dynamic Stochastic General Equilibrium
GI Guerrieri and Iacoviello (2017)
HANK Heterogeneous Agent New Keynesian
HP Hodrick-Prescott
MCMC Markov Chain Monte Carlo
MDD Marginal data density
MPC Marginal propensity to consume
NK-FF New Keynesian model with financial frictions
NK-noFF New Keynesian model without financial frictions
RS Regime-Switching
SCF Survey of Consumer Finances
Std. Standard deviation

Summary

This dissertation consists of three essays that investigate the effects and transmission mechanisms of monetary policy to the macroeconomy, and the role of financial frictions in modeling the business cycle. The first essay focuses on the question of how to include financial sector dynamics into macroeconomic models in order to improve their efficacy for macroeconomic policy analysis. We augment a standard New Keynesian model with a financial accelerator mechanism and show that financial frictions generate large state-dependent amplification effects. We fit the model to US data and show that the nonlinear model produces much stronger propagation of shocks than the linear model, particularly when shocks drive the model far away from the steady state. We document that these amplification effects are due to endogenous variation in financial conditions and not due to other nonlinearities in the model. Motivated by these findings, we propose a regime-switching DSGE framework where financial frictions endogenously fluctuate between moderate (low risk) and severe (high risk) depending on the state of the economy. This framework allows for efficient estimation with many state variables and improves fit with respect to the linear model.

The second essay focuses on the following question: does monetary policy effectiveness in influencing the economy depend on households' balance sheets in the US economy? We investigate the interrelation between household balance sheets, collateral constraints, and monetary policy. 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 predic-

tion in the 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. By contrast, monetary policy shocks have only small and mostly insignificant effects when net worth is high.

The third essay focuses on the following question: how do credit constraints affect households' consumption response to monetary policy in the US economy? Combining detailed survey data on household portfolios, loan rejections, and consumption, I estimate the consumption response to exogenous changes in interest rates at the household level. I find large and statistically significant heterogeneity in the consumption responses across households, with constrained households being significantly less responsive. Specifically, the consumption response of unconstrained households to a monetary policy shock is between two to three times larger than the average response across all households. Using a New Keynesian model with heterogeneous households, I argue that this empirical finding is consistent with a model where financially constrained households have a low direct sensitivity to interest rates and indirect effects of monetary policy take time to materialize.

Zusammenfassung

Diese Dissertation besteht aus drei Aufsätzen, welche die Auswirkungen und Transmissionsmechanismen der Geldpolitik auf die Makroökonomie, sowie die Rolle von Finanzmarktfriktionen bei der Modellierung von Konjunkturzyklen untersuchen. Der erste Aufsatz konzentriert sich auf die Frage, wie Dynamiken im Finanzsektor in makroökonomische Modelle einbezogen werden können, um deren Brauchbarkeit für die makroökonomische Politikanalyse zu verbessern. Wir erweitern ein standard Neukeynesianisches Modell mit einem finanziellen Beschleunigungsmechanismus und zeigen, dass Finanzmarktfriktionen große zustandsabhängige Verstärkungseffekte erzeugen. Wir schätzen unser Modell mit US-Daten und zeigen, dass das nichtlineare Modell eine viel stärkere Ausbreitung von Schocks erzeugt als das lineare Modell, insbesondere wenn Schocks das Modell weit vom stationären Zustand wegtreiben. Wir dokumentieren, dass diese Verstärkungseffekte auf endogene Variation der finanziellen Bedingungen und nicht auf andere Nichtlinearitäten im Modell zurückzuführen sind. In Anbetracht dieser Ergebnisse schlagen wir ein DSGE-Modell mit Zustandsänderungen vor, bei dem der Grad der Finanzmarktfriktionen je nach Wirtschaftslage endogen zwischen moderat (geringes Risiko) und schwer (hohes Risiko) schwanken. Dieser Rahmen ermöglicht eine effiziente Schätzung mit vielen Zustandsvariablen und verbessert die Datenanpassung im Hinblick auf das lineare Modell.

Der zweite Aufsatz befasst sich mit der folgenden Frage: Hängt die Fähigkeit der Geldpolitik in den USA, die Wirtschaft zu beeinflussen, von den Bilanzen der Haushalte ab? Wir untersuchen die Beziehung zwischen den Bilanzen der Haushalte, ihren Sicherheitbeschränkungen und der Geldpolitik. Wir schätzen ein monetäres DSGE-Modell mit Finanzmarktfriktionen und zeitweise verbindlichen Kreditaufnahmebeschränkungen. Das Modell impliziert stärkere Auswirkungen geldpolitischer Interventionen, wenn die Kreditaufnahmebeschränkung

verbindlich ist, im Vergleich zu Situationen, in denen sie gelockert wird. Mit Hilfe einer Prognoseanalyse zeigen wir, dass innerhalb einer Reihe alternativer plausibler endogener Modellvariablen die Höhe des Nettovermögens der Haushalte der beste Einzelindikator für die Straffheit der Sicherheitbeschränkung ist. Dies impliziert, dass die Geldpolitik wirksamer ist, wenn das Nettovermögen der Haushalte niedrig ist. Wir testen diese Modellvorhersage in den Daten und liefern robuste empirische Evidenz zu den asymmetrischen Effekten der Geldpolitik über den gesamten Zyklus des Nettovermögens der privaten Haushalte, welche die Modellvorhersagen unterstützt.

Der dritte Aufsatz konzentriert sich auf die folgende Frage: Wie beeinflussen Kreditrestriktionen die Konsumreaktion der Haushalte auf die Geldpolitik in den USA? Durch die Kombination detaillierter Umfragedaten über die Portfolios der Haushalte, die Ablehnung von Kreditanfragen und den Konsum schätze ich die Konsumreaktion auf exogene Zinsänderungen auf Haushaltsebene. Ich stelle eine große und statistisch signifikante Heterogenität in den Konsumreaktionen der Haushalte fest, wobei eingeschränkte Haushalte deutlich weniger stark reagieren. Insbesondere die Konsumreaktion nicht eingeschränkter Haushalte auf einen geldpolitischen Schock ist zwei- bis dreimal größer als die durchschnittliche Reaktion aller Haushalte. Unter Verwendung eines Neukeynesianischen Modells mit heterogenen Haushalten argumentiere ich, dass dieses empirische Ergebnis mit einem Modell konsistent ist, bei dem finanziell eingeschränkte Haushalte eine geringe direkte Sensitivität gegenüber Zinssätzen haben und indirekte Auswirkungen der Geldpolitik Zeit brauchen, um sich zu materialisieren.

Introduction and Overview

Objective of the study

How does monetary policy influence the economy? How does the financial sector affect the propagation of macroeconomic shocks and the business cycle? These are long-standing questions in macroeconomics. Yet, over the past decades, events such as the financial crisis of 2008 and the Great Recession that followed have challenged our understanding of these issues.

This dissertation investigates the effects and transmission channels of monetary policy to the macroeconomy, and the role of financial frictions in modeling the business cycle. More precisely, it addresses three questions that have gained relevance among academics and policymakers over the past years. First, how should we include financial sector dynamics into macroeconomic models in order to improve their efficacy for macroeconomic policy analysis? Second, does monetary policy effectiveness in influencing the economy depend on the financial position of households? And third, how do credit constraints affect households' consumption response to monetary policy?

The first question has been at the forefront of the research agenda for central banks since the financial crisis of 2008. Central banks across the world achieved exceptional success in bringing down inflation and stabilizing the economy during the so-called Great Moderation –from the mid-1980s' to 2007. But the financial crisis highlighted that the models used by central banks lacked important features to accurately model the highly nonlinear dynamics of the financial sector. The typical Dynamic Stochastic General Equilibrium (DSGE) model used by central banks is a large and complex representation of the macroeconomy. For this reason, a standard practice –especially before the crisis– was to linearize these models in order to make computations feasible in a reasonably short time. Incorporating the complexities highlighted by the financial crisis into these models comes with an important trade-off: solving and estimating nonlinear models can be computationally very costly.

In the first chapter (joint with Raf Wouters) we tackle that trade-off with the objective of improving the accuracy of these models in an efficient way, so that they can be of practical use for policymakers. We consider the model by Christiano et al. (2014), which includes many of the core elements present in the models used by most central banks, to address several questions. Do financial frictions generate important nonlinear effects in this framework, as documented in empirical studies? How large are the accuracy costs of linearizing the model? Can we incorporate these nonlinearities into a solution and estimation routine that is fast enough for practical purposes? In order to answer these questions, we consider different nonlinear solution and estimation techniques.

We start by characterizing the nonlinearities implied by the financial frictions and their effects on the real variables in the model. Do firms react differently to shocks in periods of financial tranquility and distress, and why? A subsequent objective is to obtain a quantitative measure of the cost of linearizing the model in terms of accuracy: how far off is the linear approximation from the nonlinear dynamics? The last objective of the chapter is to incorporate the mechanism responsible for the nonlinear effects in the model into an efficient solution and estimation routine. Ultimately, the goal is to be able to conduct policy experiments using the workhorse DSGE model used by central banks allowing for state-dependent financial frictions.

The second question is motivated by a large empirical literature that has documented that the financial position of households is key to understand the propagation of economic shocks and policies (Jordà et al., 2016; Mian and Sufi, 2012). Against this background, a natural question is whether the potency of monetary policy is also determined by the financial position of households. This question has gained relevance for policymakers –and central banks in particular– because, over the last decade, massive fluctuations in households' balance sheets have happened together with large monetary policy interventions, both in the US and in Europe.

In the second chapter (joint with Mathias Klein) we tackle this question from a theoretical and empirical perspective. The first objective of the chapter is to study the relation between the financial position of households, collateral constraints, and monetary policy. For this purpose, we employ a New Keynesian model with financial frictions and an occasionally binding collateral constraint following Guerrieri and Iacoviello (2017), which predicts that monetary policy has larger effects when the collateral constraint is binding. The literature has suggested using different indicators of "financial excess" to measure collateral constraints in the data, such as household net worth, leverage, credit, house prices and credit-to-GDP gaps. Which one should we use? And how does it affect the transmission of monetary policy to the economy? To answer these questions, we use the DSGE model to conduct a prediction analysis in order to find out which model variable is the best predictor of when the constraint is binding or slack, and to study how household net worth affects the transmission mechanism of monetary policy.

We then ask whether the DSGE model predictions hold in the empirical data for the US economy. In order to tackle this question, we estimate state-dependent impulse responses using local projections. We consider several alternative specifications and robustness tests to show that household balance sheets play a key role for monetary policy transmission.

The third question is motivated by the results of the second chapter –that collateral constraints and household net worth play an important role for monetary policy transmission. Do different types of credit constraints affect households' consumption response to interest rate changes differently? Chapter 2 documents that households facing a binding collateral constraint react strongly to changes in interest rates because a drop in the interest rate relaxes their borrowing constraint, granting them additional access to credit and ultimately enhancing their consumption possibilities. What if constrained households are unable to adjust their borrowing in response to interest rate changes? This can happen, for instance, if households are partially or fully excluded from credit markets. How sensitive is the consumption response of households in this case?

The third chapter studies this question, focusing on the role of credit constraints –measured as the probability of loan rejections– for households' consumption response to exogenous changes in interest rates. Answering this question provides key information for central banks to understand which households are more – or less– responsive to their policy actions, and why. More specifically, the first objective of the chapter is to answer the following questions: what are the key determinants of credit constraints for households? How does the consumption response differ between constrained and unconstrained households? In order to tackle these questions, I combine detailed data on household portfolios and loan rejections with data on consumption, interest rates and monetary policy shocks identified at high frequency.

What does theory say about the relation between credit constraints and the consumption response to monetary policy? Several papers have documented that households with weaker balance sheets, or facing loan portfolio refinancing or adjustment constraints are less responsive to monetary policy (see, e.g., Alpanda et al., 2019; Beraja et al., 2019; Eichenbaum et al., 2018; Wong, 2019). The second objective of the chapter is to investigate this issue using a Heterogenous Agent New Keynesian (HANK) model. These models have become popular in the monetary policy literature and highlight the role of two distinct channels of monetary transmission: direct effects that act via households' Euler equation –an intertemporal substitution effect– and indirect effects that act via the general equilibrium response of aggregate quantities and prices –an income and wealth effect. The chapter studies how the interaction between these effects is consistent with the empirical findings.

Overview of the study

The first chapter of this thesis asks the following question: how can we incorporate nonlinear financial dynamics into the workhorse model used by central banks efficiently, in order to improve their accuracy for policy analysis? We make two relevant contributions. First, we show that the cost of ignoring state-dependent effects of financial frictions is substantial. We take a typical New Keynesian model with financial frictions (NK-FF) off the shelf and use a higher-order perturbation solution to investigate the extent to which nonlinear effects of financial frictions matter empirically. We document that the model generates large amplification effects in periods of financial distress or high risk, and mild amplification effects in periods of financial tranquility or low risk.

We estimate the model with US data and find that output and investment drop by an additional 130% during the Great Recession in the nonlinear model, while consumption drops by an additional 50% and the spread jumps by an additional 6.7 (annualized) percentage points. Importantly, we document that the bulk of these amplification effects are driven by variation in financial conditions, and not by other nonlinearities in the model. By contrast, amplification is almost absent throughout the 1980s and 1990s, which is consistent with the view that linear models provided a relatively good approximation of US business cycles during the Great Moderation.

Second, we propose a regime-switching DSGE framework where financial frictions endogenously fluctuate between moderate (low risk) and severe (high risk) depending on the state of the economy. Thereby, the model captures the key nonlinearity stemming from the financial frictions. Combining a perturbation solution from Maih (2015) and an adaptation of the Kalman filter from Chang et al. (2018) allows for efficient estimation with many state variables.

We then compare the accuracy of three alternative specifications: a linearized model, a regime-switching model with constant switching probabilities, where the switching follows an exogenous process, and a regime-switching model with time-varying switching probabilities that are endogenous to financial conditions. We show that both regime-switching models outperform the linear model and, most importantly, that the endogenous switching model outperforms the exogenous switching model in terms of marginal data density. This is because, on average, high risk states coincide with high spreads. By incorporating this information explicitly, the endogenous probability model produces better one-step-ahead forecasts when evaluating the likelihood function, which results in improved fit.

We conclude that regime switching with endogenous time-varying switching probabilities is a promising avenue to model state-dependent financial frictions in the context of the workhorse model used by many central banks. Alternatives to this approach include using higher-order or projection (global) nonlinear solutions and a particle filter to evaluate the likelihood. However, these approaches are computationally more costly than our implementation of the regime-switching filter, and they do not exploit the extra flexibility implied by the time-varying nature of parameters and equilibria in our regime-switching framework.

The second chapter asks the following question: does monetary policy effectiveness in influencing the economy depend on the financial position of households? In this chapter we make two important contributions. First, we estimate a New Keynesian DSGE model with financial frictions on US data, in which household balance sheets influence how monetary policy shocks transmit to the economy. Specifically, the model illustrates that monetary policy has stronger effects when borrowing constraints bind and household net worth is low. Second, we test this result on US data and find robust empirical evidence supporting the model predictions.

We start from the DSGE model by Guerrieri and Iacoviello (2017), which on top of the standard New Keynesian ingredients features financial frictions on the household side. We use the estimated DSGE model to study 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 or becoming slack. This result implies that monetary policy is significantly more effective during periods in which 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.

We then 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 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. By 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 as the corresponding GDP response in a high net worth state.

These empirical results are robust to a battery of robustness tests regarding the sample, identification, definition of the state variable, and indicator measuring the policy stance. Additionally, we refine the empirical analysis looking at regional data for US geographical states. These state-level estimates confirm our findings at the aggregate level. Notably, our results are robust when we condition on three other prominent state variables: the business cycle, the level of household debt, and financial stress in the economy. We conclude that the state of the household net worth cycle plays a particularly important role in understanding the transmission of monetary policy.

Finally, the third chapter asks the following question: how do credit constraints affect households' consumption response to monetary policy? This is my most recent research and should be understood as work in progress. I tackle this question by combining two detailed micro-surveys for the US. Using a measure of credit constraints based on loan rejections, I show that credit constraints significantly dampen the consumption response to a monetary policy shock. I then use a model with heterogeneous households to interpret this result.

I start with a characterization of financially constrained households in the US. First, I extend the work of Jappelli (1990) and estimate a probability model of the determinants of credit constraints using Survey of Consumer Finances (SCF) data from 1995 to 2016. The measure of credit constraints is a self-reported indicator of whether households have had their request for credit rejected over the past years. I document that household net worth, age, and debt are key predictors of loan rejections.

I then combine this measure of credit constraints with consumption data from the Consumer Expenditure Surveys (CEX) to study the role of credit constraints for the short-run consumption response to monetary policy. Specifically, I use the estimated probability model from the SCF to create and index of credit constraints for the CEX measuring the probability that a household is partially or fully turned down when applying for a loan. With this information at hand, I use Treasury yields and monetary policy shocks identified at high frequency to estimate the consumption response to monetary policy shocks for constrained and unconstrained households. I rely on two prominent series of monetary policy shocks in the literature, by Nakamura and Steinsson (2018) and Jarociński and Karadi (2020).

I find large and statistically significant heterogeneity in the short-run consumption responses across constrained and unconstrained households. Specifically, constrained households are significantly less responsive to monetary policy shocks. The drop in consumption in response to a contractionary monetary policy shock for unconstrained households is between two and three times as large as the average across all households. The response becomes smaller in absolute terms as the probability of being constrained increases and turns insignificant when the probability becomes sufficiently large.

The second part of the chapter studies the theoretical mechanism underlying the empirical findings. I set up a Heterogeneous Agent New Keynesian (HANK) model in which borrowing constraints and households' balance sheets play an important role for their consumption response to changes in interest rates. In the model, households that hold few or no assets have relatively large marginal propensities to consume (MPCs) and are relatively insensitive to changes in interest rates via direct –intertemporal substitution– effects. The model implies that most of the consumption response to a monetary policy shock comes from households in the middle of the asset distribution. However, due to their high MPCs, households at the lower tail of the distribution are also the ones that exhibit the largest indirect –income and wealth– effect in response to interest rates. These facts combined suggest that one plausible explanation for the empirical results is that low asset –financially constrained– households have a low direct sensitivity to interest rates and that the indirect effects take time to materialize, as documented in Holm et al. (2020).

I conclude that loan rejections provide a strong and significant indicator to understand the consumption response of households to exogenous interest rate changes, and the theoretical analysis provides a plausible explanation for the underlying mechanism. Since this chapter presents research that is still in progress, I added a section called "Discussion and outlook" to the empirical and theoretical parts of the chapter where I discuss caveats, challenges, and paths for future research.

CHAPTER 1

Risk and State-Dependent Financial Frictions (with Raf Wouters)

1.1 Introduction

Financial markets are one of the essential blocks of the macroeconomy and as such play an important role in shaping business cycle dynamics. Since the Great Recession, much research has focused on incorporating financial factors into macro models (Christiano et al., 2018; Gertler and Gilchrist, 2018). In parallel, several empirical studies have shown that changing financial conditions alter the way in which the financial sector affects the real economy (e.g., Adrian et al., 2019; Barnichon et al., 2018; Brunnermeier, 2009; Hubrich and Tetlow, 2015; Prieto et al., 2016). In particular, financial frictions tend to amplify the effects of macroeconomic shocks during periods of financial distress.

In this chapter, we study the role of state-dependent financial frictions in a medium-sized New Keynesian model of the business cycle. New Keynesian models with financial frictions (NK-FF) have become a fundamental policy tool for central banks.[1] At the same time, they have been heavily criticized in the years after the 2008 financial crisis (Christiano et al., 2018). Two popular critiques are that, because NK-FF models take an overly simplified approach to modeling financial intermediaries, they fail to take the crucial role of financial factors for business cycle dynamics into account. And that because they are often lin-

[1]See, e.g., Coenen et al. (2012) and Lindé et al. (2016) for a description and comparisons of the workhorse models used by central banks.

earized, they are unable to take the highly nonlinear dynamics of the financial sector into account.

Against this background, we address two questions in this chapter. First, whether financial frictions in a standard nonlinear NK-FF model generate large amplification of shocks in macro and financial variables, as found in empirical studies. This directly relates to assessing the costs of linearizing these models for empirical analysis. And second, how to introduce these nonlinear dynamics in a framework that allows for efficient estimation.

Our contribution is twofold. First, we show that the cost of ignoring state-dependent effects of financial frictions is substantial. We take a NK-FF model off the shelf (Christiano et al., 2014) and use a higher-order perturbation solution to investigate the extent to which nonlinear effects of financial frictions matter empirically. We document that the model generates large amplification effects in periods of financial distress or high risk, and mild amplification effects in periods of financial tranquility or low risk. Second, we propose a regime-switching DSGE model in which the economy endogenously fluctuates between low risk and high risk states. Thereby, the model captures the key nonlinearity stemming from the financial frictions and allows for efficient estimation with many state variables.

We start by investigating the empirical relevance of the state-dependent financial frictions in the NK-FF model. We fit the model to US data and show that the nonlinear model produces much stronger propagation of shocks than its linearized version. We find that output and investment drop by an additional 130% during the Great Recession in the nonlinear model, while consumption drops by an additional 50% and the spread jumps an additional 6.7 (annualized) percentage points. Importantly, we document that the bulk of these amplification effects are driven by variation in financial conditions, and not by other nonlinearities in the model. By contrast, amplification is almost absent throughout the 1980s and 1990s, which is consistent with the view that linear models provided a relatively good approximation of US business cycles during the Great Moderation. These two facts combined highlight the importance of allowing for state-dependent financial frictions in macroeconomic models.

We then propose a regime-switching DSGE framework where financial frictions endogenously fluctuate between moderate (low risk) and severe (high risk) depending on the state of the economy. We model the probability of switching from one state to the other as a function of the spread. Making the transition between states an endogenous function of the spread allows us to link the nonlinear effects of financial frictions in the model to a measure of financial conditions in the data. We solve the regime-switching model using perturbation methods following Maih (2015), which gives us a key efficiency advantage with respect to projection methods.

We then illustrate how this framework, combined with the filter proposed by Chang et al. (2018), can be used for efficient estimation of the New Keynesian model with state-dependent financial frictions. We generate data from the nonlinear NK-FF model and fit three models to these data: a linearized NK-FF model, a regime-switching NK-FF model with constant switching probabilities, where the switching follows an exogenous process, and a regime-switching NK-FF model with time-varying switching probabilities that are endogenous to financial conditions.

We show that both regime-switching models outperform the linear model and, most importantly, that the endogenous switching model outperforms the exogenous switching model in terms of marginal data density. This is because, on average, high risk states coincide with high spreads. By incorporating this information explicitly, the endogenous probability model produces better one-step-ahead forecasts when evaluating the likelihood function, which results in improved fit. This is important because it shows that model fit improves as a result of the improved probabilistic assessment about when financial frictions matter most. Ultimately, both model fit and the mechanisms that improve it are of interest for policymakers.

Alternatives to this approach include evaluating the nonlinear model, either solved with higher-order perturbation methods or fully nonlinear projection methods, using a particle filter. However, these approaches are computationally more costly than our implementation of the regime-switching filter. Moreover, while both these solutions take the nonlinear nature of the financial contract into account, they do not exploit the extra flexibility implied by the time-varying nature of parameters and equilibria in our regime-switching framework.

We work with the New Keynesian model proposed by Christiano et al. (2014). The basic structure follows Christiano et al. (2005) and Smets and Wouters (2007), while financial frictions are introduced as in Bernanke et al. (1999) (henceforth, BGG). We choose this approach for two main reasons. First, several influential central banks have built their DSGE models on this structure,[2] which gives a sense of relevance for the results of this study. Second, recent studies have highlighted the empirical relevance of this approach, both in terms of explaining the business cycle (Christiano et al., 2014) and forecasting performance (Cai et al., 2018; Del Negro et al., 2015, 2016; Del Negro and Schorfheide, 2013).

In the BGG model, an agency problem between financial intermediaries and productive firms gives rise to a premium for external finance. When firms' balance sheets weaken, the premium increases and real activity slows down, which has a further negative effect on borrowers' financial health, increasing the premium further, and so on. This is BGG's *financial accelerator* and its size is determined by the sensitivity of the premium to firm leverage. Crucially, this sensitivity is increasing in entrepreneurs' risk, defined as the variance of idiosyncratic productivity shocks faced by entrepreneurs.[3] Using this definition of risk, we exploit this relation to model state-dependent financial frictions.

Contribution to the literature.– Recent studies have provided empirical evidence of asymmetric effects of financial shocks and frictions on the real economy. Adrian et al. (2019) document a nonlinear relationship between financial conditions and the conditional distribution of GDP growth. They argue that DSGE models with financial frictions should therefore allow for nonlinear equilibrium relationships. Hubrich and Tetlow (2015) use a regime-switching VAR to show that the model that best explains the Great Recession features both changes in shock variances and in the parameters ruling the transmission of shocks. In a related study, Alessandri and Mumtaz (2017) indicate the presence of a regime change during the 2008 financial crisis. Barnichon et al. (2018) empirically document that financial shocks have asymmetric effects on the real economy, while Prieto et al. (2016) provide evidence of time-varying linkages between the financial sector and the macroeconomy. We build on this body of empirical evidence to develop a DSGE model that takes similar state-dependent dynamics into account.

We also contribute to the literature that has analyzed developments in DSGE models before and after the 2008 financial crisis. Christiano et al. (2018) revise this literature and conclude that financial frictions in pre-crisis DSGE models seem to

[2] Policy institutions that use a New Keynesian model with financial frictions as in BGG for policy analysis include the IMF (GIMF model), the Federal Reserve Board (SIGMA model), the European Central Bank (New Area Wide Model), the Federal Reserve Bank of New York (FRBNY-DSGE model), and the Riksbank (Ramses II model), among others.

[3] The empirical relevance of this concept of risk for the business cycle goes back to Bloom (2009).

have only small quantitative effects, an observation that goes back to Kocherlakota (2000). Importantly, most studies discussed there consider linearized versions of NK-FF models, thereby neglecting the potential state-dependent effects of financial frictions over the business cycle. Other studies, (e.g., Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2014) have shown that nonlinear models with financial frictions can generate large amplification effects. Our results provide additional evidence supporting the view that it is important to take nonlinear model dynamics into account for business cycle analysis, even in the pre-crisis generation of models.

Additionally, there is a growing literature studying the nonlinear effects of financial frictions in DSGE models. On the one hand, several papers have used New Keynesian models with occasionally binding constraints and regime switching to study the effects of different types of nonlinear financial constraints (Bluwstein, 2017; Guerrieri and Iacoviello, 2017; Holden et al., 2018; Lindé et al., 2016; Maria and Júlio, 2018; Pietrunti, 2017). Some of these papers take an empirical approach. For instance, Guerrieri and Iacoviello (2017) estimate a NK-FF model with an occasionally binding collateral constraint that captures the boom-bust dynamics observed in the US housing market in 2001-2009. Bluwstein (2017) documents that financial busts are more procyclical than booms and estimates a DSGE model with banks that face an occasionally binding borrowing constraint to explain this finding. More generally, the papers by Lindé et al. (2016), Del Negro et al. (2016), and Del Negro and Schorfheide (2013) have shown that allowing for time variation in the effects of financial frictions improves the forecasting performance of DSGE models.

On the other hand, various papers have used smaller nonlinear models that include important features of the financial sector, such as the endogenous buildup of financial risk and the asymmetric effects of financial constraints in normal times and in periods of financial distress (Adrian and Boyarchenko, 2012; Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2014; Mendoza, 2010) to show that financial frictions generate large amplification effects on macroeconomic variables. Many of these features are yet to be introduced to the models used by central banks. Importantly, due to the high computational burden involved in solving these models, they are typically much smaller than the standard NK-FF model. For the same reason, estimation of nonlinear DSGE models becomes computationally challenging (see, e.g., Gust et al., 2017). We contribute to this literature by combining elements of these two strands to develop a framework that features state-dependent financial frictions with time-varying risk in an otherwise standard NK-FF model, and allows for efficient estimation with many state variables.

Outline.– The chapter is organized as follows. Section 2 describes the NK-FF model and discusses the nonlinear dynamics in the financial sector. Section 3 provides the details about the estimation and documents the quantitative effects of state-dependent financial frictions. Section 4 introduces the regime-switching DSGE model and discusses the estimation results. The last section concludes.

1.2 Model

We augment a standard New Keynesian model with the BGG financial accelerator following Christiano et al. (2014) (henceforth, CMR). Absent financial frictions, the the building blocks are similar to the well known models by Christiano et al. (2005) and Smets and Wouters (2007). In the following we present the main features of the model.

1.2.1 Goods Production

Final goods producers take intermediate goods $Y_{jt},\ j \in [0,1]$ to produce an homogeneous good Y_t using the Dixit-Stiglitz technology:

$$Y_t = \left[\int_0^1 Y_{jt}^{\frac{1}{\lambda_{f,t}}} dj\right]^{\lambda_{f,t}}, \quad 1 \leq \lambda_{f,t} < \infty, \tag{1.1}$$

where $\lambda_{f,t}$ is a price-markup shock. The intermediate goods producer is a monopolist with technology

$$Y_{jt} = \begin{cases} \varepsilon_t K_{jt}^{\alpha}(z_t l_{jt})^{1-\alpha} - \Phi z_t^* & \text{if } K_{jt}^{\alpha}(z_t l_{jt})^{1-\alpha} > \Phi z_t^* \\ 0 & \text{otherwise} \end{cases}, \tag{1.2}$$

where $0 < \alpha < 1$ and ε_t is a transitory technology shock. z_t^* is a shock with a stationary growth rate with the property that Y_t/z_t^* converges to a constant in the non-stochastic steady state. Each firm supplies Y_{jt} at price P_{jt} and is subject to Calvo-style price rigidities, so that in each period only a random fraction $(1-\xi_p)$ can re-optimize their price. The remaining fraction sets a price $P_{jt} = \tilde{\pi}_t P_{j,t-1}$, where

$$\tilde{\pi}_t = (\pi_t^{target})^{\iota}(\pi_{t-1})^{1-\iota}. \tag{1.3}$$

Here, $\pi_{t-1} \equiv P_{t-1}/P_{t-2}$ and π_t^{target} is the target inflation rate. Homogeneous goods can be converted to consumption goods, C_t, at a one-to-one rate. Alternatively, one homogeneous good can be converted to $\Upsilon^t \mu_{\Upsilon,t}$ investment goods, where $\Upsilon > 1$ and $\mu_{\Upsilon,t}$ is a shock. Perfect competition in these markets implies that the prices of consumption and investment goods are P_t and $P_t/(\Upsilon^t \mu_{\Upsilon,t})$, respectively. The trend rise in technology for producing investment goods is the second source of growth in the model, and $z_t^* = z_t \Upsilon^{\left(\frac{\alpha}{1-\alpha}\right)t}$.

1.2.2 Labor Market

As in the goods market, the labor market features a representative, competitive labor contractor that aggregates differentiated labor services, $h_{i,t},\ i \in [0,1]$, into homogeneous labor, l_t, using the Dixit-Stiglitz technology with production function

$$l_t = \left[\int_0^1 (h_{t,i})^{\frac{1}{\lambda_w}} di\right]^{\lambda_w}, \quad 1 \leq \lambda_w. \tag{1.4}$$

It then sells labor l_t to intermediate good producers at the nominal wage W_t. For each labor type, a monopoly union sets the wage rate $W_{i,t}$, subject to Calvo-style frictions. Hence, only a fraction $(1 - \xi_w)$ set their wage optimally while the remaining firms set their wage according to $W_{i,t} = (\mu_{z^*,t})^{\iota_\mu}(\mu_{z^*})^{1-\iota_\mu}\tilde{\pi}_{w,t}W_{i,t-1}$ where μ_{z^*} is the steady state growth rate of z_t^* and

$$\tilde{\pi}_{w,t} \equiv (\pi_t^{target})^{\iota_w}(\pi_{t-1})^{1-\iota_w}, \quad 0 < \iota_w < 1. \tag{1.5}$$

1.2.3 Households

Each household contains every type of differentiated labor and a large number of entrepreneurs. Households also act as capital producers it the economy. Capital is produced according to the technology

$$\bar{K}_{t+1} = (1-\delta)\bar{K}_t + (1 - S(\zeta_{I,t}I_t/I_{t-1}))I_t. \tag{1.6}$$

Households buy investment I_t to produce new capital subject to investment adjustment costs embodied in S, which is an increasing and concave function that we characterize below. $\zeta_{I,t}$ is a shock to the marginal efficiency of investment. In addition, households buy the existing stock of capital at price $Q_{\bar{K},t}$ and sell new capital at the same price.

Households' preferences are given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \zeta_{C,t} \left\{ \log(C_t - bC_{t-1}) - \psi_L \int_0^1 \frac{h_{i,t}^{1+\sigma_L}}{1+\sigma_L} di \right\} \quad b, \sigma_L > 0, \tag{1.7}$$

where $\zeta_{C,t}$ is a preference shock and C_t represents per capita consumption of the household. The associated budget constraint reads

$$\begin{aligned} (1+\tau^c) P_t C_t + B_{t+1} + \frac{P_t}{\Upsilon \mu_{\Upsilon,t}} I_t + Q_{\bar{K},t}(1-\delta)\bar{K}_t \leq \\ (1-\tau^l) \int_0^1 W_t^i h_{i,t} di + R_t B_t + Q_{\bar{K},t} \bar{K}_{t+1} + \Pi_t. \end{aligned} \tag{1.8}$$

Here Π_t stands for lump-sum payments including firm profits, transfers from entrepreneurs, and lump-sum transfers from the government. B_{t+1} is a one period bond that pays returns R_t, while τ^c and τ^l are exogenous tax rates. This budget constraint ensures that the sum of expenditures in consumption goods, new deposits, and purchases of investment goods and capital (left-hand side) does not exceed the household's income from labor, returns on deposits, revenues from selling capital, and lump-sump payments (right-hand side). In equilibrium, it holds with equality.

1.2.4 Financial Frictions

Financial frictions are added in the form of the standard BGG contract. As emphasized by Christiano et al. (2018), financial frictions can be broadly categorized in two groups: those arising inside financial institutions (theories of bank runs and rollover crises) and those arising between financial institutions and the people that borrow from them (theories of collateral-constrained borrowers). This model is of the latter type.

Following CMR, we index entrepreneurs by their level of net worth $N \geq 0$ and call each of them an N-type entrepreneur. If we denote the density of entrepreneurs with net worth N as $f_t(N)$, then the aggregate net worth in the economy is given by

$$N_{t+1} = \int_0^\infty N f_t(N)\, dN. \tag{1.9}$$

Each period, an N-type entrepreneur obtains a loan B_{t+1}^N at rate R_t^L and combines it with its own net worth N to buy raw capital $\bar{K}_{t+1}^N$ at the competitive price $Q_{\bar{K},t}$. Thus, her balance sheet is $B_{t+1}^N + N = Q_{\bar{K},t}\bar{K}_{t+1}^N$. After buying capital, she faces an idiosyncratic shock ω which converts $\bar{K}_{t+1}^N$ into $\omega\bar{K}_{t+1}^N$ units of effective capital. ω is log-normal distributed with mean one and standard deviation σ_t, which characterizes the cross-sectional dispersion in ω and, as in CMR, we interpret as a *risk shock*. After observing rates of return and prices, entrepreneurs decide what utilization rate u_{t+1}^N of effective capital units they supply to a competitive market at rate r_{t+1}^k. At the end of period $(t+1)$ each entrepreneur obtains a stochastic return ωR_{t+1}^k, regardless of her net worth, where

$$R_{t+1}^k = \frac{(1-\tau^k)[u_{t+1}r_{t+1}^k - a(u_{t+1})]\Upsilon^{-(t+1)}P_{t+1} + (1-\delta)Q_{\bar{K},t+1} + \tau^k\delta Q_{\bar{K},t}}{Q_{\bar{K},t}}. \tag{1.10}$$

Here, τ^k is an exogenous tax rate on capital income and a is an increasing and concave function that captures the costs of capital utilization.

The loan that each entrepreneur obtains in period t takes the form of a standard debt contract (R_t^L, L_t), where $L_t \equiv (N + B_{t+1}^N)/N$ stands for leverage. Let $\bar{\omega}_t$ be the threshold value under which an entrepreneur cannot repay her loan, such that

$$\bar{\omega}_{t+1} = \frac{R_{t+1}^L B_{t+1}^N}{R_{t+1}^k Q_{\bar{K},t}\bar{K}_{t+1}^N}. \tag{1.11}$$

Entrepreneurs with $\omega < \bar{\omega}_{t+1}$ default on their loan. In that case, financial intermediaries pay a monitoring cost equal to a fraction μ of the entrepreneur's assets and keep all that is left. Hence, the expected value of a loan for an entrepreneur can be written as

$$E_t\int_{\varpi_{t+1}}^\infty \left[R_{t+1}^k\omega Q_{\bar{K},t}\bar{K}_{t+1}^N - R_{t+1}^L B_{t+1}\right] dF(\omega,\sigma) = E_t[1-\Gamma_t(\bar{\omega}_{t+1})]R_{t+1}^k L_t N, \tag{1.12}$$

with $\Gamma_t(\bar{\omega}_{t+1}) \equiv [1 - F(\bar{\omega}_{t+1})]\bar{\omega}_{t+1} + G_t(\bar{\omega}_{t+1})$ and $G_t \equiv \int_0^{\bar{\omega}_{t+1}} \omega dF_t(\omega)$.

In order to extend loans to entrepreneurs, financial intermediaries issue deposits to households at the competitive rate R_t. The fact that the relevant rate on these deposits is the risk-free rate reflects that the market for funds between households and financial intermediaries is frictionless. This rate is not contingent in $t+1$ uncertainty. Hence, in order for financial intermediaries to participate in the market, their expected return must be at least R_t, that is,

$$[1 - F(\varpi_{t+1})]\, R^L_{t+1} B^N_{t+1} + (1-\mu) \int_0^{\varpi_{t+1}} \omega dF_t(\omega) R^k_{t+1} Q_{\bar{K},t} \bar{K}^N_{t+1} \geq R_t B^N_{t+1}. \quad (1.13)$$

Free entry of financial intermediaries guarantees that they make zero profits in equilibrium, which implies that equation (1.13) effectively holds with equality in equilibrium. Combining equations equations (1.11) and (1.13) we can write

$$\frac{R^k_{t+1}}{R_t} = \frac{1}{\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})} \left(1 - \frac{1}{L_t}\right). \quad (1.14)$$

The $(\bar{\omega}_{t+1}, L_t)$ combinations that satisfy equation (1.14) determine a set of state $(t+1)$-contingent standard debt contracts that are available for entrepreneurs. Entrepreneurs maximize their objective function (equation (1.12)) subject to this menu of contracts. Note that the $(\bar{\omega}_{t+1}, L_t)$ decision is independent of N. In fact, capital purchases of each entrepreneur are proportional to her net worth, with a proportionality factor that is increasing in the expected discounted return to capital. We define the expected discounted return to capital $s_t \equiv E_t(R^k_{t+1}/R_t)$. Then, we can write

$$Q_{\bar{K},t} \bar{K}^N_{t+1} = \psi(s_t) N, \quad \text{with } \psi(1) = 1,\ \psi'(\cdot) > 0. \quad (1.15)$$

Since $Q_{\bar{K},t} \bar{K}^N_{t+1}$ are the entrepreneur's assets, it follows that $L_t = (Q_{\bar{K},t} \bar{K}^N_{t+1})/N$ or $L_t = \psi(s_t)$. This expression summarizes two important characteristics of the model. First, entrepreneurs will demand a positive amount of loans only when the expected return on capital is greater than the risk-free rate. And second, they will choose a higher leverage when the expected discounted return on capital s_t is higher. In equilibrium, s_t must be equal to the marginal cost of external finance or *external finance premium*. Hence, equation (1.15) can be reformulated as

$$s_t \equiv E_t \frac{R^k_{t+1}}{R_t} = s(L_t) \quad \text{with } s(1) = 1,\ s(\cdot)' > 0. \quad (1.16)$$

This expression is useful because it shows that the external finance premium is an increasing function of leverage.[4] We will come back to this relation when we discuss the equilibrium dynamics in the loan market. Finally, at the end of each period, a random fraction $(1-\gamma_{t+1})$ of the entrepreneur's assets is transferred to the households, while the household makes a lump-sum transfer W_t^e to each entrepreneur.[5]

1.2.5 Aggregation

Aggregate raw capital is given by

$$\bar{K}_{t+1} = \int_0^\infty \bar{K}_{t+1}^N f_t(N) dN, \tag{1.17}$$

while aggregate capital rented to productive firms is $K_t = u_t \bar{K}_t$. Aggregate entrepreneurs' profits are given by $[1-\Gamma_t(\bar{\omega}_{t+1})]R_t^k Q_{\bar{K},t-1}\bar{K}_t$, so that aggregate net worth evolves according to

$$N_{t+1} = \gamma_t[1-\Gamma_{t-1}(\bar{\omega}_t)]R_t^k Q_{\bar{K},t-1}\bar{K}_t + W_t^e. \tag{1.18}$$

Aggregate debt is obtained as

$$B_{t+1} = \int_0^\infty B_{t+1}^N f_t(N) dN = Q_{\bar{K},t}\bar{K}_{t+1} - N_{t+1}, \tag{1.19}$$

and the loan rate is given by $R_{t+1}^L = R_{t+1}^k \bar{\omega}_{t+1} L_t$.

The aggregate resource constraint then reads

$$Y_t = D_t + C_t + G_t + \frac{I_t}{\Upsilon \mu_{\Upsilon,t}} + a(u_t)\Upsilon^t \bar{K}_t, \tag{1.20}$$

where the last term stands for the capital utilization costs of entrepreneurs, D_t represents the total monitoring costs incurred by financial intermediaries

$$D_t = \mu G(\bar{\omega}_t)(1+R_t^k)\frac{Q_{\bar{K},t-1}\bar{K}_t}{P_t},$$

and G_t is government spending, which follows an exogenous process.

[4] A detailed derivation of the function $s(\cdot)$ can be found in appendix A.3.

[5] This is to ensure that entrepreneurs do not accumulate a level of net worth sufficient to operate with zero debt. These concepts are exogenous.

1.2.6 Monetary Policy, Adjustment Costs and Shocks

The central bank follows the Taylor rule

$$R_t - R = \rho_p(R_{t-1} - R) + (1 - \rho_p)\left[\alpha_\pi(\pi_{t+1} - \pi^*) + \alpha_{\Delta y}(g_{y,t} - \mu_z^*)\right] + \varepsilon_t^R, \quad (1.21)$$

where R is the steady state nominal risk-free rate, π^* is the central bank's inflation target, $g_{y,t}$ is the growth rate of GDP and ε_t^R is a monetary policy shock.

Investment adjustment costs take the form

$$S(x_t) = \frac{1}{2}\{\exp[\sqrt{S''}(x_t - x)] + \exp[-\sqrt{S''}(x_t - x)] - 2\}, \quad (1.22)$$

where $x_t = \zeta_{I,t} I_t / I_{t-1}$, x is the steady state value of x_t, $S(x) = S'(x) = 0$, and $S''(x) = S''$ is a model parameter.

Utilization adjustment costs follow

$$a(u) = r^k[\exp(\sigma_a(u - 1)) - 1]\frac{1}{\sigma_a}, \quad (1.23)$$

where $\sigma_a > 0$. Note that utilization is one in the steady state, regardless of the value of σ_a.

The model dynamics are driven by 10 structural shocks: a transitory and a permanent technology shock, a price-markup shock, a consumption preference shock, and marginal efficiency of investment shock, a shock to the relative price of investment goods, a monetary policy shock, a fiscal shock, a shock to entrepreneurs' net worth and the risk shock. In the model these are ε_t, $\mu_{z^*,t}$, $\lambda_{f,t}$, $\zeta_{C,t}$, $\zeta_{I,t}$, $\mu_{\Upsilon,t}$, ε_t^R, ε_t^G, γ_t, and σ_t, respectively. We impose an AR(1) structure for all shocks except the monetary policy shock which is assumed to be i.i.d., and allow for an anticipated or *news* component for risk shocks.[6] We follow CMR and allow agents to anticipate information for up to 8 quarters. Hence, the risk shock process reads:

$$\sigma_t = \rho_\sigma \sigma_{t-1} + \xi_{0,t} + \xi_{1,t-1} + \ldots + \xi_{8,t-8}. \quad (1.24)$$

[6]CMR show that this anticipated component plays an important role in terms of model fit. They consider several alternative specifications and conclude that the *news* component matters most for the risk shock. We implement their preferred specification here.

In this specification, the innovation to the σ_t process is the sum of i.i.d., mean zero random variables, consisting of an unanticipated component $\xi_{0,t}$ and the anticipated component summarized in $\xi_{1,t-1}$ to $\xi_{8,t-8}$. We impose CMR's correlation structure for the $\xi_{j,t}$s:

$$\rho_{\sigma,n}^{|i-j|} = \frac{E\xi_{i,t}\xi_{j,t}}{\sqrt{E\xi_{i,t}^2 E\xi_{j,t}^2}}, \quad i,j = 0,\dots p, \tag{1.25}$$

where $E\xi_{0,t}^2 = \sigma_\sigma^2$ and $E\xi_{1,t}^2 = E\xi_{2,t}^2 = \dots = E\xi_{8,t}^2 = \sigma_{\sigma,n}^2$. This means that the σ process is characterized by four free parameters: ρ_σ, $\rho_{\sigma,n}$, σ_σ^2, and $\sigma_{\sigma,n}^2$.

1.2.7 Equilibrium Dynamics in the Loan Market

In order to illustrate how we use BGG's framework to model the state-dependent effects of financial frictions, it is useful to analyze the equilibrium dynamics in the market for loans. To do this, we abstract from the New Keynesian model for a moment and consider the financial contract in isolation, which allows us to compute the analytical solution of the nonlinear contract. We calibrate the model as described in Table 1.1 and solve for the combinations of $(\bar{\omega}_{t+1}, L_t)$ that satisfy equation (1.14) for an array of values of the return on capital R_t^k.[7]

Figure 1.1 illustrates the equilibrium dynamics. The left panel shows the equilibrium schedule for leverage and the spread for increasing values of R_t^k. The curvature of this schedule determines how responsive the spread is to fluctuations in the leverage position of entrepreneurs in equilibrium. Note that for low returns on capital, entrepreneurs choose low levels of leverage, which imply a low spread and a low sensitivity spread-leverage. As the return on capital increases, entrepreneurs take on more leverage and the spread increases.

Crucially, the spread does not increase linearly with leverage. Instead, the slope of the schedule increases, reflecting that the sensitivity spread-leverage increases for equilibria where leverage and the spread are high. This sensitivity is a key element in the model, since it determines the extent to which the financial health of entrepreneurs affects the real economy. In the extreme case where financial frictions are turned off, the spread and its sensitivity remain fixed at zero.

[7] For this exercise we need to assign values to the following parameters of the financial contract: μ, γ, W^e, σ. And to β, π and μ_{z^*} in order to fix the nominal rate $R_t = (\pi\mu_{z^*})/\beta = 0.0115$. Note that these values are the same that we later fix when we estimate the model.

Linearizing this model requires selecting one point on this schedule and approximating the model dynamics around that equilibrium. The curvature of the schedule highlighted in the figure illustrates that this approximation can be quite poor when the model drifts away from that equilibrium. These nonlinear effects translate to the default probability of entrepreneurs, which is also more responsive for higher combinations spread-leverage.

The right panel illustrates how the level of risk affects the spread-leverage dynamics. The solid line in this panel repeats the schedule from the left panel and the dashed lines depict the the leverage-spread schedule for the same array of R_t^k values and increasing values of σ_t –from 0.22 to 0.3. An increase in σ_t shifts the entire schedule upward: given a calibration and a value of R_t^k, an increase in σ_t implies a higher equilibrium for the spread, leverage, and the sensitivity spread-leverage. This panel provides a graphical illustration of the low-risk/high-risk setup that we present later in section 1.4, where the high-risk state not only features a high value of the time-varying σ_t process, but also a larger propagation mechanism of the financial frictions to the real economy.

The economic intuition behind these two results is that the role of financial frictions is amplified when financial intermediaries face higher expected losses from loan contracts. On the one hand, when leverage is high, entrepreneurs put a relatively small fraction of their own funds at risk to finance investment projects and the agency problem implies that the potential divergence of interest between borrowers and lenders is bigger. This is the traditional "financial accelerator" intuition, where endogenous dynamics in the credit market amplify macroeconomic shocks. On the other hand, the value of σ_t is a measure of the riskiness of entrepreneurs' returns, since a larger cross-sectional dispersion of idiosyncratic shocks yields a higher default probability in equilibrium. Hence, higher values of σ_t imply that financial intermediaries will charge a higher premium for each level of firm leverage. We next document that these nonlinear dynamics are carried over to the New Keynesian model, with quantitatively large effects on macroeconomic variables.

1.3 Estimation and State-Dependent Financial Frictions

We start by estimating the linearized model with standard full information Bayesian methods, which is the standard practice in central banks. This provides us with a relevant benchmark for the values of deep parameters and variances of shocks that we can use to assess the role of state-dependent financial frictions.

1.3.1 Data

We use quarterly US data on 11 macro and financial time series covering the period 1985Q1-2010Q4 to estimate the model.[8] The first eight are standard macro variables in business cycle analysis: GDP, consumption, investment, and hours worked, all measured in real, per capita terms, plus the real wage, the relative price of investment goods, inflation and the federal funds rate.

Additionally, we include three financial time series in the estimation: we measure the external finance premium with a BAA-rated corporate bond/10-year US treasury spread,[9] entrepreneurs' net worth with the Dow Jones Wilshire 5000 index, converted into real, per capita terms, and firm credit as debt securities and loans of nonfinancial firms from the Flow of Funds tables, converted into real, per capita units. We assume that net worth is measured with error, so that when we estimate the model there are 11 shocks and 11 observables. Further details about data sources and transformations can be found in appendix A.1.

1.3.2 Priors and Posteriors

As is standard in the literature, a subset of parameters are calibrated to match sample averages of the data. These parameters are presented in Table 1.1. We set π and π^{target} to the sample's average annual inflation rate of 2.3%. The households' discount factor β is fixed at 0.9985 to match the sample's average nominal interest rate of 4.6% and the average growth rate of the economy of 1.66%.

For the most part we stick to the parameterization of CMR, which is considered standard in the literature. We normalize ψ_L so that hours worked is unity in the steady state. The price and wage markups λ_f and λ_w are set to 1.2 and 1.05,

[8]This is the same period and variables covered by CMR, with the exception of the slope of the term structure. CMR include this concept, measured as the difference between the return on a 10-year Treasury yield and the federal funds rate, and add a long-term bond with measurement error to the model. Their goal is to diagnose whether the model dynamics are consistent with the observed slope of the term structure, and they show that the estimated model does well in this respect. The 10-year bond does not play a direct role for resource allocation in the model, but it involves the computation of expectations 40 quarters ahead, which slows down the solution and estimation. For this reason, we leave it out in our estimation.

[9]We obtain similar results when using the spread proposed by Gilchrist and Zakrajšek (2012).

respectively. The capital share in production α is set to 0.4 and the depreciation rate of capital δ to 0.025. Turning to the financial contract, we set the steady state productivity dispersion σ to 0.26 as in CMR. We fix the steady state survival rate of entrepreneurs γ at 0.979, the transfer from households to entrepreneurs W^e at 0.134, and monitoring costs μ at 0.275, such that the steady state external finance premium matches the spread's sample average of 2.12%. This parameterization implies the following steady state ratios: equity-to-debt ratio (firm leverage) of 1.9, consumption-to-output ratio of 0.54, investment-to-output ratio of 0.28, fiscal spending-to-output ratio of 0.18, and capital-to-output ratio of 8.49.

The priors and posterior estimates are presented in Table 1.2. The model does a good job in fitting not only the standard macro aggregates, but also the spread and firm credit. This is despite the fact that the model does not include labor supply or wage markup shocks. Instead, as previously shown by CMR, the risk shock plays a key role for model fit, since it jointly explains a large share of both financial and non-financial variables.[10] With the estimated parameters and shocks at hand, in the following section we use a nonlinear solution of the model to document that financial frictions produce important state-dependent effects.

1.3.3 State-Dependent Financial Frictions

In this section we show that the NK-FF model inherits the nonlinear dynamics of the financial contract illustrated in Figure 1.1. There, we argued that the propagation mechanism in the financial sector becomes stronger in periods of high spreads, high risk, and high sensitivity of spreads to firms' financial health. We now turn to the question whether financial frictions generate quantitatively large amplification of shocks in the real economy during these periods. With the estimated parameters and shocks at hand, we use higher-order perturbation methods as in Dewachter and Wouters (2014) and Aruoba et al. (2017) to solve the model and document that financial frictions generate large state-dependent effects in the real economy.

We start by asking whether the model captures the nonlinear dynamics of the spread and leverage implied by the financial contract, as illustrated in Figure 1.1. That is, whether for a given level of risk, periods of low spreads are characterized

[10] Figure A.1 in appendix A.2 shows the one-step-ahead forecasts of the model for all observables, while Figure A.2 shows the data and the model dynamics when only feeding the risk shock for selected variables.

by low sensitivity spread-leverage and vice versa. In the following we fix the estimated parameters to their posterior mode and solve the model with a third-order Taylor approximation.[11] We simulate the model for 20,000 periods and do not allow for risk shocks in order to keep the level of risk fixed at its steady state value.

Figure 1.2 shows the leverage-spread schedule implied by the model. The figure shows that when the model moves away from the steady state,[12] the third-order approximation (red crosses) captures a substantial degree of curvature that the linear model (black circles) misses. In order to assess the accuracy of the third-order approximation we also compute the nonlinear solution of the model using the Fair and Taylor (1983) method (blue squares). This method imposes certainty equivalence on the nonlinear model, but takes the nonlinear structure of the model into account when computing the propagation of shocks. The fact that the stochastic third-order solution comes close to the fully nonlinear deterministic solution suggests that it is an accurate approximation to the nonlinear dynamics of the model.[13]

As discussed above, for low (high) levels of leverage, the nonlinear solution implies a low (high) sensitivity spread-leverage. This state-dependent sensitivity, absent in the linear model, implies that the amplification effects of the financial accelerator endogenously fluctuate with the sate of the economy. The reason is that when the sensitivity is low, a shock that is contractionary for economic activity and reduces entrepreneurs' net worth triggers only a small increase in spreads, which translates into a moderate increase in the financing costs for firms. By contrast, when the sensitivity is high a contractionary shock triggers a large increase

[11] The ideal setting would be to have the fully nonlinear solution to estimate the model and run simulation experiments. However, due to the large number of state variables, the global solution of the New Keynesian model at hand involves a high computational burden, even for model simulations.

[12] The values for leverage and the spread at the non-stochastic steady state are 1.9 and 2.12%, respectively.

[13] We conduct the simulations by drawing 20,000 random shocks given the shocks' estimated standard deviation, and then feed them to each solution of the model. For the deterministic nonlinear solution, shocks hit the economy each period conditional on the state of the economy in that period and agents expect no further shocks thereafter. For the third-order solution we use pruning as implemented in Dynare 4.5.4. We also consider a second-order approximation for this exercise and get similar results (see Figure A.3 in appendix A.2). The third-order comes slightly closer to the nonlinear solution and computing time is only marginally higher than the second-order, so that we use the former as our baseline solution.

in spreads and firms' financing costs, with large effects on the real economy –as we document next.

How large are these amplification effects, as captured by the third-order approximation? To answer this question we use the smoothed shocks obtained from the estimated linear model, feed them to the nonlinear model and compare the dynamics with the linear solution.[14] These shocks generate the observed data in the linear model –in other words, they are the most likely shocks given the data and the model. If the simulated paths for the endogenous variables with the nonlinear solution is only marginally different, we would conclude that the cost of ignoring the state-dependent nature of financial frictions is negligible.

However, Figure 1.3 shows that amplification effects are quantitatively large. Panel (a) shows this exercise for the baseline estimated model, and it highlights the state-dependent nature of financial frictions. Amplification effects are large only in some states of the economy, when spreads are relatively high. Not surprisingly, the largest amplification occurs during the Great Recession, when financial conditions are worst. The nonlinear solution predicts that in 2008Q4 output and investment would have dropped by an additional 130%, while consumption would have dropped by an additional 50%. The spike in the spread is 6.7 (annualized) percentage points higher and inflation collapses by a factor of 3. Altogether the sample standard deviation is about 1.5 times larger for GDP and investment, and 2 times larger for the spread in the nonlinear model.

It is noteworthy that amplification is small except during the Dot-com crisis and the Great Recession. This is consistent with the view that throughout the Great Moderation, linear models provided a good approximation to characterize business cycle dynamics.[15] However, our results highlight that even if a linear model is a good approximation for most periods in our sample, it can fail by a large margin in times of financial distress.

An alternative interpretation of these results is that a linear model estimates the "wrong" shocks, particularly in periods of high risk. Given that the propagation mechanisms in the model are constant, it needs much larger shocks than a model with time-varying propagation mechanisms in those periods. Either way,

[14] These shocks, including the news component of the risk shock, are shown in Figure A.4 in appendix A.2.

[15] An exception is perhaps inflation, where the nonlinear solution generates also more volatility during tranquil periods. One explanation for this is that the linear model misses relevant nonlinearities in the phillips curve, as documented by Lindé and Trabandt (2018).

the inference and predictions of the model will be misleading if these nonlinear dynamics are ignored.

To be sure that the amplification effects described above are mainly due to financial frictions, panel (b) in Figure 1.3 repeats the previous exercise in a model version where financial frictions are shut down. This exercise uncovers two interesting facts. First, note that in this case the amplification in GDP, consumption, investment and inflation is minimal, even during recessions, which reassures that the amplification effects of panel (a) are due to state-dependent financial frictions and not other nonlinearities in the model. And second, that financial shocks and frictions explain a large share of real variables, especially during recessions, which is one of CMR's main findings. Note that the drop in GDP, investment and inflation is much smaller than in panel (a) also for the linear model, which reflects the important role played by the risk shock in explaining these variables through the lens of the model.[16]

An alternative way to look at the asymmetric propagation mechanisms of financial frictions is to look at impulse responses conditional on the state of the economy before a shock hits. In light of the evidence presented above, we would expect an amplification of shocks in periods of financial distress. In order to address this question, we compute generalized impulse responses and look at the responses to a risk shock in periods where spreads are relatively high or low before the shock hits.

Figure 1.4 shows the results.[17] The figure shows that the average on-impact response of the spread is more than twice as large in the high spread states as compared to the low spread states, and the on-impact amplification of net worth is of a comparable magnitude. This explains the amplified response of investment and output in these states. The thin grey lines show all the IRFs used to compute the average responses. They illustrate the asymmetric cyclical behavior of the model: there are a few (infrequent) cases where a single shock can gen-

[16]The relative standard deviations (third-order/linar simulations) in panel (a) for GDP, consumption, investment, inflation, the FFR, and the spread are 1.5778, 1.2981, 1.4397, 1.5305, 0.87178, and 2.0483, respectively. Because the model features no financial frictions in panel (b), only the non-financial shocks are fed to the model. The relative standard deviations in this case are 1.0438, 0.99567, 1.0078, 1.0408, and 0.91051.

[17]IRFs are computed by comparing two simulated paths for the endogenous variables which only differ in that one of them has a one standard deviation risk shock in period t (the first period of the IRF), while the other does not. We take the average response over the lowest 25 percentile and highest 75 percentile of the realizations of the simulated spread in $t-1$ to define the low and high spread states, respectively.

erate a massive jump in the spread and a collapse of investment and output of the order of twice the average response over all the simulations, which is consistent with the amplification that the model generates during the Great Recession documented in Figure 1.3. These results are in line with the findings of Adrian et al. (2019), who document that the skewness of the distribution of GDP growth depends on financial conditions. In particular, the lower quantiles of the distribution vary as a function of current financial conditions, while the upper quantiles are relatively stable over time.

All in all, our results suggest an alternative interpretation for the conclusion of Christiano et al. (2018) that financial frictions in a pre-crisis NK model have small quantitative effects. Namely, that the effects of financial frictions are state-dependent. For example, the paper by Brzoza-Brzezina and Kolasa (2013) discussed there only allows for constant propagation mechanisms of financial frictions and argues that financial shocks explain only a small share of the real variables' volatility. We document not only that financial shocks play an important role for real variables (as already shown by CMR), but that time-varying effects of financial frictions significantly increases the volatility in both financial and real variables. Against this background, in the next section we propose a regime-switching model that incorporates these time-varying effects and allows for efficient estimation.

1.4 A Regime-Switching DSGE Model

In the previous section we have shown that financial frictions in the NK-FF model generate important state-dependent propagation effects on the macroeconomy, in line with recent empirical studies. However, taking the nonlinear DSGE model to the data is not straightforward. This typically requires the use of computationally intensive nonlinear filters, such as the particle filter. A good example is the work by Gust et al. (2017), who estimate a Smets-Wouters-type model that is subject to the effective lower bound on interest rates using projection methods to solve the model and a particle filter to evaluate the likelihood. Despite their impressive parallel implementation of the particle filter, each evaluation of the likelihood takes about 8 seconds in a supercomputer with 300 cores, and 4.2 minutes in a standard 2-core computer. This can be problematic when using Markov Chain Monte Carlo methods to estimate the model, as is standard in the literature, since the likelihood has to be computed many times. The model that we consider here is significantly larger (it has more state variables) and the models used by many central banks are larger still. Therefore, we pursue an alternative approach that allows for efficient estimation with many state variables.

We build on the work by Lindé et al. (2016), who augment the Smets-Wouters model with the BGG financial friction and a regime-switching (RS) framework with two states: one where financial frictions are mild (low spread-leverage sensitivity) and one where they are severe (high spread-leverage sensitivity). They show that the RS model improves model fit, especially during the Great Recession. In that framework, however, the switching probabilities are constant and the transition between states is exogenous, in the sense that there is no mechanism is the structural model that translates information from the state of the economy to the probabilities of switching.

By contrast, here we work with time-varying switching probabilities and rely on the large explanatory power of the risk shock for the business cycle –documented by CMR and highlighted by our findings from section 1.3– to model state-dependent financial frictions as a function of risk. Coming back to Figure 1.1, we model periods of low spread-leverage sensitivity as periods of low risk and high sensitivity as high risk. Crucially, we model the probability of switching from one state to the other as a function of the spread, which allows us to link the nonlinear effects of financial frictions in the model to a measure of financial conditions in the data.

To illustrate how the RS framework can be used to estimate a NK-FF model with the state-dependent effects of financial frictions that we document in section 1.3, we use the third-order solution of the model discussed there as the data generating process (DGP). Knowing the DGP allows us to diagnose along what dimensions and through which channels the RS model improves upon the linear benchmark. We then estimate three types of models on these data: a RS model where the switching process is a function of financial conditions, a RS model where the switching follows an exogenous process, and a linear model. We show that both RS models greatly outperform the linear model in terms of fit, and most importantly, that the endogenous RS model outperforms the exogenous RS model. This is important because it shows that model fit improves as a result of the improved probabilistic assessment about when financial frictions matter most.

1.4.1 The Regime-Switching Framework

The model structure is as described in section 1.2. However, instead of solving the model by linearizing around the non-stochastic steady state, now we consider two steady states and assume that the agents know that with a certain probability the economy finds itself in one state or the other. Specifically, the problem can be formulated as solving for optimality conditions of the form

$$E_t \sum_{r_{t+1}=1}^{h} p_{r_t,r_{t+1}} f(x_{t+1}(r_{t+1}), x_t(r_t), x_{t-1}, \theta_{r_t}, \theta_{r_{t+1}}, \varepsilon_t) = 0 \tag{1.26}$$

where r_t stands for the regime in place in period t, $p_{r_t,r_{t+1}}$ is the probability of switching regimes from t to $t+1$, $x_t(r_t)$ is a vector of endogenous variables, θ_{r_t} is a vector of parameters and ε_t is a vector of exogenous variables. In our application, the number of regimes h is equal to two. We solve the model using perturbation methods as described in Maih (2015) and take a linear approximation around the non-stochastic steady state in each regime, $\bar{x} = \{\bar{x}_{\sigma_l},\ \bar{x}_{\sigma_h}\}$, where σ_l and σ_h stand for the level of risk in the low and high risk states, respectively. This gives us two distinct policy functions that map the exogenous to the endogenous variables of the form $x_t(r_t) = \Gamma_{r_t}(\varepsilon_t, \theta_{r_t})$.

1.4.1.1 Transition Probabilities

We consider two alternative frameworks: in the terminology of Chang et al. (2018), one exogenous switching model and one endogenous switching model. The exogenous switching model follows the tradition of Markov switching models, where the switching is governed by a Markov chain that is independent of the model dynamics –in that sense, it is exogenous to the model. Yet in many applications there are good reasons to think that the model dynamics or the state of the economy plays an important role in characterizing the switching process. Think of the interest rate dynamics in a model where the states are "constrained" or "unconstrained" by the effective lower bound, or –as in our application– of financial conditions when the states are financial tranquility or distress. The endogenous switching model follows the formulation of Chang et al. (2018), where a threshold-type switching process uses information from the sate of the economy to determine the switching probabilities.

The transition probabilities in the exogenous case are constant, and can be written as[18]

$$P^{l,h} = \frac{1}{1+\exp(\alpha_{x,1})}; \qquad P^{h,l} = \frac{1}{1+\exp(\alpha_{x,2})}, \tag{1.27}$$

where $P^{l,h}$ is the probability of switching from the low risk state to the high risk state, $P^{h,l}$ is the probability of switching from the high risk state to the low risk state, and $\alpha_{x,1}$ and $\alpha_{x,2}$ are parameters.

By contrast, we postulate the following time-varying endogenous switching probabilities

$$P_t^{l,h} = \frac{1}{\exp(\alpha_{n,1}) + \exp\left(-\bar{\gamma}_1 \frac{s_t - \bar{s}_1}{\sigma_s}\right)}; \quad P_t^{h,l} = \frac{1}{\exp(\alpha_{n,2}) + \exp\left(\bar{\gamma}_2 \frac{s_t - \bar{s}_2}{\sigma_s}\right)}. \tag{1.28}$$

Note that this formulation allows for an exogenous component, captured by the parameters $\alpha_{n,1}$ and $\alpha_{n,2}$,[19] and an endogenous component where s_t is the spread at time t, σ_s is its standard deviation, $\bar{s}_1$ and $\bar{s}_1$ are threshold values, and $\bar{\gamma}_1$ and $\bar{\gamma}_2$ are parameters. This formulation implies that when the spread is relatively high, $P_t^{l,h}$ is relatively high and $P_t^{h,l}$ is relatively low, and vice versa when the spread is low. Note that when $\bar{\gamma}_1 = \bar{\gamma}_2 = 0$, $\alpha_{n,1} = \alpha_{x,1}$ and $\alpha_{n,2} = \alpha_{x,2}$, the endogenous switching model collapses into the exogenous switching model. In other words, we allow for, but do not restrict the switching process to be driven by financial conditions.

1.4.2 Model Estimation and Fit

In order to illustrate how the state-dependent estimation works and the accuracy gains of the RS models, we proceed as follows. We generate a sample of 5,000 observations from the third-order NK-FF model and fit the RS models and a linear model to these data.[20] Since our interest is on modeling state-dependent

[18] They could also just be written as $P^{l,h} = \alpha_{x,1}$ and $P^{h,l} = \alpha_{x,2}$, but the formulation above simplifies the comparison between the exogenous and endogenous frameworks.

[19] We restrict these parameters to be non-negative to ensure that the probabilities are between zero and one. The endogenous component (the expression inside the second $\exp(\cdot)$) in each probability function is unrestricted

[20] Adding more observations leaves the correlation structure of the variables and other moments essentially unchanged, so that 5,000 observation provides a good approximation to the DGP. Figure A.5 in appendix A.2 shows the simulated data used for this estimation exercise.

financial frictions, we keep most of the deep parameters fixed at the values of the DGP and estimate a small subset of parameters. We estimate the level of risk in each regime, the parameters in the probability functions and the discount factor in each regime.[21] The idea behind this is to identify a low risk regime where financial frictions play a minor role, and a high risk regime where they generate large amplification effects in the real economy, keeping most deep parameters ruling other economic relations fixed. We estimate the RS models using the adaptation of the Kalman filter developed by Chang et al. (2018) (endogenous-switching Kalman filter) and the linear model with the standard Kalman filter.[22] We use full information Bayesian methods for both types of models.

Table 1.3 shows a comparison of the time required to evaluated the likelihood of the different model solutions that we consider, and we include the times reported by Gust et al. (2017) as a reference for the particle filter. Each evaluation of the likelihood with 5,000 observations takes 3.8 seconds for the RS models and about 1.1 second for the linear model using a standard desktop computer. When we consider a sample of 104 observations (the sample size used in section 1.3) each evaluation takes about 0.5 seconds for the RS models and about 0.1 seconds of the linear model. While the RS models are significantly slower to evaluate than the linear model, they are orders of magnitude faster than the particle filter. At these speeds it is still feasible to estimate the RS models using a standard desktop computer.

Table 1.4 shows the priors and the estimation results. The priors for the discount factor are standard while for the level of risk we choose values that are reasonably close to 0.26, which corresponds to the DGP. The priors for $\alpha_{x,1}$ and $\alpha_{x,2}$ are chosen such that the steady state probabilities $P^{l,h}$ and $P^{h,l}$ of the exogenous model are between 0.01–0.25 and 0.1–0.5, respectively, with a 95% probability. We use the same priors for $\alpha_{n,1}$ and $\alpha_{n,2}$ in order to facilitate the comparison between the two models, but as we mentioned before we restrict these parameters to be nonnegative. There is no natural value for the priors of $\bar{\gamma}_1$ and $\bar{\gamma}_2$ so that we

[21] We abstract from the *news* shocks described in section 1.2 in this exercise. Instead of the *news* shocks we calibrate the innovation to the risk process to be consistent with the size of the anticipated and unanticipated components of the risk shock. We also estimate the discount factor in each regime to allow for distinct nominal interest rates in each regime, which is important to avoid counterfactual steady states for the real variables in the low and high risk states.

[22] We use the implementation of the RISE toolbox for Matlab of these filters. See `https://github.com/jmaih/RISE_toolbox`.

choose a loose prior centered around one. Finally, we calibrate $\bar{s}_1$ and $\bar{s}_2$ to the lower 25 and higher 75 percentiles of the observed spread.

Coming to the estimation results, the RS models identify a low risk regime with σ_l around 0.238–0.239 and σ_h around 0.267, while the linear model estimates a level of risk of $\sigma = 0.2623$, which is close to the DGP. These values imply different steady state spread-leverage sensitivities, computed as $\frac{d\log s}{d\log L}$ and summarized in the lower part of the table.[23] The sensitivity for the RS models is close to 0.03 in the low risk regime and 0.064–0.065 in the high risk regime, while the value for the linear model falls in between, at 0.059. A sensitivity of 0.03, for instance, means that if equilibrium leverage increases by one percent, then the equilibrium spread will increase by three percent to be consistent with that level of leverage.

To illustrate how this state-dependent sensitivity affects the model dynamics, Figure 1.5 shows the impulse responses to a one standard deviation risk shock in the low and high risk states. We also include the average response of the third-order model (the DGP) from Figure 1.4 (black solid lines) as a reference. The generalized impulse responses for the RS models are computed under the same logic as for the third-order model. The "low risk" ("high risk") response is computed as the average response when the model is predicted to be in the low risk (high risk) regime before the shock hits. Note that the GIRFs are not fully "smooth" because we allow for regime switches throughout the simulations.

The key asymmetry becomes apparent when looking at the responses of leverage and the spread. The response of net worth is about 65% larger in the high risk state, which translates into an amplification of the order of 2.5 in the spread. The sharp increase in financing costs in the high risk state translates into large amplification effects in output, mostly through a sharp decline in investment. The additional drop in output and investment in the high risk regime 5 quarters after the shock amounts to 20% and 25%, respectively. The responses of the third-order model lie between the low risk and high risk average responses from the RS model, given that the average propagation strength of financial frictions in this model lies somewhere between the propagation of the RS model in each regime.

How does this flexibility of the RS models translate into improved forecasting performance with respect to the linear model? In order to quantify these gains, the last row of Table 1.4 compares the marginal data densities (MDDs) of the three models. The exogenous RS model has a MDD 1,161 log points higher than the

[23] The derivation for this expression in the steady state can be found in appendix A.3.

linear model, while the endogenous RS model outperforms the exogenous model by 328 log points.[24] These gains in MDD result from improved one-step-ahead forecasts of the RS models when evaluating the likelihood. Given that the effects of financial frictions get amplified when financial conditions deteriorate, the RS models –and the endogenous RS model in particular– produce better forecasts in those periods by assigning a high probability to the high risk regime, which features a stronger financial accelerator effect.

Another way to illustrate this is by looking at the smoothed regime probabilities and shocks. Figure 1.6 shows the smoothed regime probabilities for the RS models together with the spread (upper panel), as well as the smoothed risk shocks for the RS and linear models (lower panel). First, note that both RS models track the spread quite closely, but as expected the endogenous RS model is more responsive. Note also that the estimated shocks of the exogenous model are slightly smaller than those of the endogenous model in periods of low spreads, given that the estimate for σ_l is slightly larger in this case. Second, the linear model systematically overestimates the risk shocks in periods of high spreads –for example, between periods 50 and 100 or after period 350. This is because the propagation mechanism of financial frictions is constant in this case, which translates into worst forecasts and fit.

As for the comparison between the RS models, the time-varying switching probabilities is what gives the endogenous switching model an advantage. Figure 1.7 shows the switching probabilities for both models as a function of the spread. The black dashed line shows the (constant) probabilities for the exogenous switching model, while the blue solid line shows how the endogenous probabilities fluctuate around the exogenous probabilities depending on the values of the spread. For instance, the exogenous RS model has a constant probability $P^{l,h}$ of moving from the low risk to the high risk state of 0.06. In the endogenous RS model, by contrast, that probability is close zero when the spread is close to zero, and it is about twice as large as the exogenous probability for high values of the spread. Given that on average high risk states correspond with high spreads and vice versa, the spread informs the switching probabilities in the endogenous model in a way that results in improved fit. All told, the endogenous RS model

[24] These differences are larger than typically found in empirical studies (as, for instance, in Hubrich and Tetlow, 2015; Lindé et al., 2016) because our estimations are carried out in samples that are much larger than the typical macroeconomic time series.

provides an efficient alternative to model state-dependent financial frictions that endogenously evolve with the state of the economy.

1.5 Conclusion

Over the past decade, much research in macroeconomics has focused on incorporating financial factors into macro models. Much of this agenda grew as a response to the questions and challenges to macro models brought about by the 2008 financial crisis and the Great Recession in the US (Lindé et al., 2016). Christiano et al. (2018) discuss several research agendas on how to fine-tune pre-crisis New Keynesian models to improve their accuracy. They highlight that taking the nonlinear dynamics of these models into account is important to characterize business cycle dynamics.

In this chapter we contribute to this literature in two ways. First, we show that a pre-crisis New Keynesian model like the one used by many central banks generates large amplification of shocks in macro and financial variables during episodes of financial distress, once nonlinearities are taken into account. These amplification effects are almost absent during the Great Moderation and become quantitatively large during recessions, especially during the Great Recession. Importantly, we document that amplification is due to a state-dependent propagation mechanism of the financial frictions and not due to other nonlinearities in the model. And second, we propose a regime-switching framework that incorporates these state-dependent effects, allowing for efficient estimation with many state variables and improving model accuracy in terms of fit.

The papers by Lindé et al. (2016) and Christiano et al. (2018) leave many interesting topics open for future research in this area. Our framework adds one alternative to this debate, and its tractability makes it an attractive alternative for applied researchers and policy institutions.

1.6 Tables

Table 1.1: Calibrated parameters

Parameter	Value	Description	Source/target
σ_L	1	Labor disutility	CMR
λ_f	1.2	Steady state wage markup	CMR
λ_w	1.05	Steady state price markup	CMR
α	0.4	Share of capital in production	CMR
δ	0.025	Depreciation rate of capital	CMR
τ^c	0.047	Tax rate consumption	CMR
τ^k	0.320	Tax rate capital	CMR
τ^l	0.241	Tax rate labor	CMR
μ	0.275	Monitoring cost	St.st. spread-lev.
γ	0.979	Survival rate of entrepreneurs	St.st. spread-lev.
W^e	0.134	Transfer from households to entrepr.	St.st. spread-lev.
σ	0.26	Steady state risk shock	CMR
β	0.9985	Discount factor	Data
π	1.006	Steady state inflation	Data
π^{target}	1.006	Central bank's inflation target	Data
μ_{z^*}	0.004	Steady state economy growth rate	Data
Υ	0.004	Steady state invest. specific growth rate	Data

Table 1.2: Estimated parameters

		Prior Distribution	Posterior			
	Description	Dist. mean[std.]	mode	5%	median	95%
ξ_w	Calvo wages	$\mathcal{B}$ 0.7500 [0.10]	0.8191	0.7785	0.8329	0.8886
b	Habit in consumption	$\mathcal{B}$ 0.5000 [0.10]	0.7770	0.7184	0.7859	0.8537
σ_a	Curvature capital util. cost	$\mathcal{G}$ 1 [1]	1.8811	0.5930	1.8339	3.5529
S	Curvature invest. adjust. cost	$\mathcal{N}$ 5 [3]	7.6377	5.0116	7.5521	10.6585
ξ_p	Calvo prices	$\mathcal{B}$ 0.5 [0.1]	0.8077	0.7757	0.8165	0.8581
α_π	Taylor rule: inflation	$\mathcal{N}$ 1.5 [0.25]	1.7439	1.6099	1.8367	2.0810
ρ_p	Taylor rule smoothing	$\mathcal{B}$ 0.75 [0.1]	0.8325	0.8120	0.8428	0.8731
ι	Indexing price inflation	$\mathcal{B}$ 0.5 [0.15]	0.8706	0.7984	0.8799	0.9580
ι_w	Indexing wage inflation	$\mathcal{B}$ 0.5 [0.15]	0.4713	0.2401	0.4770	0.7106
ι_μ	Indexing productivity	$\mathcal{B}$ 0.5 [0.15]	0.9133	0.8898	0.9354	0.9761
$\alpha_{\Delta y}$	Taylor rule GDP	$\mathcal{N}$ 0.25 [0.1]	0.3625	0.1485	0.3155	0.4743
ρ_{λ_f}	AR price markup	$\mathcal{B}$ 0.5 [0.2]	0.9738	0.9038	0.9633	0.9971
ρ_ε	AR transitory technology	$\mathcal{B}$ 0.5 [0.2]	0.9455	0.8318	0.9182	0.9866
ρ_{ζ_I}	AR investment efficiency	$\mathcal{B}$ 0.5 [0.2]	0.5104	0.3346	0.5080	0.6651
ρ_{ζ_C}	AR intertemporal preference	$\mathcal{B}$ 0.5 [0.2]	0.8449	0.8340	0.8992	0.9611
ρ_μ	AR technology growth rate	$\mathcal{B}$ 0.5 [0.2]	0.1232	0.0190	0.0897	0.1691
ρ_σ	AR risk	$\mathcal{B}$ 0.5 [0.2]	0.9643	0.9479	0.9696	0.9883
$\rho_{\mu\Upsilon}$	AR price of investment	$\mathcal{B}$ 0.5 [0.2]	0.9255	0.8863	0.9246	0.9619
ρ_g	AR fiscal	$\mathcal{B}$ 0.5 [0.2]	0.9444	0.9067	0.9406	0.9740
ρ_γ	AR equity	$\mathcal{B}$ 0.5 [0.2]	0.3394	0.2344	0.3544	0.4749
σ_ε	Std. transitory technology	$\mathcal{IG}2$ 0.0020 [0.0033]	0.0052	0.0045	0.0051	0.0057
σ_{λ_f}	Std. price markup	$\mathcal{IG}2$ 0.0020 [0.0033]	0.0105	0.0073	0.0107	0.0146
σ_{ζ_I}	Std. investment efficiency	$\mathcal{IG}2$ 0.0020 [0.0033]	0.0196	0.0163	0.0195	0.0228
σ_{ζ_C}	Std. intertemporal preference	$\mathcal{IG}2$ 0.0020 [0.0033]	0.0239	0.0213	0.0299	0.0395
σ_R	Std. monetary policy	$\mathcal{IG}2$ 0.5830 [0.8250]	0.1158	0.1011	0.1155	0.1313
σ_μ	Std. technology growth rate	$\mathcal{IG}2$ 0.0020 [0.0033]	0.0095	0.0080	0.0091	0.0103
σ_{σ_0}	Std. unanticipated risk	$\mathcal{IG}2$ 0.0020 [0.0033]	0.0103	0.0051	0.0103	0.0152
$\sigma_{\mu\Upsilon}$	Std. price of investment	$\mathcal{IG}2$ 0.0020 [0.0033]	0.0043	0.0041	0.0047	0.0052
σ_N	Std. net worth ME	$\mathcal{W}$ 0.0100 [5.00]	0.0672	0.0631	0.0713	0.0799
σ_γ	Std. equity	$\mathcal{IG}2$ 0.0020 [0.0033]	0.0068	0.0061	0.0069	0.0077
σ_g	Std. fiscal	$\mathcal{IG}2$ 0.0020 [0.0033]	0.0228	0.0194	0.0219	0.0245
σ_{σ_n}	Std. anticipated risk	$\mathcal{IG}2$ 0.0008 [0.0012]	0.0066	0.0047	0.0071	0.0100
$\rho_{\sigma,n}$	Corr. between signals	$\mathcal{N}$ 0 [0.5]	0.9976	0.9019	0.9688	1.0000

Notes: Estimation results for the linear NK-FF model. Prior distributions $\mathcal{B}$, $\mathcal{G}$, $\mathcal{N}$, $\mathcal{IG}2$, and $\mathcal{W}$ denote beta, gamma, normal, inverse gamma type 2, and weibull distributions, respectively. Posterior statistics based on 4 chains of 250,000 MCMC replications, where the first 50.000 are discarded as burnin.

Table 1.3: Likelihood evaluation time

	linear	RS	Gust et al. (2017)
US data	$\simeq$ 0.1 seconds	$\simeq$ 0.5 seconds	8 seconds to 4 minutes
5000 obs.	$\simeq$ 1 seconds	$\simeq$ 4 seconds	—
Filter	Kalman	Endo-switch Kalman	Particle

Notes: The computing times for the linear and RS models correspond to a desktop computer with a processor Intel Core i7-6700 with 3.40 GHz and 16GB RAM. The variation in the times reported by Gust et al. (2017) corresponds to the difference between their parallel implementation of the filter in a 300-core supercomputer (8 seconds) and the implementation in a standard dual-core desktop (4 minutes).

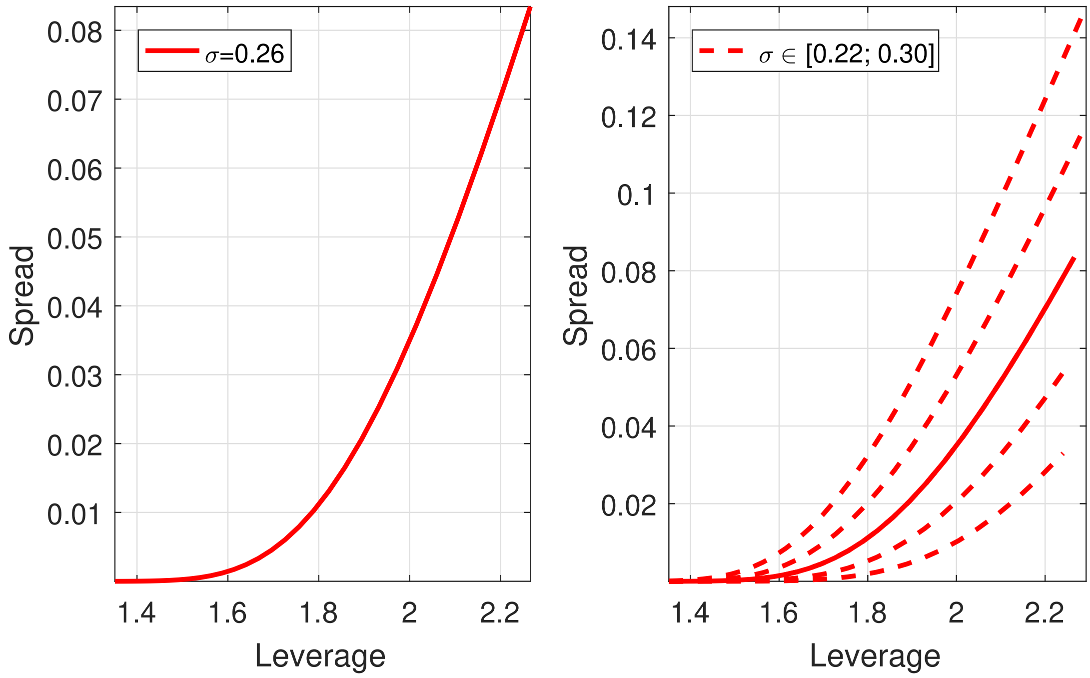
Table 1.4: Estimated parameters: RS and linear models

		Prior Distribution	Posterior Modes		
	Description	Dist. mean[std.]	Linear	Exo. RS	Endo. RS
β_l	Discount factor (l)	$\mathcal{B}$ 0.9950 [0.0010]	0.9979	0.9952	0.9952
β_h	Discount factor (h)	$\mathcal{B}$ 0.9980 [0.0010]	—	0.9993	0.9992
σ_l	Risk level (l)	$\mathcal{B}$ 0.2450 [0.0050]	0.2623	0.2391	0.2378
σ_h	Risk level (h)	$\mathcal{B}$ 0.2850 [0.0050]	—	0.2678	0.2667
$\alpha_{x,1}$	Probs. exo	$\mathcal{N}$ 2.8469 [0.8920]	—	2.7717	—
$\alpha_{x,2}$	Probs. exo	$\mathcal{N}$ 1.0986 [0.5605]	—	4.2952	—
$\alpha_{n,1}$	Probs. endo	$\mathcal{N}$ 2.8469 [0.8920]	—	—	2.2605
$\alpha_{n,2}$	Probs. endo	$\mathcal{N}$ 1.0986 [0.5605]	—	—	1.7584
$\bar{\gamma}_1$	Probs. endo	$\mathcal{G}$ 1 [0.50]	—	—	5.1682
$\bar{\gamma}_2$	Probs. endo	$\mathcal{G}$ 1 [0.50]	—	—	2.4047
	Implied steady states and model fit		Linear	Exo. RS	Endo. RS
	St. st. probabilities [$P^{l,h}$; $P^{h,l}$]		—	[0.0589; 0.0135]	[0.0183; 0.1390]
	St. st. leverage [l; h]		1.9	[1.87; 1.9]	[1.87; 1.9]
	St. st. sensitivity spread-lev. [l; h]		0.0590	[0.0303; 0.0649]	[0.0292; 0.0637]
	ΔLog-marginal data density		—	Exo-linear: 1,161	Endo-exo: 328

Notes: Prior distributions $\mathcal{B}$, $\mathcal{N}$, and $\mathcal{G}$, denote beta, normal, and gamma distributions, respectively. The priors of the parameters $\alpha_{n,1}$ and $\alpha_{n,1}$ are truncated at zero. The subscripts $\{l, h\}$ stand for "low risk" and "high risk", respectively. In the case of the linear model, β_l and σ_l stand for the parameter values in the unique regime that we allow for. The second block of the table shows the implied steady state values for the probabilities, leverage, and the sensitivity spread-leverage, and model fit. For the RS models, the squared brackets indicate the steady state values in each regime. In the last row, Exo-linear and Endo-exo stand for the difference between the MDD of the exogenous model with the linear model, and the endogenous model with the exogenous model, respectively.

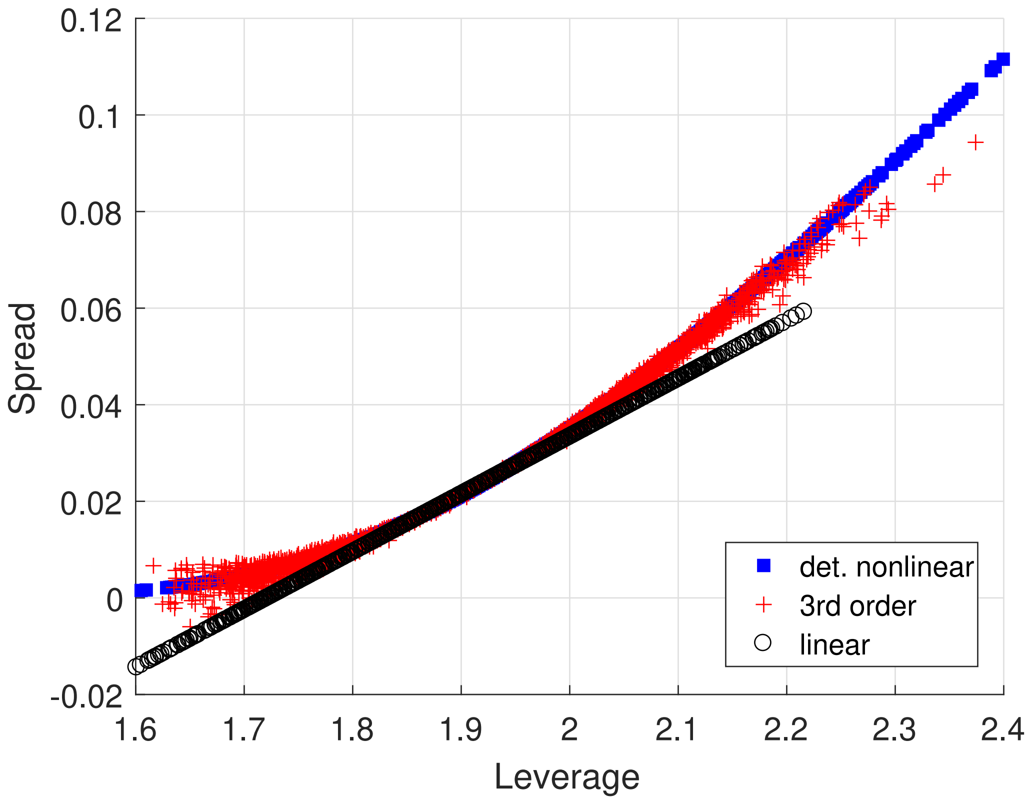
1.7 Figures

Figure 1.1: Equilibrium values: spread, leverage, and risk



Notes: The left panel shows (annualized) equilibrium values for the spread and leverage given the baseline calibration of the model (see Table 1.1) for an array of values of $R_t^k \in [0.0115, 0.0326]$. The right panel repeats the exercise for different values of σ_t. The solid line in this panel repeats the line of the left panel; the dashed lines (from lowest to highest) are computed by fixing the value of σ_t at 0.22, 0.24, 0.26 (baseline calibration, solid line), 0.28, and 0.30, respectively. In this last case, $R_t^k \in [0.0115, 0.0489]$.

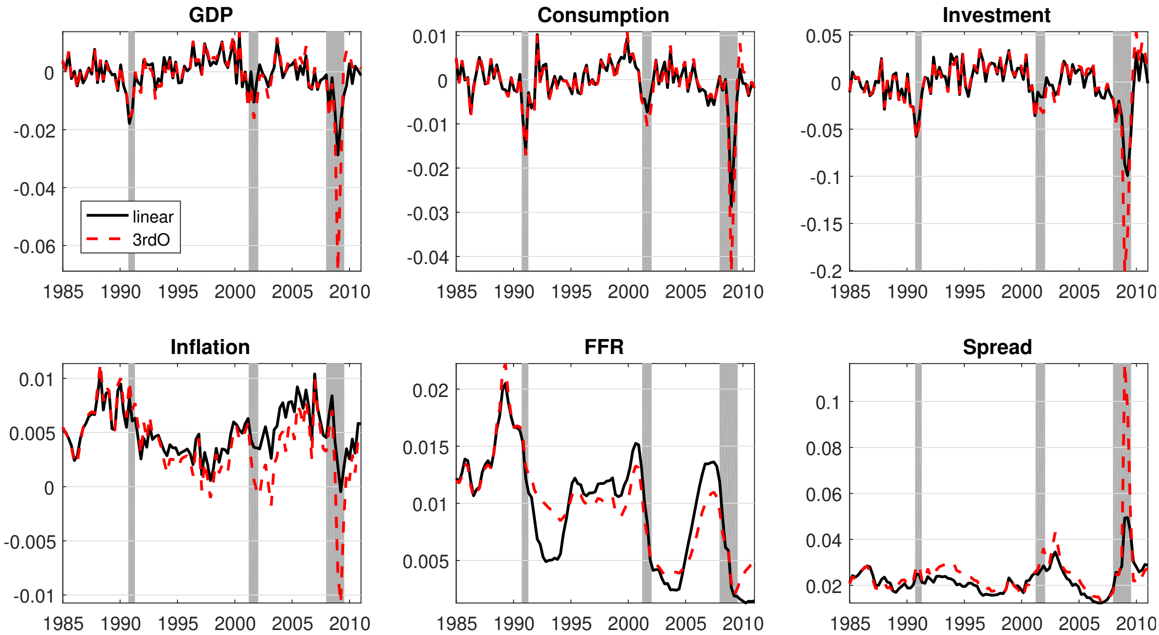
Figure 1.2: Leverage-spread schedule



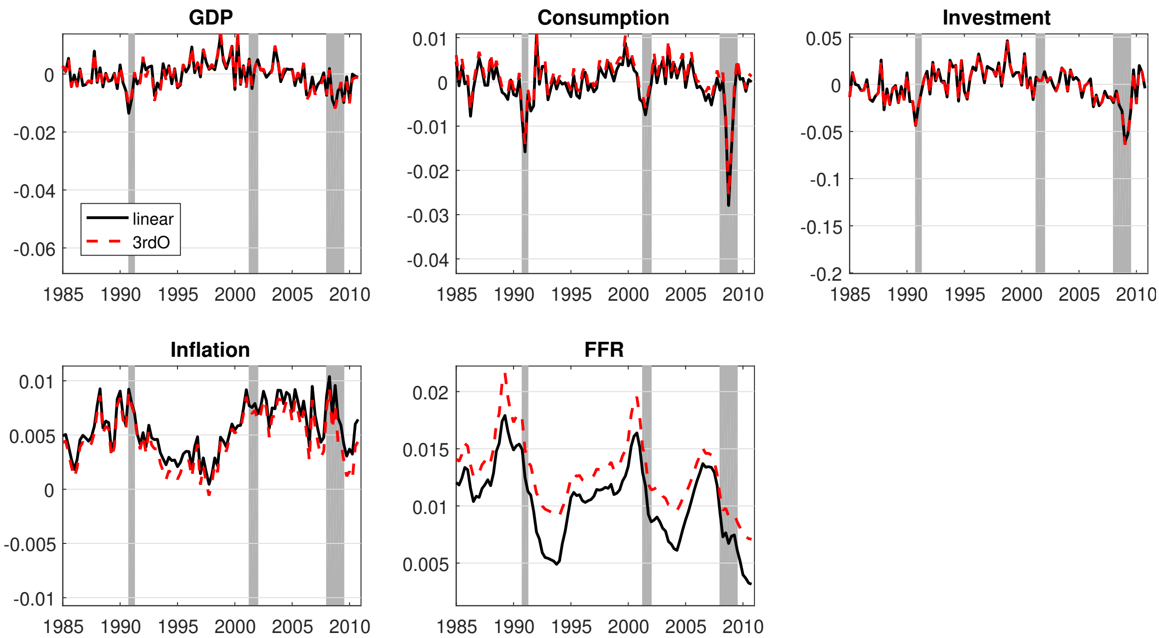
Notes: Simulations conducted by drawing random shocks for 20,000 periods, given the shocks' estimated standard deviation, and then feeding them to each solution of the model. For the deterministic nonlinear solution, we conduct the simulations period-by-period where agents are surprised each period. That is, each period t an unexpected shock hits, given the predetermined state of the economy from period $(t-1)$, and agents expect no further shocks thereafter. In period $(t+1)$ agents are surprised again by an unexpected shock, given the state of the economy in t and expect no shocks thereafter, and so on. For the third-order solution we use pruning as implemented in Dynare 4.5.4.

Figure 1.3: Amplification effects of financial frictions

(a) NK-FF model

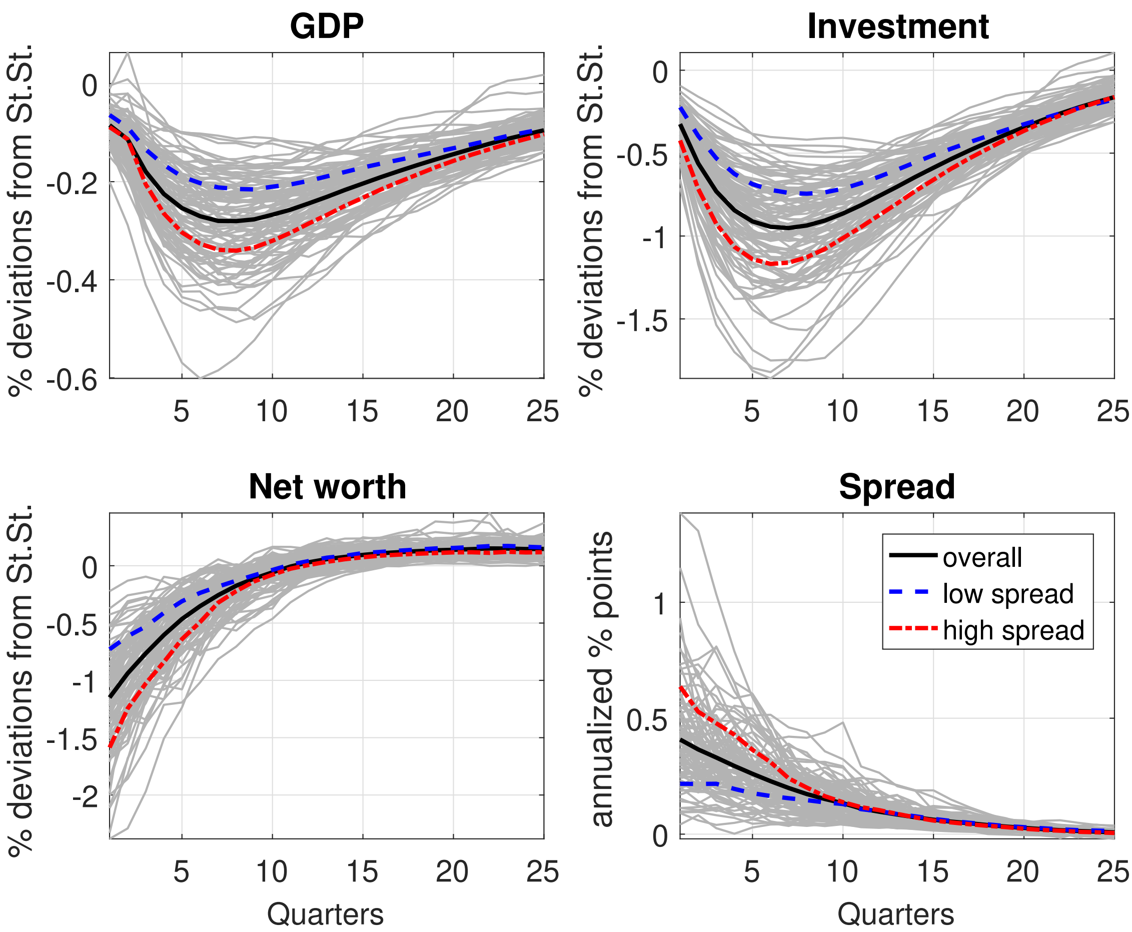


(b) NK-noFF model



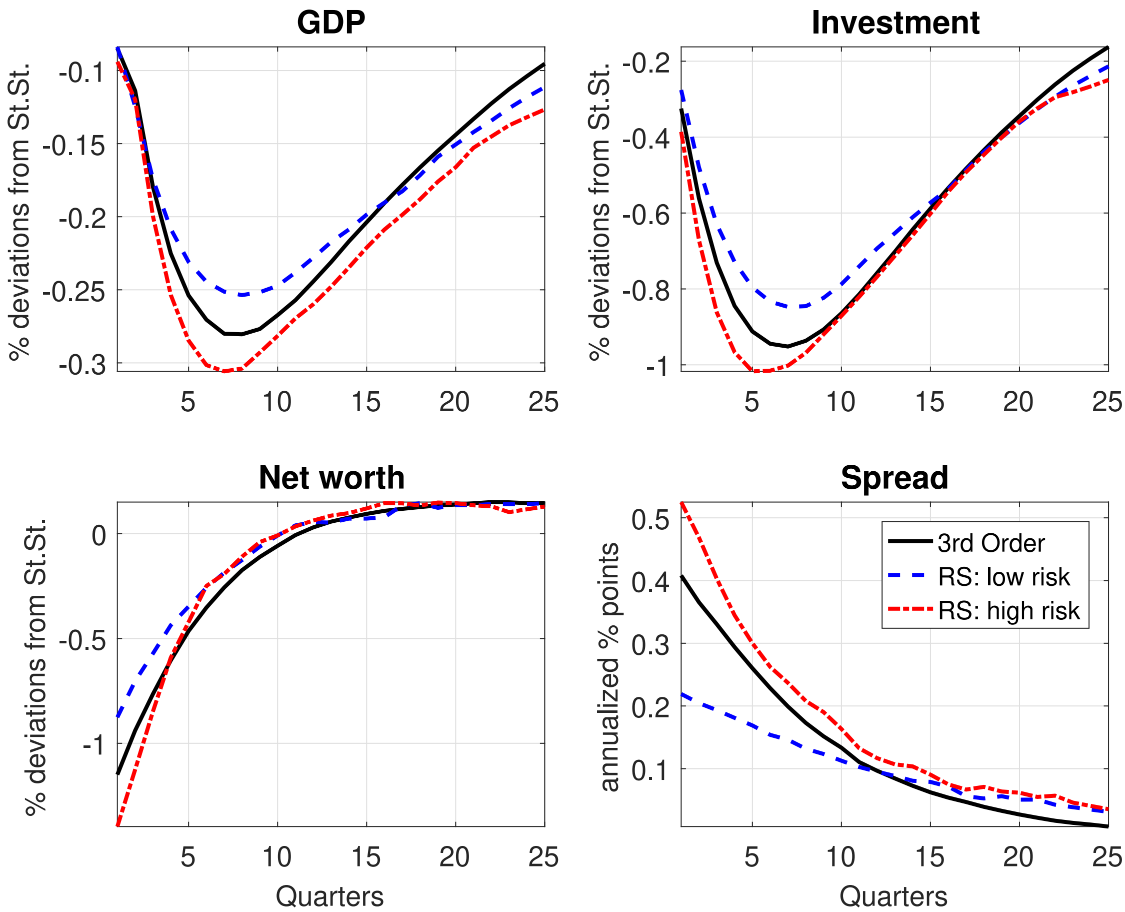
Notes: Simulated paths for endogenous variables based on the smoothed shocks from the estimation of the linear model. The black (solid) line depicts the simulated variables using the linear solution of the model and the red (dashed) line using the nonlinear (third-order approximation) solution of the model. In panel (a), we feed all estimated shocks to the model. Since all variables depicted are measured without error, the solid line corresponds to the data used for the estimation. For the NK-noFF model in panel (b), only the non-financial shocks are fed to the model. Grey areas show NBER recessions.

Figure 1.4: State-dependent GIRFs to a 1-std. risk shock



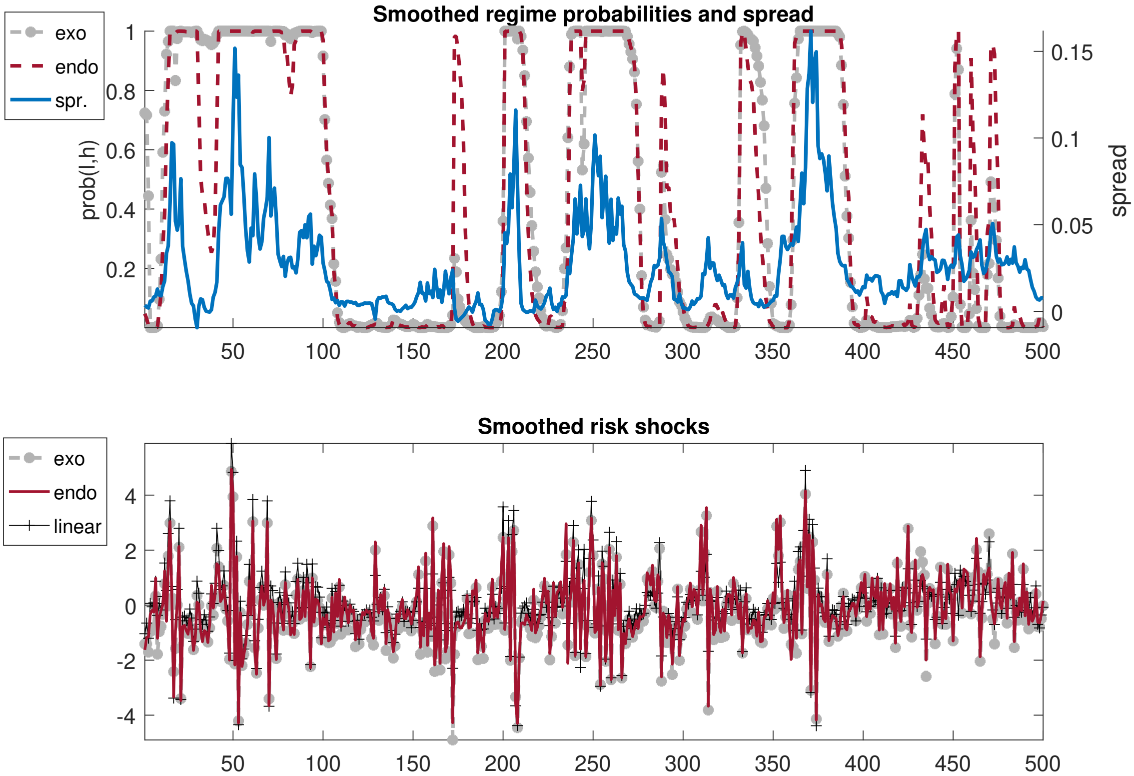
Notes: The spread is shown in annualized percentage points, while all other variables in percentage deviations from their respective steady state. GIRFs are computed by simulating the model for 600 periods, once with all shocks evaluated at their estimated standard deviations and a second time where an additional 1-std. risk shock is added in period 501. Each IRF (thin grey lines) is computed as the difference between these two paths, dropping the first 500 periods of the simulation. The steady state concept in this exercise is that of the ergodic mean: we compute it by taking the average of each variable over the first simulation path for observations 501 to 600. To compute the GIRFs we repeat this process 100 times and take the average over all the IRFs (black solid line). The GIRFs for high and low spread states are computed by taking the average over the IRFs corresponding to the lowest 25 and highest 75 percentiles of the realizations of the simulated spread in period 500 (one period before the shock hits), respectively.

Figure 1.5: GIRFs to a 1-std. risk shock: third-order and RS models



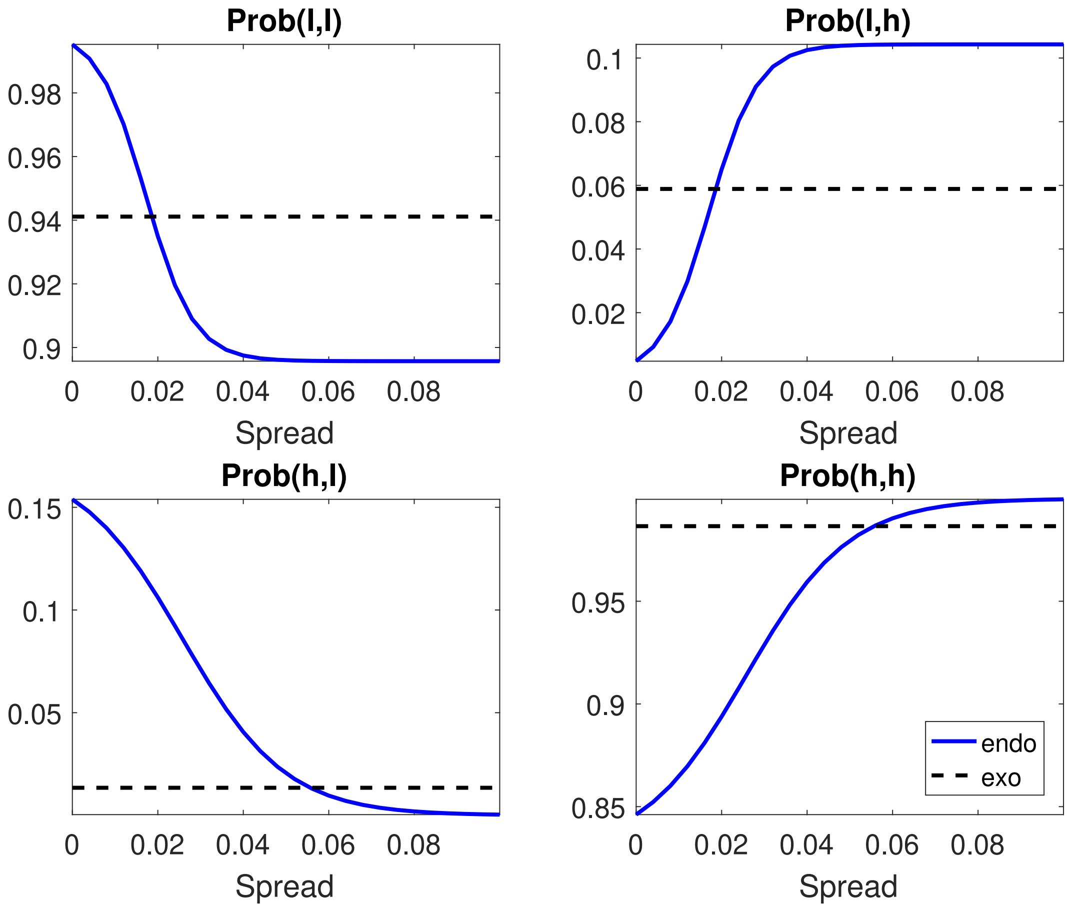
Notes: The spread is shown in annualized percentage points, while all other variables in percentage deviations from their respective steady state. The GIRFs in each regime are computed by simulating the model for 600 periods, once with all shocks evaluated at their estimated standard deviations and a second time where an additional 1-std. risk shock is added in period 501. We then take the difference between these two paths, dropping the first 500 periods of the simulation. We repeat this process 100 times and compute the GIRFs as the averages over the simulations. The blue (dashed) line shows the average response when the model is in the low risk state state before the shock hits, while the red (dotted-dashed) line shows the average response when the model is in the high risk regime before the shock hits. The steady state concept in this exercise is that of the ergodic mean: we compute it by taking the average of each variable over the first simulation path for observations 501 to 600.

Figure 1.6: Smoothed probabilities and shocks: RS and linear models



Notes: The upper panel shows the smoothed regime probabilities **Prob(r1,r2)** for the estimated endogenous and exogenous probability models, together with the spread used as observable. The lower panel shows the smoothed risk shocks from the RS and linear models. The models are estimated on 5,000 simulated observations from the nonlinear NK-FF model, but here we show a subset corresponding to the first 500 observations in order to facilitate the visualization of the results.

Figure 1.7: Estimated probabilities as function of the spread: exogenous and endogenous RS models



Notes: The black dashed lines show the estimated probabilities for the exogenous probability model. The blue solid lines show the probability functions for the endogenous probability model, evaluated at the posterior mode for an array of values of the spread. Notation **Prob(r1,r2)** refers to the probability of visiting regime r2 in $t+1$ conditional on being in regime r1 in t; **l** refers to the low risk regime and **h** to the high risk regime.

CHAPTER 2

Monetary Policy and Household Net Worth (with Mathias Klein)

2.1 Introduction

Since the beginning of the 2000s, private household net worth has fluctuated substantially in the US 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 contribute to this literature by showing 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

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

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 DSGE model with financial frictions on US data, in which household balance sheets influence how monetary policy shocks transmit to the economy. Specifically, the model illustrates that monetary policy has stronger effects when borrowing constraints bind and household net worth is low. Second, we test this result on US 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 generate artificial 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 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[2] 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 chapter, 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

[2] Throughout the chapter, we refer to the change in the real value of debt that results from changes in inflation as debt-deflation effect because this is the standard term used in the literature. However, note that our analysis focuses on a contractionary monetary policy shock that triggers a *drop* in inflation and hence a debt-*revaluation* effect.

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. By 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 as the corresponding GDP response in a high net worth state.

These empirical results are robust to alternative definitions of low and high 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. Additionally, we conduct an analysis based on more disaggregated data. For this purpose, we construct monetary policy shocks at the level of US geographical states by relying on the identification approach proposed by Nakamura and Steinsson (2014). The state level estimates confirm our findings at the aggregate level: the effects of monetary policy shocks are significantly amplified during periods of low household net worth.

Notably, our findings prove to be robust when we condition on three other prominent state variables. First, previous studies find that the state of the business cycle affects the impact of a monetary policy shock (Angrist et al., 2018; Tenreyro and Thwaites, 2016). However, we show that in periods of low household net worth, a contractionary monetary policy shock induces a significant fall in aggregate activity both in economic expansions and in recessions. Moreover, the cumulative effects are considerably larger when compared to the respective responses in high net worth states.

Second, in a related paper, Alpanda and Zubairy (2019) find that the level of household debt influences the effectiveness of monetary policy interventions. We show that the effects of a monetary policy shock are amplified in periods of low household net worth, both when household debt is high and low. By contrast, during high household net worth periods, a monetary tightening induces mostly insignificant effects irrespective of the level of household debt.

Third, our results are robust when we condition on financial stress in the economy. When household net worth is low, a contractionary monetary policy shock induces a significant decline in economic activity in tranquil times but also in periods of financial stress. By contrast, during a high household net worth episode, monetary policy only has a significant impact on the economy when financial stress is low. Overall, our findings suggest that the household net worth cycle is of first order importance for the effectiveness of monetary policy interventions whereas the state of the business cycle, the level of household debt, and financial stress only play a secondary role.

Contribution to the literature.– Our paper contributes to the growing literature on the role of household balance sheets for understanding the impact of macroeconomic shocks. Mian and Sufi (2012) show that those US 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. Several papers have documented important heterogeneity in households' response to monetary policy depending on their financial profiles (e.g., Cloyne et al., 2020; Di Maggio et al., 2017; Gelos et al., 2019; Wong, 2019, among others). 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 US data.

On the other hand, a growing number of theoretical papers highlights the role of borrowing constraints for the transmission of monetary policy. Prominent examples include Kaplan et al. (2018) and Auclert (2019), who show that monetary policy can have drastically different implications for different households across the net worth distribution. Our main finding, namely that low net worth households are more responsive to monetary policy, is consistent with the result of Kaplan et al. (2018) that low net worth households are very responsive to changes in interest rates via income and wealth general equilibrium effects.

Our paper also contributes to the literature looking at macro state variables to assess the effectiveness of monetary policy (Alpanda and Zubairy, 2019; Tenreyro and Thwaites, 2016) and highlights the leading role of household net worth over other macro aggregates. Finally, the paper provides guidance for empirical work on which data to focus on to characterize the time-varying tightness of borrowing constraints.

Outline.– The remainder of the paper is organized as follows. Section 2.2 gives an overview of the structure of the DSGE model and presents results of the model estimation. Moreover, it investigates the transmission mechanism of monetary policy depending on the tightness of the borrowing constraints and discusses the findings of our prediction analysis. In section 2.3, we conduct the empirical analysis and find strong support for the theoretical predictions. Finally, section 2.4 concludes.

2.2 Theoretical Analysis

We consider the model by GI, which is a standard New Keynesian model with financial frictions on the household side.[3] 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 affects the monetary policy transmission mechanism. 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 US. In this section, we also describe the model estimation and the predictive analysis to detect which endogenous model variable best predicts the tightness of the collateral constraint.

2.2.1 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

[3]In the following we discuss the model features that are central to our analysis, while additional model equations are provided in appendix B.1.

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

$$E_0 \sum_{t=0}^{\infty} \mathsf{z}_t \left(\beta^i\right)^t \left(\Gamma_c^i \log(c_t^i - \varepsilon_c c_{t-1}^i) + \Gamma_h^i \mathsf{j}_t \log(h_t^i - \varepsilon_h h_{t-1}^i) - \frac{1}{1+\eta}(n_t^i)^{1+\eta}\right) \tag{2.1}$$

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

$$c_t^I + q_t h_t^I + \frac{R_{t-1} b_{t-1}}{\pi_t} = \frac{w_t^I n_t^I}{x_{w,t}^I} + q_t h_{t-1}^I + b_t, \tag{2.2}$$

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 $\pi_t = P_t/P_{t-1}$ is the gross inflation rate. In addition, they face the following borrowing constraint

$$b_t \leq \gamma \frac{b_{t-1}}{\pi_t} + (1-\gamma) M q_t h_t^I, \tag{2.3}$$

where $\gamma > 0$ is the degree of debt inertia[4] 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 is given by

$$\log(\pi_t/\bar{\pi}) = \beta E_t \log(\pi_{t+1}/\bar{\pi}) - \varepsilon_\pi \log(x_{p,t}/\bar{x}_p) + u_{p,t}, \tag{2.4}$$

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 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

$$\log(\omega_t/\bar{\pi}) = \beta E_t \log(\omega_{t+1}/\bar{\pi}) - \varepsilon_w \log(x_{w,t}/\bar{x}_w) + u_{w,t}, \tag{2.5}$$

$$\log(\omega_t^I/\bar{\pi}) = \beta^I E_t \log(\omega_{t+1}^I/\bar{\pi}) - \varepsilon_w^I \log(x_{w,t}^I/\bar{x}_w^I) + u_{w,t}, \tag{2.6}$$

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

[4] 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.

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

$$R_t = \max\left[1, R_{t-1}^{r_R}\left(\frac{\pi_t}{\pi}\right)^{(1-r_R)r_\pi}\left(\frac{y_t}{y}\right)^{(1-r_R)r_Y}\bar{R}^{(1-r_R)}\mathsf{e}_t\right]. \tag{2.7}$$

$\bar{R}$ 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.

2.2.2 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.[5] 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, 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

[5]We provide the main equations and implementation details in appendix B.2.

explicitly in order to make the model consistent with US 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.

2.2.2.1 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 1960Q1-2018Q4.[6] A detailed description of the data and the transformation undertaken to make it consistent with model variables is provided in appendix B.3. 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 estimates differ from those obtained by GI.

2.2.2.2 Calibration and Priors and Posteriors

We calibrate some of the parameters as described in Table 2.1. This calibration follows GI –with the exception of steady state inflation, because average inflation is higher in our sample– 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]

Steady state annual inflation is 3% to match the sample average. The patient household's discount factor β is set to 0.995 implying an annual real interest rate of 2%. Housing weight in the utility function $\bar{j}$ is 0.04 implying a steady state ratio of housing wealth to annual income ratio of 1.5. The capital share in production α is 0.3 and capital depreciation δ is 0.025, implying a capital to output ratio of 8.3 and an investment to output ratio of 0.21. Labor disutility η is set to one, and

[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.

the price and wage markups $\bar{x}_p$ and $\bar{x}_w$ are 1.2. The weight of GDP in the Taylor rule r_Y and the maximum LTV ratio M are 0.1 and 0.9, respectively.

The estimated parameters are shown in Table 2.2. 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 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.

2.2.3 Collateral Constraints and Monetary Policy Transmission

How important are borrowing constraints for the transmission of monetary policy shocks? Figure 2.1 shows the responses of output and consumption (aggregate and household-specific) to an exogenous annualized 100 basis points increase in the policy rate when the borrowing constraint binds (dashed lines) and when it is slack (solid lines). 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 when comparing the slack to the binding regime.

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 puts pressure on firms to lower prices. Impatient households take advantage of existing borrowing possibilities and respond to the shock by increasing their debt position in order to minimize the drop in their consumption stream. 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 explain 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. Because they are against the borrowing constraint, they cannot increase their borrowing to counteract these effects. In fact, they are forced to reduce their borrowing in order to meet their outstanding debt obligations. Second, this debt-revaluation 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 and housing demand strongly when an adverse shock hits the economy, are responsible for the asymmetric responses to a monetary policy shock. The lower panels of Figure 2.1 illustrate these dynamics.[8] While the peak consumption response of borrowers is amplified by 90%, 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

[8] Figure B.1 in appendix B.4 shows the responses of additional variables. It is worth noting the asymmetric response of credit across states. As described in the main text, this is the main driver of the amplified consumption response of impatient households when the constraint binds. Moreover, the figure also clearly illustrates that for a similar sized fall in house prices, the housing demand of impatient households is significantly amplified when collateral constraints are binding. House prices fall by about the same amount in both cases, since housing supply is fixed and the sharp decline in housing demand of impatient households is absorbed by the patient ones.

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.[9]

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 2.2. 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 2.1. 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 being slack 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

[9]See Figure B.2 in appendix B.4 for the impulse response functions of this model specification.

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

2.2.3.1 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 dummy 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 Y_t. Thus, we use the DSGE model to infer which variable best predicts periods in which the effects of the monetary policy are amplified. This analysis is also intended to discipline the empirical investigation in the second part of the paper.[10]

Formally, we run regressions

$$\Pr(Y_t = 1 \mid X_{k,t}) = \Phi(X_{k,t}^T \beta_k), \quad k = 1 \ldots K \tag{2.8}$$

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.[11] We consider variables separately in levels, growth rates, and detrended with a one-sided Hodrick-Prescott (HP) filter. In order to assess

[10] We thank an anonymous referee for this suggestion.

[11] We focus on net worth and leverage of the impatient household rather and on the aggregate levels, since these concepts are more directly related to the borrowing constraint. Hence, the model definitions of net worth and leverage are: $nw_t^I = q_t h_t^I - b_t$ and $lev_t^I = b_t/(q_t h_t^I)$, respectively. Credit-to-GDP gaps are defined as the difference between the credit-to-GDP ratio and its long

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.[12]

Table 2.3 shows the predictive performance for a number of predictor candidates. Overall, we find the highest shares of correctly predicted states when the variables are considered in levels. Among these, it turns out that the best predictor of binding borrowing constraints is net worth, which on average correctly predicts binding and slack regimes 87% of the time, while leverage ranks closely behind at 83%. This should be expected, since both concepts are closely related in the model. In particular, both measures are mainly determined by house price and credit fluctuations. House prices is the third best predictor, followed by credit and credit-to-GDP gaps. While the relative rankings of variables changes when looking at variables in growth rates or HP-detrended, the prediction performance in 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 B.2 and B.3 in appendix B.5).

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 (2.8) 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 2.3 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

run trend (extracted from an HP filter with $\lambda = 400,000$), following the tradition of the BIS (see, e.g., Drehmann and Tsatsaronis, 2014).

[12] 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).

test the hypothesis that both sub-samples are drawn from the same distribution. The test strongly rejects the null hypothesis that the distributions of net worth in binding and slack 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 the transmission of monetary policy shocks we re-compute the impulse responses of Figure 2.1, 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.[13] 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.

2.3 Empirical Evidence

In this section, we test the DSGE model predictions using data on the US economy. 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

[13]The shape of these impulse responses is almost identical to those in Figure 2.1. We report these responses in Figure B.3 in appendix B.4.

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. By contrast, monetary policy shocks have only small and mostly insignificant effects when net worth is high.[14] We show that these findings are robust to several modifications of the baseline model and when controlling for other important state variables.

2.3.1 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 (see, e.g., Auerbach and Gorodnichenko, 2012a; Ramey and Zubairy, 2018). 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.[15]

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

$$y_{t+h} = \alpha_h + \tau t + \psi_h(L)x_t + \beta_h \epsilon_t + u_{t+h}, \text{for } h = 0, 1, 2, ..., \tag{2.9}$$

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

[14] In a previous version of this paper we analyzed extensively the asymmetric effects of monetary policy shocks across the household leverage cycle (Harding and Klein, 2019). The main result of that exercise is that monetary policy shocks have larger effects on macro aggregates during periods of household deleveraging. This is consistent with the empirical results presented in this section, and with the prediction analysis described in the previous section: leverage ranks closely behind net worth in terms of predicting when the borrowing constraint is binding or slack. However, given that net worth outperforms leverage in the prediction exercise, in what follows we focus on household net worth.

[15] 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 can be erratic because of the loss of efficiency, especially at longer horizons. For a more detailed discussion, we refer to Ramey and Zubairy (2018).

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

$$\begin{aligned} y_{t+h} = \tau t + I_{t-1}\left[\alpha_{A,h} + \psi_{A,h}(L)x_t + \beta_{A,h}\epsilon_t\right] \\ + (1 - I_{t-1})\left[\alpha_{B,h} + \psi_{B,h}(L)x_t + \beta_{B,h}\epsilon_t\right] + \nu_{t+h}, \end{aligned} \tag{2.10}$$

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, e.g., 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 with the aggregate series on net worth held by households and nonprofit organizations provided by the Flow of Funds tables.[16] 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 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. (2012) propose the use

[16] Details on data construction and sources are given in appendix B.3.

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 components 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 2.4, 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 US economy. The first low household net worth episode precedes the so-called Credit Crunch in 1966. The second episode, which lasts with some minor break from the mid-1970s until the mid-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 2.4 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.[17]

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, e.g., Christiano et al., 2005). As shown by Barnichon and Brownlees (2016), when estimating local projections, such a timing restriction corresponds 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,

[17]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 definition of low and high household net worth states.

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 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 with 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 (2.9) and (2.10), 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 (2.9) and (2.10). 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 (1960Q1-2018Q4).

One concern that arises when testing the DSGE model predictions using this local projection model is that both models are not fully consistent with each other. In particular, in the DSGE model the current and future regimes depend on the realizations of structural shocks, while states in the local projections are not allowed to vary with the realizations of shocks. In order to assess how severe this misspecification is, we compute impulse responses to exogenous monetary policy shocks on the simulated data from the DSGE model using the local projections model. If misspecification is not a serious concern, we would expect that these impulse responses are at least qualitatively similar to the impulse responses from the DSGE model. Figure B.4 in appendix B.4 documents that this is the case. As predicted by the DSGE model, the local projections computed on simulated data show that the drop in GDP and consumption in response to an exogenous monetary policy shock is strongly amplified when household net worth is low.

2.3.2 Baseline Results

In this section, we present our baseline empirical findings. Figure 2.5 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, and 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. By 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 2.6 shows the cumulative effects of each variable in both household net worth states. 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. By contrast, monetary policy only has a small and mostly insignificant impact on the economy when household net worth is above its long run trend.

2.3.3 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. Finally, we show that our results are robust to controlling for three additional prominent states of the economy: the business cycle, the level of household debt, and the level of financial stress. For easier visual comparison, in this section we focus 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.[18] The first row of Figure 2.7 shows that our empirical findings are robust to this alternative identification approach (the dashed line shows the baseline responses for reference). 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, by contrast, the GDP response is only of limited magnitude and estimated to be insignificant for most periods of the forecast horizon.[19]

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 (2.10). As shown in the second row of Figure 2.7, our main empirical results are robust to using this long-term interest rate to measure the stance of monetary policy.

Finally, we use the estimated monetary policy shocks from our DSGE model to test for the robustness of our results. In particular, we use the exogenous monetary policy innovations from the Bayesian model estimation as shock measure in

[18] This series is available at: `http://silviamirandaagrippino.com/research/`. Figure B.5 in appendix B.4 shows this series together with the shocks from our baseline sate-dependent and linear specifications.

[19] We also verify that our results remain when following Tenreyro and Thwaites (2016) and using a nonlinear Romer and Romer (2004) regression, to account for the possibility that the central banks' reaction function changes across different states of the household net worth cycle. These results are shown in Figure B.6 in appendix B.4.

our local projections.[20] As the third row of Figure 2.7 indicates, our main results are robust when using this alternative shock series. GDP declines significantly and strongly when household net worth is low, whereas the GDP response is only borderline significant when household net worth is high. Moreover, the cumulative GDP response at the end of the horizon is almost three times as large when household net worth is low compared to periods of high household net worth.

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 fourth row of Figure 2.7 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.[21]

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 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).[22] As the fifth and sixth rows of Figure 2.7 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 cycle. Rather, it is possi-

[20]These shocks are shown in Figure B.7 in appendix B.4, together with the remaining smoothed structural shocks from the DSGE model. See Ramey (2016) for a similar approach of using shock series from an estimated DSGE model as exogenous innovations in local projections.

[21]Our results are also robust to assigning different values to the smoothing parameter of the HP filter.

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

ble 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. (2018) 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 B.8 in appendix B.4 shows the distribution of shocks across states.

2.3.3.1 Controlling for Alternative State Variables

In addition to the robustness tests presented above, in this section we show that our results are robust when controlling for three other prominent state variables in the literature: the state of the business cycle, the level of household debt, and the level of financial stress.

Business cycle.– Jordà et al. (2017) and Tenreyro and Thwaites (2016) show that the effects of monetary policy interventions differ substantially according to the state of the business cycle. They find that monetary policy is significantly more effective in an economic expansion. Given this, it is possible that our emphasis on nonlinear effects of monetary policy across the household net worth cycle is simply a relabeling of nonlinear effects across the business cycle. In this subsection we show, however, that our household net worth-dependent effects of monetary policy cannot be attributed to the large effects of monetary policy shocks during economic expansions.

We start by investigating whether low household net worth states mainly coincide with periods of low economic slack, whereas high household net worth periods overlap strongly with periods of economic slack. Our sample includes 32 quarters of official NBER recessions. Out of these periods, 7 quarters coincide with episodes of high household net worth, while the remaining 25 quarters overlap with low household net worth periods.

A similar picture emerges when relying on the output gap, measured as the deviation of GDP from its long-run HP trend ($\lambda = 1,600$). We classify 70% of the periods for which we observe a positive output gap as high household net worth states, while the remaining 30% of periods with a positive output gap coincide with periods of low household net worth states. Hence, if anything, periods of low net worth tend to overlap more with periods of high economic slack, suggesting that our main findings cannot be rationalized by monetary policy shocks generally having a larger effect during economic expansions.

To further check whether our findings are sensitive to the state of the business cycle, we condition equation (2.10) on expansionary and recessionary states. We use the output gap, measured as the deviation of GDP from its HP trend ($\lambda = 1,600$), as indicator for economic slack. The first and second rows of Figure 2.8 present the GDP responses for the four states of the economy. It turns out that when private household net worth is low, GDP falls significantly in response to a contractionary monetary policy shock in recessionary but also in expansionary periods. By contrast, when household net worth is high and the economy is an expansion, the GDP response is mostly insignificant. We find a more short lived fall in GDP in periods of high household net worth that coincide with periods of high economic slack. Nevertheless, after around two years the response turns positive and significant such that the cumulative fall in GDP at the end of the forecast horizon is substantially smaller compared to the corresponding one in a low net worth state.

Level of household debt.– Alpanda and Zubairy (2019) find that the effectiveness of monetary policy depends on the level of household debt in the economy. When household debt is below its long-run trend, monetary policy shocks have a larger impact on economic activity compared to a situation in which household debt is above its long-run trend. Against this background, our results could be explained by the fact that low household net worth periods mainly coincide with periods of low debt whereas high household net worth periods mostly happen when household debt is high. However, in the following, we demonstrate that this narrative is not supported by the data.

Following Alpanda and Zubairy (2019), we define high (low) household debt states as periods in which the total household liabilities-to-GDP ratio is above (below) its long-run HP trend. As in their paper, we use a relatively smooth trend ($\lambda = 100,000$) to account for the long duration of credit cycles. We find that 66% of the low debt periods coincide with low household net worth periods, while the remaining 34% overlap with high net worth periods. Thus, there is no conclusive evidence of a systematic relation between low household net worth states and periods of low household debt.

To further rule out that our results are driven by the level of household debt, we estimate equation (2.10), but further condition on the level of household debt. The third and fourth rows of Figure 2.8 show the results of this exercise. Irrespective of the level of household debt, we find that in a low household net worth state a contractionary monetary policy shock leads to a significant decline in aggregate output. By contrast, the GDP responses are more erratic and mostly insignificant when household net worth is high. The GDP response turns significantly negative only at the end of the forecast horizon when debt is low. Overall, the cumulative decline in GDP is amplified when the monetary interventions take place during periods of low household net worth.

Financial stress.– One alternative explanation for our results might be that low household net worth periods are linked to shifts in credit supply by banks. For example, it is possible that changes in household net worth are caused by stress in the banking sector which reduces credit availability.[23] To study the systematic relation between the household net worth cycle and banking stress, we make use of the Financial Conditions Index provided by the Chicago Fed. This index

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

provides an update on US financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems. Here we focus on the leverage subindex of the aggregate indicator. A positive value of this index indicates that financial conditions are tighter than on average and vice versa. The data are just available from 1971 onwards, so all remaining results are based on this shorter sample period. There is indeed a slight overlap between financial stress periods and low household net worth episodes, as 61% of all financial stress states coincide with low household net worth states.

However, to further test whether our results depend on the banking stress cycle, we proceed as before and estimate equation (2.10), but condition on banking stress. The last two rows of Figure 2.8 present the results. When household net worth is low, GDP falls significantly following an increase in the policy rate, irrespective of the level of financial stress. By contrast, in a high household net worth state GDP responds significantly only when the level of financial stress is low, while there is no significant response when financial markets are tight. Moreover, when comparing the responses during normal times, the contractionary effect following the increase in the interest rate is more precisely estimated in low household net worth states.

In sum, the findings of the last exercises suggest that the household net worth cycle is of greater importance for the effectiveness of monetary policy than the state of the business cycle, the level of household debt, and financial stress.

2.3.4 US State-Level Evidence

So far, we have relied on aggregate data to study household net worth-dependent effects of monetary policy. In the following, we demonstrate that our main findings can also be obtained when relying on more disaggregated data. In doing so, we use annual data from US geographical states. To identify monetary policy shocks at the US state level, we make use of the approach suggested by Nakamura and Steinsson (2014) in the context of exogenous government spending shocks. The main regression takes the following form:

$$\Delta z_{i,t} = \beta_H r_{i,t} + (\beta_L - \beta_H) r_{i,t} I_{i,t} + \delta_i + \psi_t + \omega_{i,t}, \tag{2.11}$$

where $\Delta z_{i,t}$ is the annual growth rate of the variable of interest (GDP or employment in our case) in state i in year t, $r_{i,t}$ is a measure of the interest rate in region i in year t, δ_i, and ψ_t represent state and year fixed effects. The inclusion of state fixed effects implies that we are allowing for state specific time trends in output or employment and the interest rate. The inclusion of time fixed effects allows us to control for aggregate shocks and aggregate policy –such as changes in distortionary taxes and government spending. $I_{i,t}$ is an indicator for a period of low household net worth, implying that the effects of the interest rate in high and low household net worth periods are given by β_H and β_L respectively.

We use annual panel data at the US state level for 1990-2014 and account for the overlapping nature of the observations in our regression by clustering the standard errors by state. To measure household net worth at the state level, we use data on the loan-to-value ratio from the Monthly Interest Rate Survey conducted by the Federal Housing Finance Agency. We define low household net worth periods as those episodes in which the loan-to-value ratio is below its smooth long-run trend.[24]

US states are part of a monetary union, such that the main monetary policy instrument –the federal funds rate– does not differ between states. Therefore, we have to rely on an adequate proxy to measure the stance of monetary policy across individual regions. Because the housing sector is one of the most important drivers of the business cycle in the US, and because the household net worth cycle is directly linked to financing conditions in the real estate market, we use the mortgage interest rate as an indicator for the state-specific stance of monetary policy. State-specific mortgage interest rates are also obtained from the Federal Housing Agency. Data on real GDP and employment are taken from the Regional Economic Accounts of the Bureau of Economic Analysis.

An important challenge in identifying the effect of monetary policy is that interest rates are potentially endogenous. Therefore, we follow Nakamura and Steinsson (2014) and estimate equation (2.11) using an instrumental variables approach. In the first stage, we instrument for the state mortgage interest rate using

[24] We construct state-specific HP trends with a smoothing parameter $\lambda = 200$ to account for the longer length of financial cycles. Based on the calculations in Ravn and Uhlig (2002) this value implies that the household financial cycle is around 2.5 times longer than the traditional business cycle which is comparable to our smoothing parameter of $100,000$ assigned to the quarterly frequency and the choices taken in related studies (Alpanda and Zubairy, 2019; Drehmann and Tsatsaronis, 2014).

an aggregate monetary policy shock interacted with a state dummy. Thus, we allow for different interest rate sensitivities to an exogenous national monetary policy intervention across different states. This procedure yields scaled versions of mortgage interest rates as fitted values for each state, which are then used in the second stage to estimate equation (2.11). To check for the robustness of our results, we use two different measures of national monetary policy shocks. We use the monetary policy shocks employed in our local projection estimation and the extended Romer and Romer (2004) narrative series described above.

Table 2.4 shows the results of this exercise. The estimates indicate that the economy does not respond significantly to a contractionary monetary policy shocks in a high household net worth state. By contrast, the effects are significantly amplified when the shock hits the economy during a low household net worth episode. As an example, for the local projection shocks we find that output insignificantly declines by around 2% when household net worth is high and that the drop is significantly amplified by another 0.05% in low household net worth states. Put differently, the impact of a monetary policy shock is estimated with a substantial amount of uncertainty when household net worth is high, whereas the additional impact obtained when moving from a high to a low net worth state is estimated quite precisely. This result holds irrespective of the identification of monetary policy shocks for GDP and employment.

All told, in addition to our evidence at the national level, we find that the effects of monetary policy shocks are amplified during periods of low household net worth at the US state level as well. Thus, the empirical evidence strongly supports the predictions we obtained from our model simulations.

2.4 Conclusion

This chapter 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 US data. 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 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 US 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. By contrast, in a high household net worth state monetary policy has only small and mostly insignificant effects. Our paper shows that the state of the household net worth cycle plays a particularly important role in understanding the transmission of monetary policy.

2.5 Tables

Table 2.1: Calibrated parameters

Parameter	Description	Value
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 2.2: Estimated parameters

		Prior Dist.	Posterior Distribution			
	Description	Dist. mean[std.]	mode	5%	median	95%
ε_c	Habit in consumption	$\mathcal{B}$ 0.70[0.10]	0.4295	0.3804	0.4559	0.5270
ε_h	Habit in housing	$\mathcal{B}$ 0.70[0.10]	0.9208	0.8888	0.9223	0.9415
ϕ	Invest. adjustment cost	$\mathcal{G}$ 5.00[2]	11.0144	8.5145	11.2128	14.3330
σ	Wage share impatient H.	$\mathcal{B}$ 0.50[0.05]	0.4324	0.4046	0.4320	0.4705
r_π	Taylor rule, inflation	$\mathcal{N}$ 1.50[0.10]	1.4427	1.3901	1.6175	1.7673
r_R	Taylor rule, inertia	$\mathcal{B}$ 0.75[0.10]	0.2506	0.1419	0.2248	0.3284
θ_p	Calvo, prices	$\mathcal{B}$ 0.50[0.07]	0.9294	0.7960	0.8655	0.9374
θ_w	Calvo, wages	$\mathcal{B}$ 0.50[0.07]	0.9011	0.8764	0.8975	0.9154
ρ_J	AR(1) housing shock	$\mathcal{B}$ 0.75[0.10]	0.9876	0.9553	0.9763	0.9909
ρ_K	AR(1) investment shock	$\mathcal{B}$ 0.75[0.10]	0.5804	0.5289	0.5839	0.6373
ρ_R	AR(1) monetary shock	$\mathcal{B}$ 0.25[0.10]	0.4223	0.3371	0.4864	0.6035
ρ_Z	AR(1) preference shock	$\mathcal{B}$ 0.75[0.10]	0.8573	0.7559	0.8035	0.8675
σ_J	std. housing shock	$\mathcal{IG}$ 0.01[1]	0.0470	0.0394	0.0686	0.0971
σ_K	std. investment shock	$\mathcal{IG}$ 0.01[1]	0.0944	0.0702	0.0955	0.1222
σ_P	std. price markup shock	$\mathcal{IG}$ 0.01[1]	0.0061	0.0059	0.0068	0.0078
σ_R	std. monetary shock	$\mathcal{IG}$ 0.01[1]	0.0051	0.0048	0.0053	0.0058
σ_W	std. wage markup shock	$\mathcal{IG}$ 0.01[1]	0.0084	0.0077	0.0084	0.0092
σ_Z	std. preference shock	$\mathcal{IG}$ 0.01[1]	0.0154	0.0138	0.0155	0.0175

Notes: Prior distributions $\mathcal{B}$, $\mathcal{G}$, $\mathcal{N}$, and $\mathcal{IG}$ denote beta, gamma, normal, and inverse gamma distributions, respectively. Posterior statistics based on one chain of 55,000 MCMC replications, where the first 5,000 are discarded.

Table 2.3: Prediction of binding collateral constraints

Predictor candidate x_k	Levels	Growth rates	HP cycle
Net worth	0.87	0.55	0.69
Leverage	0.83	0.54	0.65
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 (2.8) 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.

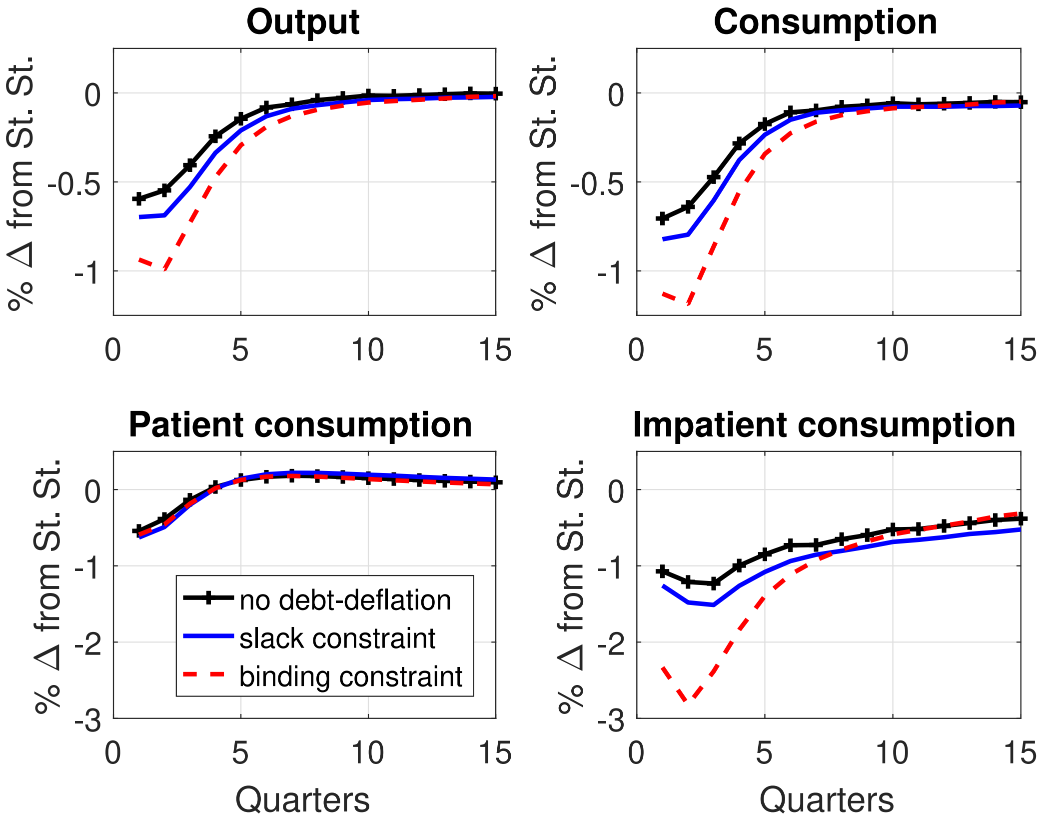
Table 2.4: US state-level evidence

	LP-Shocks		Romer/Romer Shocks	
	Output	Employment	Output	Employment
β_H	-2.167	-1.079	0.012	-1.312
	(1.919)	(0.820)	(2.255)	(1.028)
$\beta_L-\beta_H$	-0.055^{**}	-0.031^{***}	-0.047^{*}	-0.024^{**}
	(0.026)	(0.011)	(0.025)	(0.011)
Obs.	1224	1224	1122	1122

Notes: Standard errors clustered at the state level are in parentheses. The unit of observation is US geographical states for all regressions in the table. β_H measures the effect in high household net worth periods and $\beta_L - \beta_H$ measures the difference between the effect in low and high household net worth periods. LP-Shock refers to the shocks obtained by the local projections at the federal level. The regressions include state and time fixed effects interacted with the low household net worth dummy. The regressions are estimated by two-stage least squares. * Significant at the 10 percent level, ** significant at the 5 percent level, *** significant at the 1 percent level.

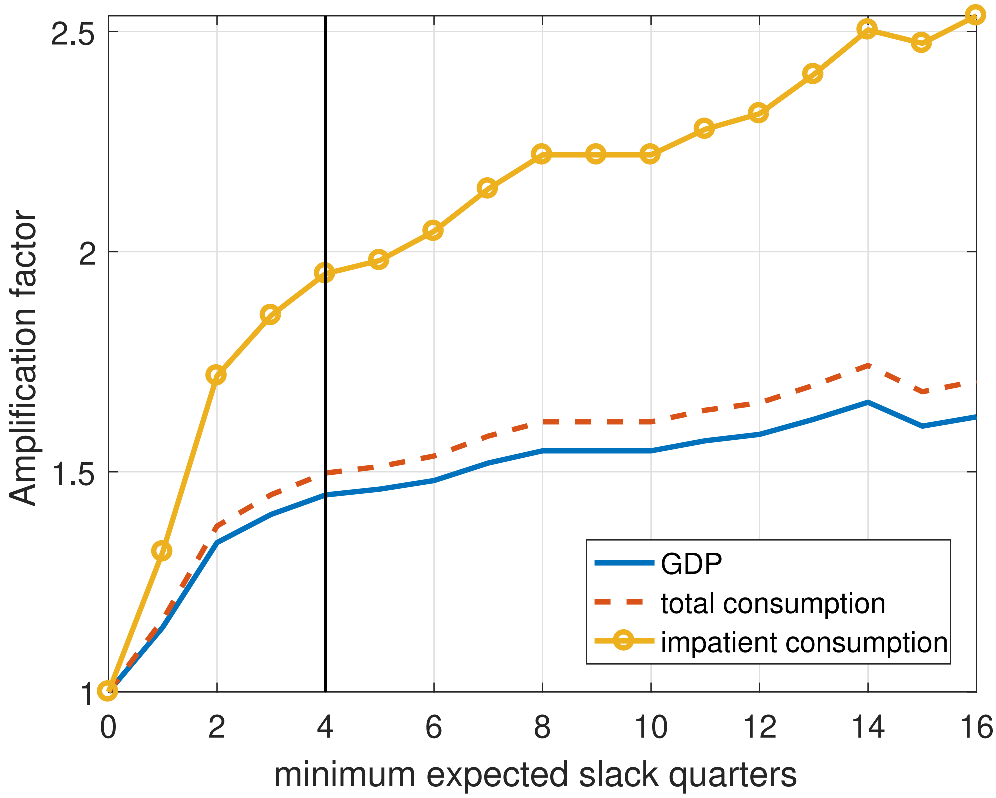
2.6 Figures

Figure 2.1: IRFs to a 1% contractionary monetary policy shock



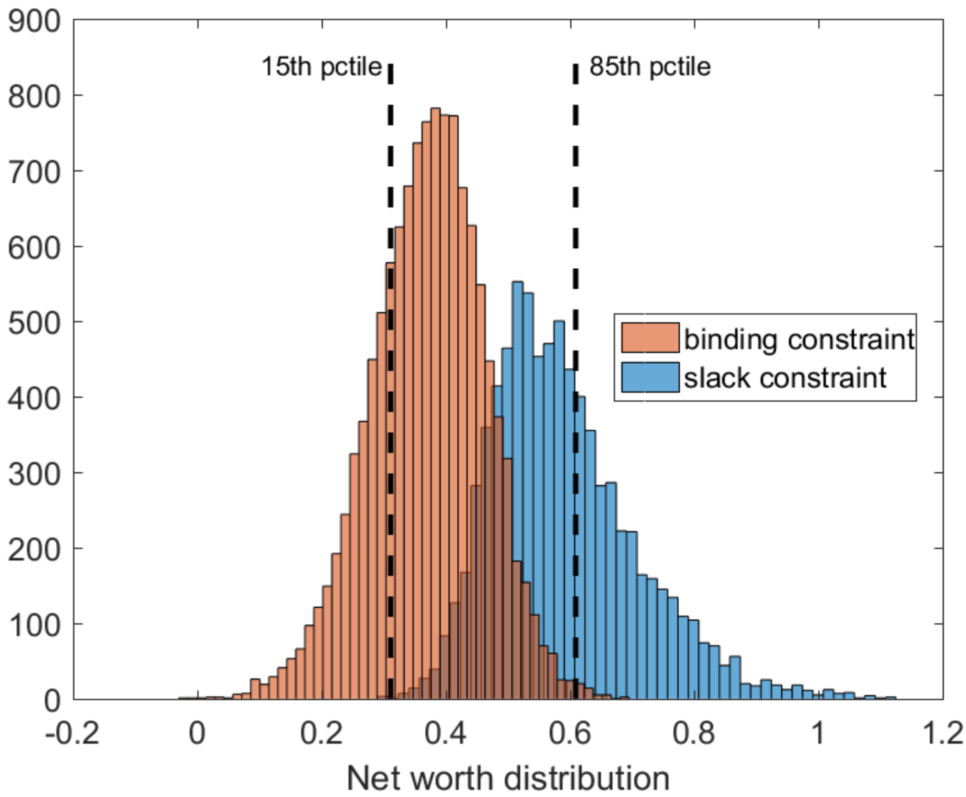
Notes: Generalized IRFs to an (annualized) 100 basis points monetary policy shock under binding and slack collateral constraints. GIRFs are computed by simulating the model for 600 periods, once with all shocks evaluated at their estimated standard deviations and a second time where, on top of that, 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 2.2: Amplification effects after a monetary policy shock



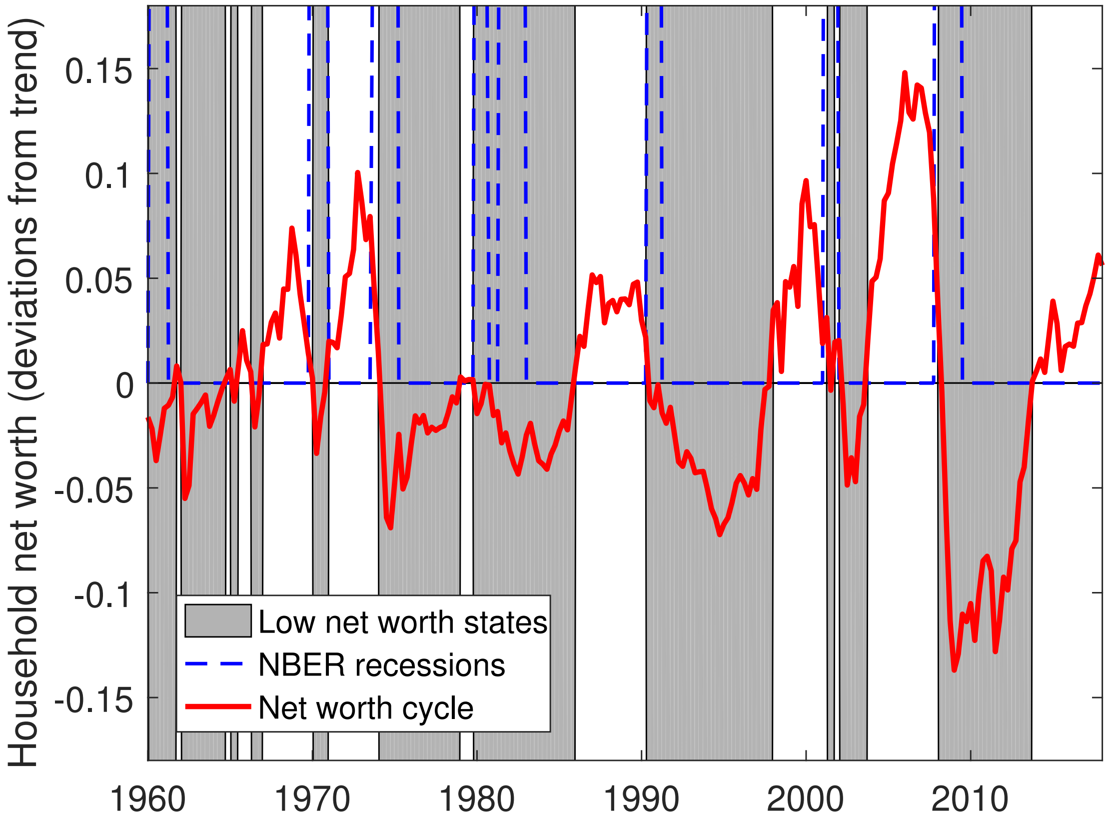
Notes: Amplification of the maximum response of GDP, aggregate consumption and consumption of the impatient household is computed as the average amplification of the maximum response for each horizon of expected slack constraints in the x axis. Impulse responses are calculated as described in Figure 2.1. The black vertical line indicates the baseline scenario from Figure 2.1, where the constraint is expected to remain slack for at least 4 quarters after the shock hits.

Figure 2.3: Net worth distribution across states of the borrowing constraint



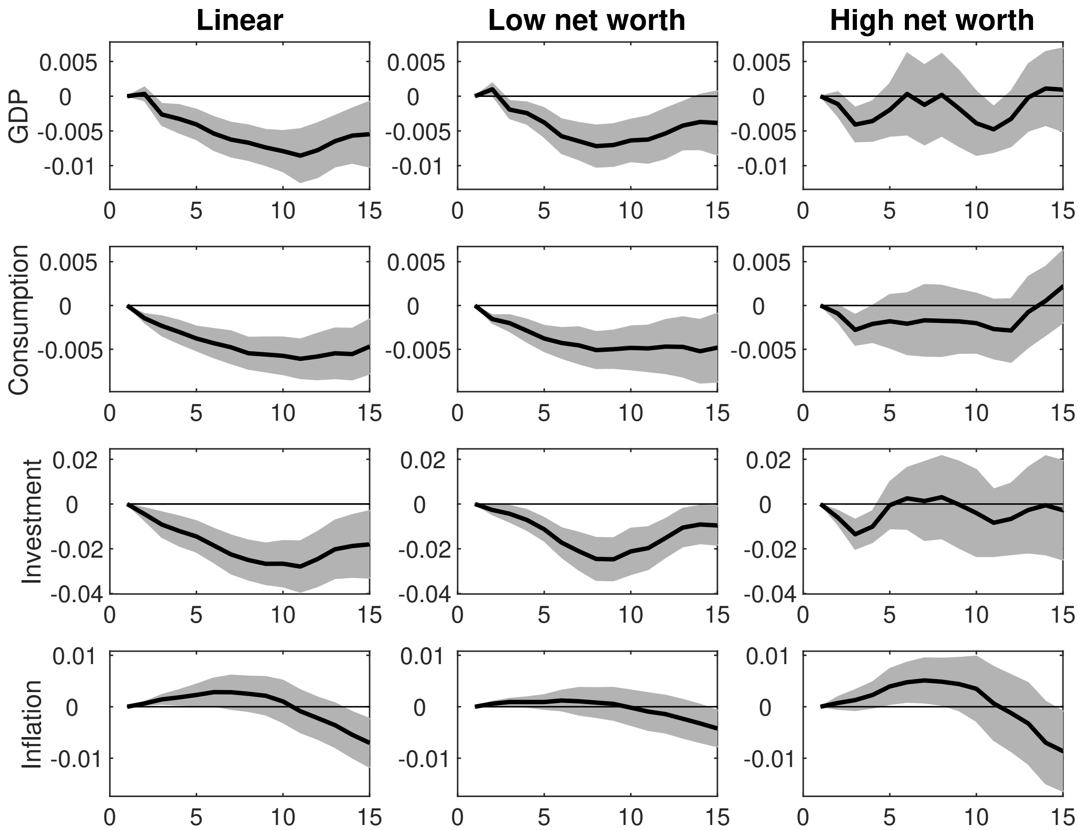
Notes: Net worth distribution across binding and slack states of the borrowing constraint. The distributions correspond to a simulation of 22,000 periods, where the first 2,000 are discarded.

Figure 2.4: Household net worth cycle



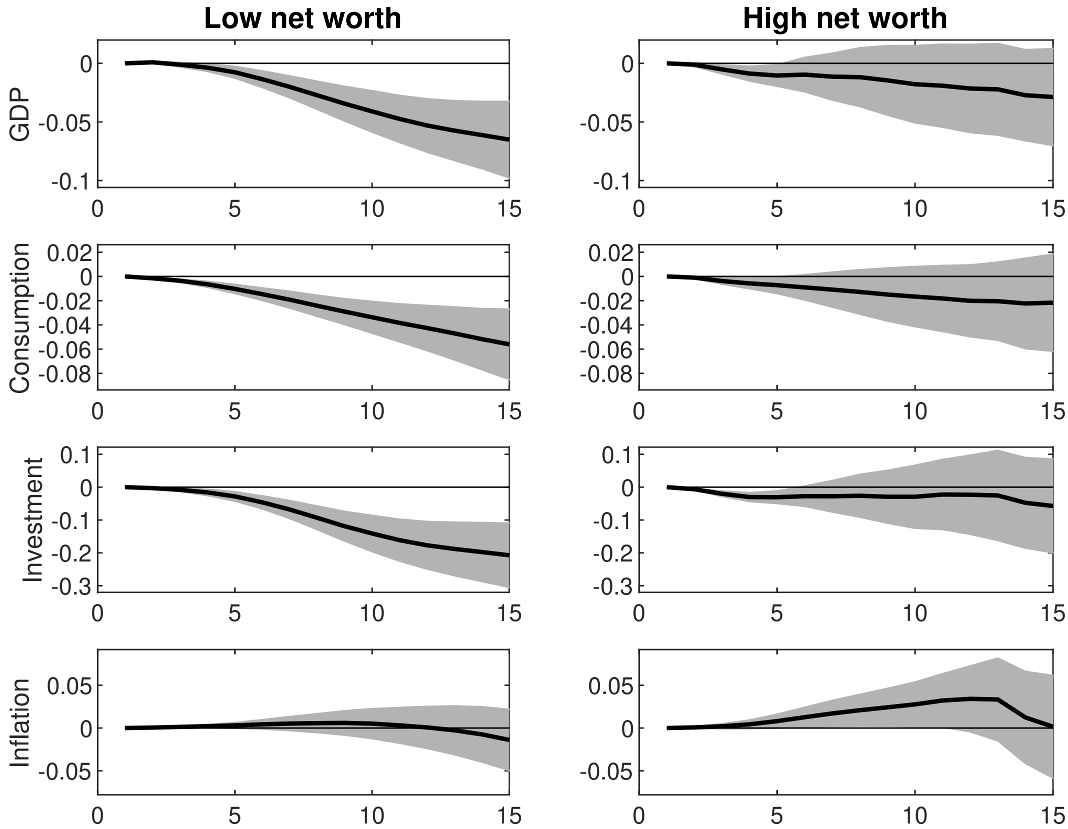
Notes: Household net worth is measured as the net worth held by households and nonprofit organization provided by the Flow of Funds tables and deflated by the CPI price index. To calculate the cyclical component, the real household net worth series is filtered by a smooth HP trend, where the smoothing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

Figure 2.5: Impulse responses to a 1% contractionary monetary policy shock



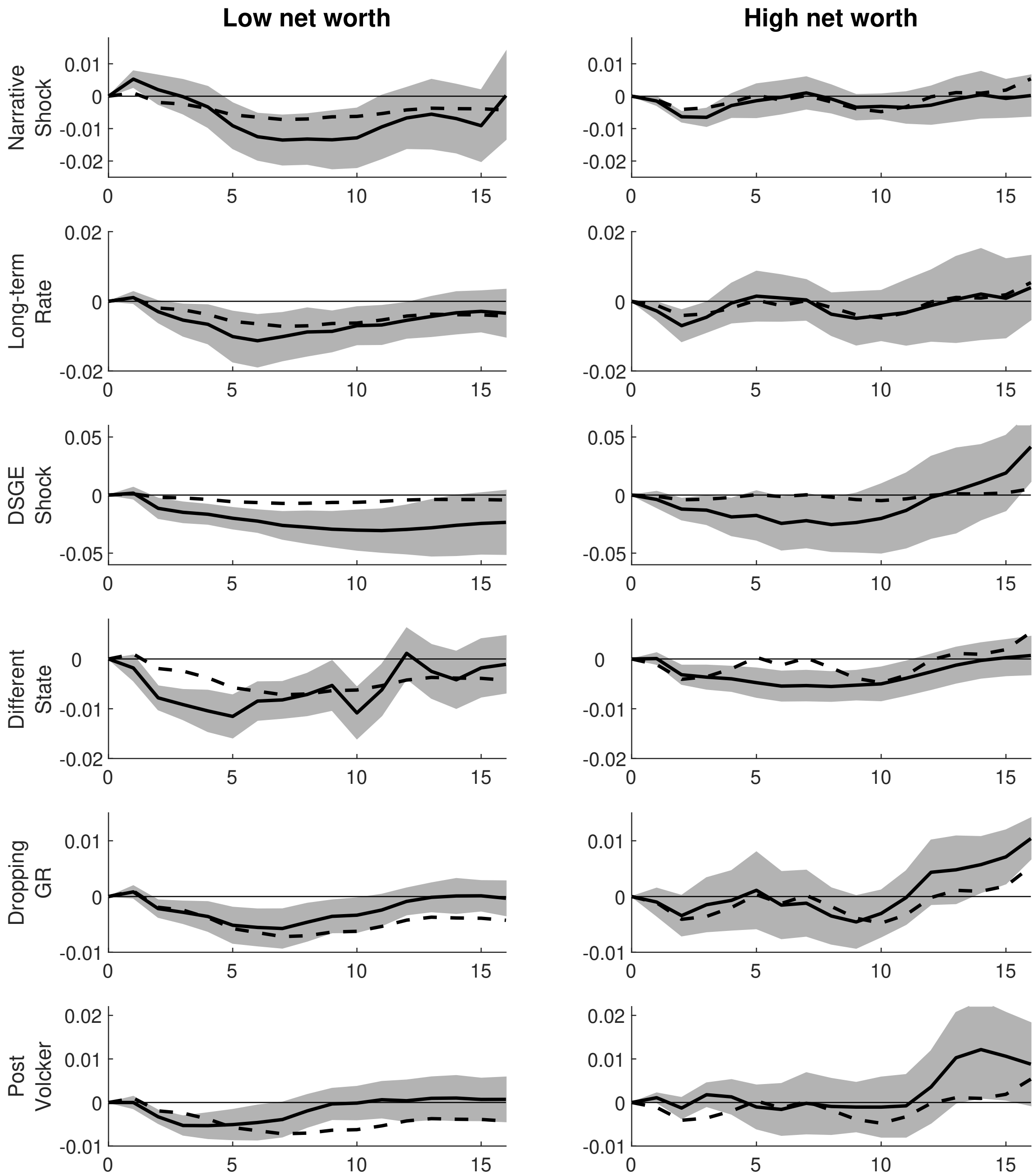
Notes: Baseline results: The first column shows the impulse responses of a 1% contractionary monetary policy shock on a variable in the linear model. The second and third column show analogous impulse responses in a low household net worth (second column) and high household net worth (third column) state. The shaded areas indicate 90% confidence bands based on Newey and West (1987) standard errors.

Figure 2.6: Cumulative effects of a 1% contractionary monetary policy shock



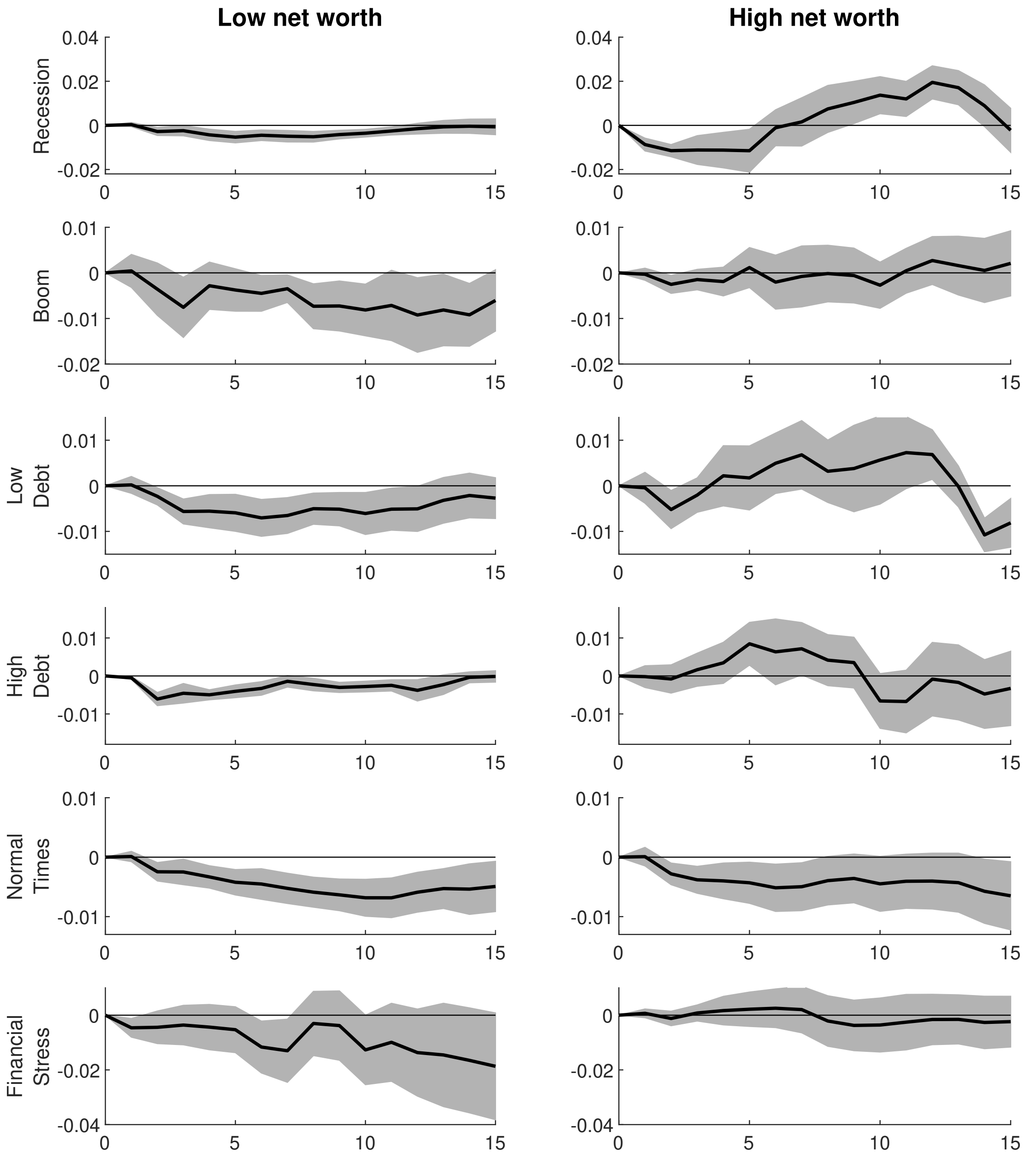
Notes: Baseline cumulative effects: The first column shows the cumulative effects of a 1% contractionary monetary policy shock on a variable in a low household net worth state. The second column shows the cumulative effects of a 1% contractionary monetary policy shock on a variable in a high household net worth state. The shaded areas indicate 90% confidence bands based on Newey and West (1987) standard errors.

Figure 2.7: Robustness: GDP impulse responses to a 1% contractionary monetary policy shock



Notes: The rows show the results of using alternative identification strategies (rows 1, 2 & 3), an alternative definition of the net worth states (row 4), and changes in the sample (rows 5 & 6). The first column shows the impulse responses of a 1% contractionary monetary policy shock on GDP in a low household net worth state. The second column shows the impulse responses of 1% contractionary 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.

Figure 2.8: Robustness: GDP impulse responses to a 1% contractionary monetary policy shock



Notes: The rows show the results of controlling for three additional states: the business cycle, the level of household debt, and financial stress. The first column shows the impulse responses of a 1% contractionary monetary policy shock on GDP in a low household net worth state. The second column shows the impulse responses of a 1% contractionary 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.

CHAPTER 3

Credit Constraints and the Transmission of Monetary Policy to Consumption

3.1 Introduction

In recent years there has been much debate about the effectiveness of central banks' monetary policy and the channels through which it affects the real economy. One of the channels that has been on the spotlight of the discussion is the response of household consumption to changes in the policy stance, partly as a result of the large shifts in the financial position of households due to the 2008 financial crisis and the period of low interest rates that followed. While it is clear that households' balance sheets play a central role in determining how they respond to economic shocks (Mian et al., 2013; Schularick and Taylor, 2012), it is still unclear how credit constraints affect their reaction to monetary policy shocks.

A priori, different types of credit constraints can affect the transmission of monetary policy to the economy in various ways. On the one hand, if constrained households are unable to adjust their borrowing in response to interest rate changes, the effects of monetary policy could be dampened due to a reduced adjustment of consumption. This can happen if, for instance, households are partially or fully excluded from credit markets. On the other hand, if a drop in the interest rate relaxes the borrowing constraints of households, the consumption response can be amplified due to enhanced consumption possibilities that result from gaining access to additional credit.

In this chapter, I ask how household credit constraints affect the transmission of monetary policy to consumption in the US economy. I tackle this question by combining two detailed micro-surveys for the US –the Survey of Consumer Finances (SCF) and the Consumer Expenditure Surveys (CEX)– and exploiting these detailed household portfolio and consumption data to assess the role of household credit constraints for the effectiveness of monetary policy. Using a measure of credit constraints based on loan rejections, I show that credit constraints significantly dampen the consumption response to a monetary policy shock. I then use a model with heterogeneous households to interpret this result.

I start with a characterization of financially constrained households in the US. First, I extend the work of Jappelli (1990) and estimate a probability model of the determinants of credit constraints using SCF data from 1995 to 2016. The measure of credit constraints is a self-reported indicator of whether households have had their request for credit rejected in the past years. Using this definition, the share of constrained households in the US oscillates between one-quarter and one-third over the last decades. I document that household net worth, age, and debt are key predictors of loan rejections.

I then combine this measure of credit constraints with consumption data from the CEX to study the role of credit constraints for the consumption response to monetary policy. The challenge of combining the CEX with the SCF is that they differ in terms of frequency, structure and variables covered. However, they do share a large set of common variables, including income, other relevant household characteristics, and even some balance sheet data. Using these common variables, I use the estimated probability model from the SCF to create and index of credit constraints for the CEX measuring the probability that a household is partially or fully turned down when applying for a loan.

With this information at hand, I exploit the 4-quarter panel dimension of the CEX and monetary policy shocks identified at high frequency to estimate the short-run consumption response to exogenous changes in interest rates at the household level. I find large and statistically significant heterogeneity in the consumption responses across constrained and unconstrained households. Specifically, constrained households are significantly less responsive to monetary policy shocks. The drop in consumption in response to a contractionary monetary policy shock for unconstrained households is between two and three times as large as the average across all households. The response becomes smaller in absolute terms as the probability of being constrained increases, and turns insignificant for a high enough value of the probability.

I measure the monetary policy stance using two-year maturity Treasury yields and obtain exogenous variation by instrumenting them with the monetary policy shocks, but the results are robust to using either one-year or five-year rates. I rely on two prominent series of monetary policy shocks in the literature, which use changes in asset prices around FOMC meetings to measure monetary policy surprises. I first consider the shocks by Nakamura and Steinsson (2018), which measure the change in a composite measure of interest rates (a policy indicator) at different maturities spanning the first year of the term structure, in a 30-minute window around scheduled FOMC announcements. Thereby, in addition to contemporaneous surprises in interest rates, this measure also captures potential effects of "forward guidance". As an alternative, I consider the shocks by Jarociński and Karadi (2020), which distinguish between pure monetary surprises and central bank information effects –that capture the release of new information about the economic outlook that potentially occurs when central banks take a policy decision.

The heterogeneous responses for constrained and unconstrained households hold for the two shocks series considered. Durable consumption of unconstrained households drops by about three times as much as the average across all households in response to a contractionary monetary policy shock. The heterogeneity in the responses is smaller for non-durable consumption, but it is still economically and statistically significant. For the Jarociński-Karadi shocks, I find that non-durable consumption of unconstrained households drops by up to twice as much as the average across all households in response to the shock.

The second part of the chapter studies the theoretical mechanism underlying the empirical findings. Following a large number of recent papers, I set up a Heterogeneous Agent New Keynesian (HANK) model in which borrowing constraints and households' balance sheets play an important role for their consumption response to changes in interest rates. The model choice is motivated by the work of Auclert (2019) and Kaplan et al. (2018), who emphasise the importance of distinguishing between the direct and indirect effects of monetary policy on household consumption. The direct effect acts via the intertemporal substitution motive embedded in households' Euler equation. After a drop in interest rates, this effect triggers an increase in households' consumption because saving becomes relatively less attractive. On the other hand, the indirect effect increases households' income stream and wealth, which triggers an increase in their consumption in response to these changes.

In the model, households with few or no assets have relatively large marginal propensities to consume (MPCs) and are relatively insensitive to changes in interest rates via direct effects. This is because they are at their borrowing constraint or close to hitting it, and thus unable to significantly adjust their asset position in response to a change in interest rates. The model implies that most of the consumption response to a monetary policy shock comes from households in the middle of the asset distribution. However, due to their large MPCs, households at the lower tail of the distribution are also the ones with the largest indirect response to interest rate changes. These facts combined suggest that one plausible explanation for the empirical results is that low asset, financially constrained households have a low direct sensitivity to interest rates and that the indirect effects take time to materialize, as documented in Holm et al. (2020).

Contribution to the literature.– Several recent empirical and theoretical papers document that monetary policy shocks have heterogeneous effects across households, depending on their financial position and access to credit. While many theoretical papers have looked at the role of household heterogeneity for monetary policy (e.g., Auclert, 2019; Auclert et al., 2020; Bilbiie, 2019; Kaplan et al., 2018; Luetticke, 2018; McKay et al., 2016; Werning, 2015, among others), here I briefly discuss the relation to the most relevant ones for my work. Auclert (2019) highlights the role heterogeneity in MPCs and interest rate exposure across households to understand their heterogeneous responses to monetary policy. Kaplan et al. (2018) decompose the effects of monetary policy into a direct (Euler equation) effect and an indirect (general equilibrium income and wealth) effect. They show that the financial position of households fundamentally determines the relative importance of these effects. Taking these insights into account, I provide new empirical evidence that borrowing constraints play an important role in understanding the consumption response to monetary policy.

On the empirical front, Cloyne et al. (2020) show that the housing tenure status of households and whether they hold a mortgage is crucial to determine the consumption response to monetary policy shocks. They show that homeowners with a mortgage and renters are more responsive than outright owners. Gelos et al. (2019) document that households with higher debt respond more to monetary policy shocks. Both papers provide evidence that liquidity constraints in the spirit of Kaplan and Violante (2014) wealthy and poor hand-to-mouth amplify the effects of these shocks, but they do not look at loan rejections. I contribute to this discussion by showing that credit constraints in the form of loan rejections act in the opposite way, dampening the effects of monetary policy shocks. Moreover, I show that the notion of constrained households based on loan rejections measures something different than these hand-to-mouth classifications.

The papers by Alpanda et al. (2019) and Beraja et al. (2019) argue that households with weaker balance sheets are less responsive to monetary policy shocks because they are not able to adjust their loans in response to interest rate changes. In a similar vein, Wong (2019) and Eichenbaum et al. (2018) show that households that are more likely to adjust or refinance their loans are more responsive to monetary policy. Wong (2019) shows that younger households who hold a mortgage explain most of the aggregate consumption response, and Eichenbaum et al. (2018) document that monetary policy has larger effect on households that have larger potential savings from refinancing fixed rate mortgages. These papers provide evidence that is consistent with my finding that a restricted access to credit dampens the consumption response to interest rate changes, but they focus on different data. Holm et al. (2020) provide empirical evidence supporting some of the HANK model predictions for Norway using administrative tax data. Interestingly, they show that the indirect effects take at least one year to unfold in the data, which provides a plausible explanation for the muted short-term response of financially constrained households documented in this chapter.

While most of the literature focuses on the mortgage market to study heterogeneous effects of monetary policy shocks, I propose a new index of credit constraints based on loan rejections and study how this self reported measure affects the transmission of monetary policy shocks to household consumption. The finding that this type of credit constraints dampens the effects of monetary policy shocks is a novel contribution to this literature.

Outline.– The chapter is organized as follows. Section 3.2 describes the data, provides a characterization of credit constraints for the US economy, and discusses the main empirical results regarding the consumption response of constrained and unconstrained households to monetary policy. Section 3.3 presents the model and discusses the theoretical mechanism. Section 3.4 concludes.

3.2 Empirical Evidence

3.2.1 Data

In order to conduct the empirical analysis, I combine household-level data from two surveys that are representative of the US population with macro aggregates. I briefly describe the main data sources here, while a more detailed description of the data and construction of the variables is provided in appendix C.1.

Survey of Consumer Finances (SCF).– I use SCF data to define when households are credit constrained, and to estimate the determinants of credit constraints. This is a triennial cross-sectional survey that contains detailed information on households' portfolios, income, demographics and loan rejections. The data is collected and made publicly available by the Federal Reserve.[1] I use 8 survey waves, covering the period from 1995 to 2016.

Consumer Expenditure Surveys (CEX).– I use the CEX survey to estimate the response of consumption to exogenous changes in interest rates. The CEX contains detailed data on durable and non-durable consumption expenditures, income, and demographic characteristics of consumers. This is a quarterly survey, with a 4-quarter panel dimension and is collected and made publicly available from 1980 onwards by the US Bureau of Labor Statistics.[2] I focus on the period between 1996Q1 and 2017Q4.

Aggregate data.– In addition to the survey data, I use CPI data to express variables in real terms, and data on Treasury yields to measure the stance of monetary policy. I obtain these data from FRED Economic Data, Federal Reserve Bank of St. Louis.[3]

3.2.2 Determinants of Credit Constraints

This section measures credit constraints in the US economy and estimates their main determinants. I rely on loan rejections data from the SCF to define an indi-

[1] See `https://www.federalreserve.gov/econres/scfindex.htm`
[2] See `https://www.bls.gov/cex/`
[3] See `https://fred.stlouisfed.org/`

cator of credit constraints. The survey gathers information on loan rejections by asking the following two questions:

- Q1: "In the past five years, has a particular lender or creditor turned down any request you or your (spouse/partner) made for credit, or not given you as much credit as you applied for?" Answer: [Yes/No];

- Q2: "Was there any time in the past five years that you or your (spouse/partner) thought of applying for credit at a particular place, but changed your mind because you thought you might be turned down?" Answer: [Yes/No].

With this information at hand, I follow Jappelli (1990) and define an indicator of credit constraints that takes the value of one if either of these questions is answered with "Yes", and zero otherwise. That is

$$cc = \begin{cases} 1 & \text{if answer to Q1 or Q2 is ``Yes''} \\ 0 & \text{otherwise.} \end{cases} \tag{3.1}$$

In addition to data on loan rejections, the SCF provides detailed data on income, household portfolios, and demographics, which can be used to estimate the determinants of credit constraints –that is, the characteristics summarizing which households are more likely to be credit constrained.

Table 3.1 provides summary statistics of the SCF data, waves 1995 to 2016, distinguishing between constrained and unconstrained households. Constrained households have on average lower income and much lower net worth, with lower levels of both liquid and illiquid assets. On the other hand, constrained households hold only slightly less debt than unconstrained ones, particularly when it comes to mortgage debt. Another important difference is that constrained households are on average younger than unconstrained ones. It is not surprising that households with a lower income stream, weaker balance sheet, or lower collateral are more likely to get loans rejected. In that sense, this measure of credit constraints is similar to a measure of credit score, where households with lower credit score are less likely to obtain loans.

Over the entire sample, 10,587 households or 27% of the total are credit constrained. There is also important variation over time in the share of constrained households. The share is 29% at the beginning of the sample, it drops to 27%

before the financial crisis in 2007, it jumps to 31% in the years after the crisis –as measured in 2010–, and it declines thereafter.[4]

Before studying the determinants of credit constraints in more detail, it is worth looking at how this measure compares to other prominent measures of household balance sheets used to study state-dependent effects of monetary policy in the literature. Cloyne et al. (2020) show that homeowners with mortgage and renters are the households that respond the most to monetary policy. They argue that their tenure status definition is consistent with the hand-to-mouth (HtM) classification of households proposed by Kaplan and Violante (2014) and Kaplan et al. (2018).

Figure 3.1 compares these alternative measures to my definition of credit constraints. The figure shows that unconstrained households are fairly evenly distributed between renters, owners with mortgage and outright owners. In contrast, constrained households are mostly either renters (59%) or owners with mortgage (35%). The figure highlights that the constrained/unconstrained categories cannot be summarized uniquely by housing tenure status in the data. When it comes to the hand-to-mouth classification, it is clear that most of the unconstrained households (65%) correspond to non-HtM households. However, the constrained households are quite evenly distributed between the three types. Again, this shows that constrained households cannot be summarized by a single HtM type in the data.

In order to study the characteristics of credit constrained households, in the following I estimate a probability model of the determinants of credit constraints. In particular, I estimate the following logit model

$$P(cc = 1 \mid X) = \frac{\exp(X^T \beta)}{1 + \exp(X^T \beta)}, \tag{3.2}$$

where X contains the following household observables, including interaction and squared terms: income, net worth, debt, age, family size, housing tenure, marital status, race, sex, college education, employment status, a dummy for households that have negative net worth, and a dummy for households with positive savings. This exercise is similar to model specification of Jappelli (1990), with the differ-

[4] Figure C.2 in appendix C.2 shows the evolution of the share of constrained households from 1995 to 2016. The most recent data shows a drastic decline to 17% in 2016, but this sharp drop is at least partly explained by the fact that the horizon over which households are asked about loan rejections changed from 5 years (as in all previous surveys) to 1 year in the 2016 survey.

ence that I pool the data for 8 waves of the SCF instead of relying on a single wave.

Table 3.2 shows the estimation results.[5] As expected, net worth is highly significant and plays an important role to determine the probability of being credit constrained. A 1% increase in net worth decreases the probability of being constrained by 2.3 percentage points, while households that have negative net worth, other things equal, have a probability of being constrained 3.6 percentage points higher. Older households are also significantly less likely to be constrained. Intuitively, a higher debt level increases the probability of being constrained. It turns out that households with married and white household heads have a significantly lower probability of being constrained. As discussed above, housing tenure is an important factor, with renters being on average 5.8 percentage points more likely to be constrained than homeowners with a mortgage. Finally, households that have positive savings are 9 percentage points less likely to be credit constrained.

Figure 3.2 takes a closer look at how the predicted probability of credit constraints varies across four important dimensions: net worth, age, income, and debt. The figure illustrates that net worth and age stand out as key determinants. When net worth is close to zero, small increases in net worth raise the probability of loan rejections, presumably because many households that have zero net worth do not participate actively in credit markets. After that initial jump, the probability drops very significantly as net worth increases further. A somewhat similar pattern can be seen for age. The predicted probability increases slightly for very young households as they get older, peaking for households in their late 30s' –a point in the life cycle when most households have a significant amount of debt but have not reached their peak income and wealth. Beyond that point, the predicted probability drops significantly as households get older, as they accumulate more wealth and gradually pay their outstanding debt.

Income, on the other hand, explains very little of the predicted probability, which remains almost constant and estimated with large uncertainty across the income distribution. Finally, debt matters significantly only for households that have low levels of debt. For instance, the predicted probability of being constrained increases by about 5 percentage points between households that have

[5] I have also estimated the model separately for each wave. The results, shown in Table C.2 in appendix C.2, confirm the main stylized facts from the pooled estimation regarding the determinants of credit constraints.

zero debt and households with a debt level of about 20,000 USD. But when households hold 50,000 USD or more, additional debt leads to very minor increases in the predicted probability.

These results are qualitatively comparable to those of Jappelli (1990), as is the model predictive performance. In R-squared terms, the model explains about 20% of the variation in loan rejections.[6] In terms of predictive performance, using a simple threshold rule the model correctly predicts what households are credit constrained based on their observables 75% of the time.[7] With this characterization of credit constraints at hand, in the next section I use the estimated model to construct and index of credit constraints and study the role of credit constraints for the consumption response to monetary policy.

3.2.3 Credit Constraints, Monetary Policy and Consumption

How do credit constraints affect the transmission of monetary policy to consumption? To answer this question I start by constructing a predicted index of credit constraints for the households in the CEX, which can be used to study how the consumption response to monetary policy differs between households that have a high and low probability of being constrained. This involves constructing CEX analogues for the SCF variables that are used for estimating the logit model in equation (3.2).

This mapping can be done using a large set of variables that is common across the two surveys. Both surveys have detailed information on income and households characteristics, such as age, marital status, race, sex, family size, education, housing tenure status, and unemployment status. The main difference between the two surveys is that the SCF does not include data on consumption, while

[6] In the case of the logistic model at hand, which is estimated with maximum likelihood, there is no equivalent statistic to the R-squared obtained for models estimated with OLS. There are, however, alternative measures that try to capture the concepts of explained variability or fit associated with the R-squared. For example, McFadden's R-squares is defined as $R^2_{McF} = 1 - LM_{full}/LM_{intercept}$, where the ratio between the likelihoods of the full model and a model with intercept only are compared. The baseline specification here yields $R^2_{McF} = 0.183$.

[7] To asses the predictive performance of the model, I follow Jappelli (1990) and use a threshold defined by the share of constrained households in the sample to predict which households are constrained. Let n be the number of constrained households and N the total number of households. Then, after estimating the model in equation (3.2), if $\hat{cc} > n/N$ a household is predicted to be constrained. One can then compare how many households that are predicted to be constrained using this rule are truly constrained in the data. The share of correctly predicted constrained households ($\hat{cc}_i > n/N$ & $cc_i = 1$) is 0.75, while the share of correctly predicted unconstrained households is ($\hat{cc}_i < n/N$ & $cc_i = 0$) is 0.7.

the CEX does not collect detailed portfolio data. However, while the CEX does not allow studying households' portfolio composition, it does allow constructing a measure of household net worth using information on liquid assets (balance of checking and savings accounts), household debt (consumer credits and mortgages), and the value of owned property, which accounts for the lion's share of households' illiquid wealth in the US.

With this information at hand, I use the estimated probability model from the SCF to create an index of credit constraints for the CEX by plugging the household observables from the CEX into the estimated model in equation (3.2) and computing

$$\hat{cc}_{i,t} = \frac{\exp(X_{CEX}^T \hat{\beta})}{1 + \exp(X_{CEX}^T \hat{\beta})}, \tag{3.3}$$

where $\hat{cc}_{i,t}$ denotes the predicted index of credit constraints for household i in period t, $\hat{\beta}$ collects the estimated parameters of the logit model (based on SCF data), and X_{CEX} collects the same observables as X in equation (3.2) but for the CEX instead of the SCF. Note that while the SCF and CEX survey different households, both surveys are representative of the US population.

Table 3.3 summarizes descriptive statistics for the main variables of interest in the CEX. In addition to presenting the statistics for all households (column 3), the table also splits households between the predicted constrained and unconstrained households. These groups are constructed using the predicted probability of credit constraints $\hat{cc}_{i,t}$ and a threshold rule, as discussed above. Specifically, a household is predicted to be constrained if $\hat{cc}_{i,t} > \tau_{CEX}$ and unconstrained otherwise. I set a threshold τ_{CEX} of 0.36 such that the share of predicted constrained households in the CEX matches the 27% share of truly constrained households in the SCF.[8]

The table illustrates that the predicted constrained and unconstrained households in the CEX differ along similar dimensions as the truly constrained and unconstrained in the SCF data. Most prominently, constrained households have much lower net worth, lower average income, and are on average younger than their unconstrained counterpart. The table also displays households' spending in durable and non-durable consumption in any given quarter. On average, the

[8] Figure C.3 in appendix C.3 compares the distribution of the predicted $\hat{cc}_{i,t}$ index from the CEX to its SCF analogous. By and large, both distributions follow a similar pattern.

spending in non-durable consumption is about 2.7 times larger than the expenditure in durables. Also, unconstrained households' overall consumption expenditures are about 30% higher than constrained households', which reflects their higher relative income stream and wealth.

To take a closer at the behavior of consumption, Table 3.4 presents descriptive statistics for both categories.[9] It turns out that durable consumption is much more volatile, with a 1.4 times larger standard deviation and 3.8 times larger coefficient of variation than non-durable consumption. This "lumpyness" of durable consumption has been documented in the literature (e.g., in Gelos et al., 2019). This high volatility becomes clearer when looking at the growth rates, which are one order of magnitude larger for durables. The 25th and 75th percentiles are close to -1.5 and 2, respectively, both for the quarter-on-quarter and the two-quarter growth rates, while the standard deviation is close to 3.5 in both cases.[10] It is important to keep these magnitudes in mind when analyzing the regression results of next section.

3.2.3.1 The Consumption Response to Monetary Policy

In order to estimate the consumption response to monetary policy, we still need a policy indicator measuring the monetary policy stance and exogenous variation in that indicator. Given that the period of analysis includes the years during which the federal funds rate was at its effective lower bound, in the baseline specification I measure the monetary policy stance using two-year Treasury yields, which remained essentially unconstrained throughout this period (see, e.g., Swanson and Williams, 2014). The empirical results are broadly robust to using one-year or five-year maturity Treasury yields.[11]

[9]Given that many households report zero durable consumption, the table splits the descriptive statistics for two cases: when considering all households, and when only considering those reporting positive durable consumption.

[10]Figure C.4 in appendix C.3 plots the distribution of the two-quarter growth rates for durable and non-durable consumption. It highlights that many households exhibit no variation in durable consumption, but when durable consumption does vary, the variation is large. By contrast, practically all households report quarterly variation in non-durable consumption, and the variation tends to be much smaller than that of durable consumption.

[11]Several papers have documented that exogenous changes in such aggregate policy indicators affect the consumption response of individual households via different channels, such as income effects (Cloyne et al., 2020), refinancing (Eichenbaum et al., 2018; Wong, 2019), and pass-through to mortgage rates of adjustable-rate mortgages (Di Maggio et al., 2017).

I obtain exogenous variation in the policy indicator using monetary policy shocks identified at high frequency. In the baseline specification I use the shocks computed by Nakamura and Steinsson (2018), which measure the change in a monetary policy indicator in a 30-minute window around scheduled FOMC announcements. The policy indicator is a composite measure of interest rates at different maturities spanning the first year of the term structure.[12] I add up these shocks to a quarterly frequency to match the frequency of the CEX consumption data.

Given that the CEX has a 4-quarter panel dimension, I focus on the short-term consumption response to monetary policy. This allows me to exploit the full heterogeneity of the data and estimate consumption responses at the household level.[13] I follow Gelos et al. (2019) and focus on the two-quarter ahead consumption response to a monetary policy shock. The idea behind this approach is to strike a balance between allowing enough time for consumption to respond to changes in interest rates and maximizing the number of available observations to estimate the effects, given the 4-quarter panel dimension of the data.[14]

To estimate the consumption response to exogenous changes in interest rates I estimate the following regression:

$$\ln\left(\frac{C_{i,t+1}}{C_{i,t-1}}\right) = \beta_0 + \beta_1 r_t + BZ_{i,t} + \lambda_{(t)} + u_{i,t}, \tag{3.4}$$

where $\ln(C_{i,t+1}/C_{i,t-1})$ measures the two-quarter log-difference in consumption for household i, r_t is the two-year Treasury yield instrumented with the contemporaneous value and two lags of the high-frequency monetary policy shocks, and $Z_{i,t}$ is a vector of household-specific controls including age, family size, income, and dummies for whether the household head has college education, is white,

[12] This composite measure is constructed as the first principle component of the unanticipated change over this 30-minute window in the following five interest rates: the federal funds rate immediately following the FOMC meeting, the expected federal funds rate immediately following the next FOMC meeting, and expected 3-month eurodollar interest rates at horizons of two, three and four quarters. This measure of the policy instrument is closely related to the "path factor" of Gürkaynak et al. (2005) and also captures the effects of forward guidance.

[13] An alternative to this approach is to aggregate the data into synthetic cohorts. This strategy allows estimating dynamic effects of monetary policy over longer horizons, but it implies losing the household-level granularity of the data. For examples of this approach, see Cloyne et al. (2020) and Gelos et al. (2019).

[14] A large empirical literature has documented, using both aggregate and micro data, that consumption responds sluggishly to changes in interest rates. See, e.g., Cloyne et al. (2020) and Ramey (2016).

and is married. The parameter of interest β_1 measures the log-change in consumption to an exogenous change in r_t. A negative and statistically significant value of β_1 indicates that consumption drops in response to an unexpected increase in interest rates.

To allow for heterogeneous consumption responses between constrained and unconstrained households, equation (3.4) becomes

$$\ln\left(\frac{C_{i,t+1}}{C_{i,t-1}}\right) = \beta_0 + \beta_1 r_t + \beta_2 \hat{cc}_{i,t} \cdot r_t + \beta_3 \hat{cc}_{i,t} + BZ_{i,t} + \lambda_{(t)} + u_{i,t}, \qquad (3.5)$$

where on top of the baseline specification, $\hat{cc}_{i,t}$ is the probability that household i is credit constrained. The parameter β_2 measures the incremental effects of the probability of being credit constrained on the consumption response to monetary policy. Equations (3.4) and (3.5) are estimated using an instrumental variable GMM estimator.[15]

Table 3.5 shows the results. Columns 1 and 2 show the response of durable and non-durable consumption for all households. As the first row shows, a 100 basis points increase in the two-year yield triggers a statistically significant 15% drop in durable consumption growth two quarters ahead. This translates into a 4% drop in durable consumption over two quarters.[16] On the other hand, the response of non-durable consumption is only 0.2 percentage points and not significant. As it will become clear below, these results mask a large heterogeneity in the responses across households depending on how likely they are to be credit constrained.

Columns 3 and 4 of Table 3.5 report the results for the regression in equation (3.5), where the consumption response is allowed to vary depending on whether households are likely credit constrained or not. Looking at durable consumption in column 3, first note that β_2 is positive and statistically significant, which means that households that are more likely to be credit constrained are significantly less responsive to monetary policy. The entries in the first row show the consumption response for fully unconstrained households –that is, when $\hat{cc}_{i,t} = 0$.

[15] To account for the additional uncertainty in equation (3.5) that arises from predicting $\hat{cc}_{i,t}$, standard errors are computed using a bootstrap procedure. Estimation details are provided in appendix C.3.1.

[16] To obtain this, recall from Table 3.4 that the mean two-quarter growth rate is 0.11. Hence, the percentage change in consumption in response to the shock is given by $\exp(\log(C_{t+1}/C_{t-1})) - 1 = \exp(0.11 - 0.15) - 1 = -0.04$. The corresponding figures for non-durable consumption can be obtained using the corresponding two-quarter mean growth rate of 0.01.

The estimates reveal an important degree of heterogeneity in the response of durable consumption across households. The drop in consumption growth for unconstrained households is more than 3 times larger than the response across all households, and it is more precisely estimated.[17] This translates into an average 32% drop in durable consumption over two quarters in response to the shock ($\exp(0.11 - 0.5) - 1 = -0.32$) for unconstrained households. The coefficient for non-durable consumption is also much larger in this case, although still statistically insignificant.

The regression results summarized in the table show the average effects of interest rate changes on consumption. In order to study the consumption response in greater detail, Figure 3.3 plots the marginal effects for different values of $\hat{cc}_{i,t}$. The figure illustrates that while durable consumption responds the most when households are fully unconstrained, the response gets smaller in absolute terms as the probability of being constrained increases, and it becomes statistically insignificant when the probability approaches 0.3. The figure also illustrates the higher uncertainty in the response of non-durable consumption, which remains insignificant for all values of $\hat{cc}_{i,t}$.

An alternative approach to studying the role of credit constraints for the consumption response is to classify households as constrained or unconstrained using a threshold approach instead of using the predicted index of credit constraints in the regressions. Using the threshold described previously to construct Table 3.3, where households are classified as constrained or unconstrained such that they match the respective shares in the SCF, one can estimate the regression

$$\ln\left(\frac{C_{i,t+1}}{C_{i,t-1}}\right) = \beta_0 + \beta_1 r_t + \beta_2 I_{\hat{cc}(i,t)} \cdot r_t + \beta_3 I_{\hat{cc}(i,t)} + BZ_{i,t} + \lambda_{(t)} + u_{i,t}, \tag{3.6}$$

where $I_{\hat{cc}(i,t)}$ is an indicator variable that takes the value of one if household i is predicted to be constrained in period t and zero otherwise. The remaining variables are the same as in equation (3.5). This formulation, while related to the one in equation (3.5), has a different interpretation. Here what matters is whether households are constrained or not, but not how close they are to hitting the constraint or how likely they are to be constrained.

[17] This increased precision comes despite a lower number of observations. The number of observations drops because not all households report the information necessary to compute the $\hat{cc}_{i,t}$ probability, such as data on liquid and illiquid assets, and debt.

The results of this specification are shown in columns 5 and 6 of Table 3.5. Under this specification, the asymmetry in the consumption response is even larger. β_2 is positive and statistically significant for durable and non-durable consumption, again implying that constrained households are less responsive to changes in the interest rate. The first row shows the change in the two-quarter consumption growth rate after a 100 basis points increase in the two-year rate for unconstrained households (when $I_{\hat{cc}(i,t)} = 0$). Column 5 shows that durable consumption growth drops by 0.53, which translates into a 34% drop in durable consumption over two quarters, and the parameter is more precisely estimated than in the previous formulation (column 3).

Column 6 shows that the drop in non-durable consumption turns significant and is also larger than in the previous specification, with the two-quarter growth rate dropping 0.068 after the shock. This translates into a 5% percent drop in non-durable consumption over two quarters ($\exp(0.01 - 0.068) - 1 = -0.05$). Overall, these results provide additional evidence consistent with the previous findings that households that are more likely to be credit constrained are less responsive to monetary policy.

The results described so far are robust to using either the one-year yield or the five-year yield to measure the monetary policy stance (see tables C.3 and C.4 in appendix C.3). The sign and significance patterns are preserved in both cases, and also the size of the point estimates remains very stable. The consumption responses are somewhat larger in absolute terms with the five-year yield.

The estimates of β_2 for durable and non-durable consumption are large enough to make the response of constrained households reverse, in the sense that the model predicts an increase in consumption for interest rate hikes instead of a smaller (in absolute terms) but negative –or zero– response for these households. One potential explanation for these results is that monetary policy shocks are not only a surprises about the path of interest rates, but also about the economic outlook, as proposed by Jarociński and Karadi (2020). For instance, an increase in interest rates could signal that the central bank is taking action to contain future inflation due to a better-than-expected economic outlook, which could boost economic activity and consumption. The next section explores this possibility.

3.2.3.2 Central Bank Information Effects

Two recent papers by Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2018) point to the importance of distinguishing between a "pure" monetary policy shock –an unexpected change in the policy rate– and the release of new information about the economic outlook by central banks that potentially occurs with a change in the policy stance. As discussed in Jarociński and Karadi (2020), a typical example of how disregarding these "central bank information shocks" can bias the identification of monetary policy shocks –and thus the responses of economic variables to those shocks– is the response of the stock market to a monetary easing. While standard economic models predict a stock market appreciation after an interest rate cut, it is common to observe stock market declines after such events. However, that is not necessarily a response to the monetary easing itself, but to the information about the economic outlook that the central bank is releasing with its action, such as slower growth prospects or increased economic risks.

To see whether this alternative definition of monetary policy shocks changes the results presented so far, I re-estimate regressions (3.4), (3.5), and (3.6) using the Jarociński-Karadi monetary policy shocks, which are cleansed from central bank information effects, instead of the Nakamura-Steinsson shocks to measure exogenous variation in the two-year rate. As before, I add up the shocks to quarterly frequency to conduct the estimations.

Before presenting the results, Figure 3.4 compares the two shock series. While they are relatively similar until the 2008 financial crisis, the Nakamura-Steinsson shocks tend to be larger during the crisis and smaller thereafter, highlighting the importance of central bank information effects during that period. However, at first glance it is not obvious that the consumption response should differ starkly when using one or the other series. In addition, Figure 3.5 plots the two-year yield and its predicted value from the first stage regressions of equations (3.4) –left panel– and (3.5) –right panel– for both shocks series. The figure shows that in both cases the predicted two-year yield from the first stage regressions is very similar for both series, which gives a first indication that estimating these regressions with either shock series should –at least qualitatively– yield similar results.

Turning to the results, Table 3.6 shows that overall the responses of durable and non-durable consumption are qualitatively similar to the ones of Table 3.5.

However, they are about twice as large in absolute terms. Column 3 shows that durable consumption of fully unconstrained households drops by a factor of close to 1 in response to a 100 basis points increase in the two-year rate, which implies a 58% drop over two quarters.[18] Also, β_2 is large and statistically significant, meaning that the drop in durable consumption of households that are more likely to be credit constrained is much smaller than that of unconstrained households. Column 4 shows that also the response of non-durable consumption is about twice as large as with the Nakamura-Steinsson shocks, and is now statistically significant. However, β_2 is still not significant, suggesting that on average there is still no large asymmetry between constrained and unconstrained households in the responses for non-durable consumption.

Figure 3.6 plots the responses of non-durable and durable consumption across the index of credit constraints. Note that despite the relatively large uncertainty around the responses, non-durable consumption now drops significantly for values of $\hat{cc}_{i,t}$ lower than 0.15, in contrasts to the results from the Nakamura-Steinsson shocks in Figure 3.3. As households turn more likely to be constrained, however, the response turns insignificant. On the other hand, the responses of durable consumption are much larger and more precisely estimated. They turn insignificant only for values of $\hat{cc}_{i,t}$ larger than 0.3.

Columns 5 and 6 of Table 3.6 show the results for the specification in equation (3.6). As before, the responses of both types of consumption are larger and more precisely estimated than with the Nakamura-Steinsson shocks. This is especially true for the growth rate of non-durable consumption, which drops by a significant 0.11 in this specification, implying a 10% drop in non-durable consumption over two quarters. However, the puzzle of the positive response of durable and non-durable consumption consumption for constrained households remains. This deserves attention and I leave a deeper exploration of this issue for further research.

3.2.4 Discussion and Outlook

The results presented so far suggest that the measure of credit constraints based on loan rejections discussed above carries relevant information to estimate house-

[18] Note that the Jarociński-Karadi shocks are available until 2016Q4, a slightly larger horizon than the Nakamura-Steinsson shocks. This could explain some of the difference in the size of the parameter estimates.

holds' consumption response to exogenous changes in interest rates. In fact, I document significant and quantitatively large heterogeneity in households' consumption responses depending on how likely they are to be credit constrained. There are, however, several issues that remain open for future research.

First, even after controlling for central bank information effects, households that have a very high probability of being constrained ($\hat{cc}_{i,t}$ close to one in equation (3.5)) or that are classified as constrained with the "threshold" method ($I_{\hat{cc}(i,t)}$ equal to one in equation (3.6)) show a *positive* relation between consumption and interest rates. This issue remains puzzling and deserves further analysis.

Second, while I document that households' consumption response to changes in the one-year, two-year, and five-year Treasury yields is characterized by strong and significant heterogeneity across the probability of being credit constrained, an interesting alternative is to study if this asymmetry remains for household-specific interest rates, such as individual mortgage rates. The CEX data contains some information on mortgage rates that can be used to explore this alternative.

Third, in order to study heterogeneity in the dynamic responses of consumption to monetary policy shocks over longer horizons, one alternative is to aggregate households along some relevant dimension, such as age or housing tenure status (Cloyne et al., 2020; Gelos et al., 2019). This would allow combining the measure of credit constraints developed here with longer synthetic panels, and methods such as local projections to estimate heterogeneous consumption responses to monetary policy shocks several quarters ahead. However, this comes at the cost of losing the granularity of household-level data, and preliminary experiments suggest that it becomes harder find enough variation and power in the data to identify significant heterogeneity in the responses. One alternative would be to rely on CEX historical data, that goes back to 1980, to increase the sample size and potentially resolve some of these issues.

I leave these issues as an open research agenda for the future and in the next sections of the chapter I analyse what theoretical mechanism is consistent with the empirical results discussed above.

3.3 Inspecting the Mechanism

In this section I study what theoretical mechanism is consistent with the empirical results discussed in the previous section. The papers by Auclert (2019) and

Kaplan et al. (2018) highlight the role of household heterogeneity and credit constraints to understand the transmission of monetary policy to the economy. The Heterogeneous Agent New Keynesian (HANK) model by Kaplan et al. (2018) constitutes a natural framework for studying the role of household heterogeneity and credit constraints for the transmission of monetary policy.[19]

I start the analysis from a simplified version of that model, namely a one-asset HANK model from Ahn et al. (2018), which is similar to the model by McKay et al. (2016). One important difference between the two-asset and one-asset HANK models is that the latter fails to simultaneously match the high wealth-to-output ratio and high average quarterly marginal propensity to consume (MPC) observed in the data. Under certain calibrations, however, the one-asset model closely replicates many important features of the two-asset model, such as households' average quarterly MPC and elasticity of consumption to changes in interest rates.[20] Since the focus of the analysis here is on the consumption response to changes in interest rates, the one-asset HANK model provides a simple, yet rich enough framework to analyze the question at hand. As I discuss in more detail in section 3.3.4, the analysis presented below should be understood as a first attempt to understand the empirical results. Several issues remain open, and I leave the task of analyzing this question with a richer and more complex and realistic model for future research.

3.3.1 The Model

3.3.1.1 Households

The economy is populated by a continuum of households of measure g_t that are heterogeneous in terms of their asset holdings and their idiosyncratic labor productivity. They derive utility from consumption c_t and disutility from supplying $l_t \in [0,1]$ hours of labor. Households maximize lifetime utility given by

$$\max_{c,l} \int_0^\infty e^{-\rho t} \left(\frac{c_t^{1-\gamma}}{1-\gamma} - \phi_0 \frac{l_t^{1+\frac{1}{\phi_1}}}{1+\frac{1}{\phi_1}} \right) dt \tag{3.7}$$

[19]Models with heterogeneous agents have become popular in macroeconomics (Kaplan and Violante, 2018). One key advantage of these models is that they offer a much more accurate representation of households' consumption behavior than representative agent models.

[20]See Kaplan et al. (2018), p. 735, for a detailed comparison between the one-asset and two-asset models.

where the future is discounted at rate $\rho \geq 0$, and the parameters γ, ϕ_0, and ϕ_1 measure the degree of risk aversion, disutility of working, and labor Frisch elasticity, respectively. Households can save in liquid assets a_t and earn a risk-free return r_t. Assets are liquid in the sense that there is no cost from increasing or decreasing the assets position. There are no alternative assets for households to save –in particular, there is no physical capital in this economy.

Households' assets evolve according to

$$da_t = (r_t \cdot a_t + (1-\tau_t)w_t \cdot z_t \cdot l_t + T_t + \Pi_t - c_t)dt \tag{3.8}$$

$$a_t \geq \underline{a}, \tag{3.9}$$

where τ_t is a tax on labor income, w_t are wages, z_t is labor productivity, T_t is a lump-sum governmental transfer and Π_t is the profit share. Productivity is assumed to have two states and follows an exogenous Poisson process with intensity $\lambda(z)$. Profits are distributed to households proportional to their income level.

3.3.1.2 Production

As typically assumed in New Keynesian models, there are intermediate and final goods producers, and prices are sticky. Final goods producers operate in a competitive market and aggregate a continuum of intermediate input goods indexed by $j \in [0,1]$

$$Y_t = \left(\int_0^1 y_{j,t}^{\frac{\varepsilon-1}{\varepsilon}} dj \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{3.10}$$

where ε is the elasticity of substitution between goods. From the cost minimization problem of the firm, demand for intermediate good j is given by

$$y_{j,t}(p_{j,t}) = \left(\frac{p_{j,t}}{P_t} \right)^{-\varepsilon} Y_t, \quad \text{with} \quad P_t = \left(\int_0^1 p_{j,t}^{1-\varepsilon} dj \right)^{\frac{1}{1-\varepsilon}}. \tag{3.11}$$

Intermediate goods producers produce according to the technology

$$y_{j,t} = n_{j,t}. \tag{3.12}$$

Firms hire labor in a competitive market at wage w and cost minimization implies that the marginal cost is common to all producers and given by

$$m_t = w_t. \tag{3.13}$$

These firms maximize their profits subject to price adjustment costs as in Rotemberg (1982)

$$\Theta_t \frac{\dot{p}_t}{p_t} = \frac{\theta}{2}\left(\frac{\dot{p}_t}{p_t}\right)^2 \tag{3.14}$$

where $\theta > 0$.

As shown in Lemma 1 of Kaplan et al. (2018), in this setting the aggregate inflation rate $\pi_t = \frac{\dot{P}_t}{P_t}$ is determined by the New Keynesian Phillips curve

$$\left(r_t - \frac{\dot{Y}_t}{Y_t}\right)\pi_t = \frac{\varepsilon}{\theta}(m_t - m^*) + \dot{\pi}_t, \quad \text{with} \quad m^* = \frac{\varepsilon - 1}{\varepsilon}. \tag{3.15}$$

3.3.1.3 Monetary Policy

The central bank follows the Taylor rule

$$i_t = \bar{r} + \phi_\pi \pi_t + \varepsilon_{mp,t} \tag{3.16}$$

$$d\varepsilon_{mp,t} = -\theta_{mp}\varepsilon_{mp,t} + \sigma_t dW_t, \tag{3.17}$$

where $\bar{r}$ is the steady state real risk-free rate, ϕ_π is the weight of inflation in the policy rule, and $\varepsilon_{mp,t}$ is a monetary policy shock. The last equation is a Ornstein-Uhlenbeck process where dW_t is the innovation to a standard Brownian motion, θ_{mp} is the rate of mean reversion, and σ scales the size of innovations. Finally, the Fisher equation implies $i_t = r_t + \pi_t$.

3.3.1.4 Government

The government runs a balanced budget each period and is subject to the budget constraint

$$\dot{B}_t^g + G_t + T_t = \tau_t \int w_t z l_t(a,z) g_t(a,z) da dz + r_t B_t^g. \tag{3.18}$$

Since the focus of the analysis is on the role of monetary policy, I consider the case where the supply of bonds is fixed, such that $\dot{B}_t^g = 0$ and $B_t^g = B^g_{steady\ state}$. Thus, the budget constraint can be re-written as

$$T_t = \tau_t \int w_t z l_t(a,z) g_t(a,z) da dz - G_t + r_t B_t^g. \tag{3.19}$$

Government spending G_t is not valued by households.

3.3.1.5 Equilibrium

An equilibrium in this economy is defined as paths for individual household and firm decisions $\{a_t, c_t, l_t, n_t\}_{t\geq 0}$, wages $\{w_t\}_{t\geq 0}$, returns on liquid assets $\{r_t\}_{t\geq 0}$, the inflation rate $\{\pi_t\}_{t\geq 0}$, fiscal variables $\{\tau_t, T_t, G_t, B_t\}_{t\geq 0}$, measures $\{g_t\}_{t\geq 0}$, and aggregate quantities such that, at every t: (i) households and firms maximize their objective functions taking as given equilibrium prices, taxes, and transfers; (ii) the sequence of distributions satisfies aggregate consistency conditions; (iii) the government budget constraint holds; and (iv) all markets clear.

The bond market clears when

$$B_t^g = \int a g_t(a,z) da dz. \tag{3.20}$$

The labor market clearing condition is

$$\int z l_t(a,z) g_t(a,z) da dz = N_t, \tag{3.21}$$

that is, when labor demand equals labor supply. Finally, by Walras' law the goods market clearing condition is

$$Y_t = C_t + G_t. \tag{3.22}$$

3.3.2 Calibration and Solution

The calibration of the model parameters follows the papers by Ahn et al. (2018) and Kaplan et al. (2018) and is considered standard in the literature. Table 3.7 provides the parameter values used and its source. The demand elasticity of intermediate goods $\varepsilon = 10$ implies a steady state marginal cost m^* of 0.9 and a markup $1/(\varepsilon - 1)$ of 11%. Combined with the value of the price adjustment costs θ of 100, the slope of the Phillips curve is $\varepsilon/\theta = 0.1$.

The income process has two states, low or high: $z_{i,t} \in \{0, 1\}$. Households switch from the high income to low income state with Poisson intensity $\lambda_{h,l} = 0.0376$, and from the low income to high income state with intensity $\lambda_{l,h} = 0.5$. If these states are interpreted as transitioning from employment to unemployment and vice versa, then these intensities imply that unemployed households spend on average two quarters looking for a job and the steady state unemployment rate is 7%. The borrowing limit is $\underline{a} = 0$, so that households cannot hold negative assets.[21] The model is discretized using a grid of 200 points: 100 asset grid points and two income states.[22]

The model is solved using the toolbox developed by Ahn et al. (2018),[23] which allows for an efficient and fast way to solve heterogeneous agent models with aggregate shocks. The solution method implies solving for the stationary equilibrium without aggregate shocks using a nonlinear global approximation. This gives a discretized representation of the stationary equilibrium and the distribution of agents over their individual state variables. Subsequently, a first order Taylor approximation of the discretized model with aggregate shocks is computed around the stationary equilibrium. Importantly, although the solution method relies on linearization techniques, it preserves relevant nonlinearities at the micro level. In the application that I analyze here, households are heterogeneous in terms of MPCs, which is crucial to understand their individual response to changes in interest rates.

3.3.3 The Consumption Response to Monetary Policy

One of the key insights of Kaplan et al. (2018) is that in order to understand how monetary policy works, it is necessary to distinguish between the direct and indirect effects of a monetary policy shock. The direct effect acts via the intertemporal substitution motive embedded in households' Euler equation. After an expansionary monetary policy shock, this effect implies that households will increase their consumption because saving becomes relatively less attractive. On

[21] One could alternatively consider $\underline{a} < 0$ or $\underline{a} > 0$ and the substance of the results would not change.

[22] As discussed in Ahn et al. (2018), this relatively small grid yields a highly accurate solution given the relatively small size and simplicity of the model. More complex models may require much larger grids.

[23] The codes and documentation are publicly available at `https://github.com/gregkaplan/phact`.

the other hand, the indirect or general equilibrium effect increases households' income stream and wealth and, as a consequence, their consumption.

Kaplan et al. (2018) show that in order to accurately assess the relative importance of these effects it is crucial to take household heterogeneity in terms of asset holdings and MPCs into account, and that one arrives at very different conclusions when using a representative agent instead of a HANK model.[24] Here I build on their methods to compute households' consumption response to a monetary policy shock across the asset distribution. I argue that the small consumption response of households with low asset holdings or close to the borrowing limit is consistent with the dampened consumption response to monetary policy by financially constrained households documented in the empirical part of the chapter.

I start by looking at the behavior of consumption and MPCs out of liquid assets across households in the stationary equilibrium. This conveys a first impression of how the consumption response of households may differ depending on their asset holdings. Figure 3.7 shows households' steady state MPCs[25] and consumption policy functions across the asset distribution. The figure shows that households' MPCs are large for low levels of assets, especially for the low income households. Because of their large MPCs, these households' consumption is very responsive to changes in their asset holdings. However, because they are close to –or at– their borrowing constraint, their *direct* response to changes in interest rates is typically muted.[26]

How do different groups of households respond to a monetary policy shock? Figure 3.8 shows the impulse response of consumption to a 1% expansionary monetary policy shock, across the distribution of assets.[27] The shock affects households differently depending on their asset holdings. In particular, it shifts mass from both tails of the distribution toward the center. Poorer households with low asset holdings climb in the asset distribution due to the economic boost, but de-

[24] They show that, while in a representative agent model most of the effect of monetary policy shocks happens via the direct effect, in HANK models about two thirds of the effect of a monetary policy shocks happens via general equilibrium income effects.

[25] MPCs are defined as the increase in consumption for a marginal increase in assets –the slope of the consumption policy functions.

[26] Auclert (2019) shows that the one-period *direct* or substitution effect in consumption to a change in the interest rate can be written as $-(1/\gamma_i) \times (1 - MPC_i)c_i$, where $(1/\gamma_i)$ is the intertemporal elasticity of substitution, a result generalized to a multi-period environment by Kaplan et al. (2018).

[27] Figure C.5 in appendix C.4 shows the aggregate responses for all variables.

spite their large MPCs, their response is smaller than that of households in the middle of the distribution. By contrast, households in the higher tail of the asset distribution are partly negatively affected by a drop the interest rate due to the drop in their asset returns. Hence, households that are around the middle of the distribution explain most of the consumption response. They have the strongest on-impact response, which then slowly converges to its equilibrium level. By contrast, after an initial increase, the consumption response of high and low asset households drops, because of the shift from both tails toward the center.

To get a closer look at the heterogeneous response of households across the wealth distribution, Figure 3.9 shows the difference between the on-impact response of households across the asset distribution and the aggregate on-impact response to a 1% monetary policy shock, both in percentage deviations from steady state. The blue circled line and orange crossed line decompose this difference by low and high income households. As anticipated already from Figure 3.8, households in both tails of the distribution respond less to monetary policy. Low income households in the lowest percentiles of the distribution respond about 0.05 percentage points (or 12%) less that the average consumption response, while high income households in the lowest percentiles respond 0.34 percentage points (or 80%) less than the average. This difference is due to the lower MPCs of high income households.

The yellow dashed-dotted and purple dashed lines show the increase in consumption exclusively as a result of the increase in wealth in response to the shock. Despite the fact that this effect is only meaningful for households in the first percentiles of the asset distribution –due to their high MPCs–, these households show a much lower than average consumption response. In other words, the small total response of these households despite a relatively large indirect effect indicates a small direct for these households.

These results provide a first exploration into the theoretical explanation for the empirical findings discussed above. Next, I discuss caveats and open issues for future research.

3.3.4 Discussion and Outlook

The stylized exercises in the previous section are meant to highlight how a simple HANK model can shed light on the mechanism behind the empirical results presented in the first part of the chapter –that financially constrained households are less responsive to monetary policy in the short-term. The model illustrates that households in the lower tail of the asset distribution, which resemble households that are more likely to be financially constrained in the data, are less responsive to monetary policy shocks because of their low direct sensitivity to interest rates.

However, because of their high MPCs, these households are also the most responsive in terms of the indirect effect of monetary policy. How are these two facts consistent with the empirical results? One potential explanation is that in reality, indirect effects take time to materialize. For instance, using administrative tax data for Norway, Holm et al. (2020) find that these income and wealth effects take at least one year to materialize. Hence, the empirical results are consistent with the theory that financially constrained households have a low direct sensitivity to interest rates, and that the (potentially large) indirect effects happen with a lag.

At this point it is worth emphasising that the theoretical exercises discussed here are a first and preliminary attempt to reconcile the empirical results with economic theory, and do not provide the full picture along several dimensions that I leave for future research. First, the model calibration is overly simple and does not accurately resemble key moments of US data. For instance, the calibration features too few financially constrained households. Second, the solution method, while tractable and fast, does not allow for investigating some relevant nonlinearities in the transmission of monetary policy across households. Third, the model is not rich enough to study interesting dimensions of the heterogeneous response of consumption to monetary policy, such as the role of liquid and illiquid assets.

Concrete paths for future research include using the nonlinear solution of the model to compute the direct and indirect elasticity of consumption to a monetary policy shock, as in Kaplan et al. (2018). This would allow for a detailed analysis of the circumstances under which the balance between the two effects replicate the empirical findings.

Another interesting alternative would be to consider a model where households differ in terms of default risk, in the spirit of the model by Ottonello and Winberry (2018), who analyze the firm side. In that model, an interest rate cut lowers the cost of borrowing and expands consumption possibilities for all households. However, households with low default risk are more responsive because they can adjust their loans proportionally more than high risk households. Thus, the model implies that financially constrained (high risk) households are less responsive to a given change in the interest rate, as documented in section 3.2. Moreover, such a model would potentially make the connection between the empirical and theoretical parts of this chapter stronger, since the measure of credit score in the model could be interpreted as the counterpart for the empirical index of credit constraints in the data.

Finally, one way to potentially model the delayed indirect effects of monetary policy mentioned above is to consider an environment allowing for hump-shaped responses to monetary shocks. As discussed in Auclert et al. (2020), HANK models so far, while able to match key micro moments in the data, feature an aggregate impulse response to monetary policy that peaks on impact, which is at odds with the aggregate empirical evidence. By introducing "sticky expectations" –a sluggishness in the adjustment of households' expectations of aggregate variables– they develop a HANK framework able to simultaneously match "macro humps" and "micro jumps". This is a promising avenue to study the interaction between direct and indirect effects of monetary policy across households with more realism.

3.4 Conclusion

In this chapter, I study the role of credit constraints measured as loan rejections for the transmission of monetary policy to household consumption in the US economy. Using SCF data, I estimate a probability model of the determinants of credit constraints. Combining CEX data and an index of credit constraints constructed with the model, I estimate the consumption response to monetary policy shocks across constrained and unconstrained households. I find large and statistically significant heterogeneity in the consumption responses, with constrained households being significantly less responsive. Specifically, the consumption response of unconstrained households to a monetary policy shock is between two to three times larger than the average response across all households.

These results are consistent with a HANK model where financially constrained households have a low direct sensitivity to interest rates via intertemporal substitution effects, if general equilibrium income and wealth effects take time to materialize.

3.5 Tables

Table 3.1: SCF 1995-2016 descriptive statistics

	Constrained Mean (median)	Unconstrained Mean (median)	All Mean (median)
Income	39,060 (29,045)	56,535 (30,207)	51,848 (29,885)
Net worth	93,822 (11,080)	369,997 (105,894)	295,298 (67,120)
Liq. assets	10,254 (171)	85,926 (4,030)	65,616 (1,824)
Illiq. assets	84,083 (9,600)	285,344 (92,318)	230,938 (60,000)
Debt	49,799 (1,964)	66,488 (3,021)	62,012 (2,562)
Mortgage debt	101,536 (79,285)	110,622 (81,457)	108,396 (81,183)
Married	0.42 (No)	0.53 (Yes)	0.50 (Yes)
White	0.61 (Yes)	0.77 (Yes)	0.73 (Yes)
Male	0.69 (Yes)	0.73 (Yes)	0.72 (Yes)
Family size	2.71 (2)	2.29 (2)	2.40 (2)
College education	0.46 (No)	0.48 (No)	0.48 (No)
Age	41 (40)	53 (52)	50 (48)
Obs.	10,587	28,882	39,469

Notes: Net worth is defined as the sum of liquid and illiquid assets. Liquid assets include checking and savings accounts, mutual funds, bonds, stocks, and cash or call money accounts net of revolving credit card debt. Illiquid assets include retirement and pension accounts, certificates of deposits, saving bonds, life insurance accounts, and owned property net of mortgage debt. Variables Married, White, Male, and College education are dummies indicating 1 ("Yes") or 0 ("No") for each category. All these categories, as well as age, refer to the household head. Income and financial variables are in constant 2001Q1 prices.

Table 3.2: Logit regression results and implied probabilities at sample means

Variable	β	dy/dx
Income	-0.146	0.002
	(0.124)	(0.003)
Income^2	0.002	
	(0.007)	
Net worth	0.376***	-0.023***
	(0.039)	(0.001)
Net worth^2	-0.022***	
	(0.001)	
Income*Net worth	-0.014***	
	(0.004)	
Neg. Net worth	0.242***	0.036***
	(0.086)	(0.013)
Age	-0.003	-0.002***
	(0.011)	(0.000)
Age^2	-0.001***	
	(0.000)	
Age*Income	0.006***	
	(0.001)	
Age*Net worth	0.000	
	(0.000)	
Debt	0.032***	0.005***
	(0.005)	(0.001)
Marital status	-0.313***	-0.047***
	(0.039)	(0.006)
Race	-0.294***	-0.045***
	(0.030)	(0.005)
Sex	-0.036	-0.005
	(0.038)	(0.006)
Family size	0.143***	0.021***
	(0.011)	(0.002)
Outright owner	-0.052	-0.008
	(0.064)	(0.009)
Renter	0.384***	0.058***
	(0.048)	(0.007)
College education	0.148***	0.022***
	(0.029)	(0.004)
Unemployed	0.173***	0.026***
	(0.059)	(0.009)
Positive savings	-0.578***	-0.090***
	(0.035)	(0.006)
Obs.	39,469	
Pseudo-R^2	0.183	

Notes: Regression results for pooled waves of the SCF, from 1995 to 2016. Income, net worth and debt are in logs. Pseudo-R^2 refers to McFadden's, defined as $R^2_{McF} = 1 - LM_{full}/LM_{intercept}$. The third column reports the partial derivatives (marginal effects) evaluated at the sample means. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 3.3: CEX 1994-2017 descriptive statistics

	Constrained Mean (median)	Unconstrained Mean (median)	All Mean (median)
Income	33,605 (27,348)	50,429 (38,995)	45,956 (34,859)
Durable cons.	1,454 (149)	1,803 (215)	1,717 (196)
Non-durable cons.	3,796 (3,264)	4,973 (4,129)	4,660 (3,855)
Net worth	15,787 (2,335)	201,557 (123,516)	169,727 (94,232)
Debt	50,266 (9,348)	68,490 (41,560)	62,908 (29,168)
Mortgage debt	102,737 (80,168)	99,256 (76,648)	99,701 (77,170)
Married	0.39 (No)	0.59 (Yes)	0.54 (Yes)
White	0.70 (Yes)	0.89 (Yes)	0.84 (Yes)
Male	0.44 (No)	0.52 (Yes)	0.50 (Yes)
Family size	3 (3)	2 (2)	3 (2)
College education	0.58 (Yes)	0.59 (Yes)	1 (Yes)
Age	36 (36)	55 (55)	50 (49)
Obs.	70,273	182,127	252,400

Notes: Net worth is defined as the sum of liquid and illiquid assets. Liquid assets include checking and savings accounts. Illiquid assets include owned property net of mortgage debt. Variables Married, White, Male, and College education are dummies indicating 1 ("Yes") or 0 ("No") for each category. All these categories, as well as age, refer to the household head. Income, consumption, and financial variables are in constant 2001Q1 prices.

Table 3.4: Real consumption descriptive statistics

	Percentiles					
	p25	p50	p75	Mean	Std.	Obs.
Consumption						
Non-durable	2,543	3,870	5,772	4,693	3,843	397,212
Durable (all households)	0	25	253	991	4,236	397,212
Durable (non-zero only)	60	197	729	1,769	5,536	223,680
Quarter-on-quarter growth rate						
Non-durable	-0.17	0.01	0.18	0.01	0.36	297,909
Durable	-1.46	0.00	1.88	0.12	3.54	297,909
Two-quarter growth rate						
Non-durable	-0.20	0.01	0.22	0.01	0.40	198,606
Durable	-1.56	0.00	2.01	0.11	3.61	198,606

Notes: Descriptive statistics for CEX consumption data from 1996 to 2017. The "non-zero only" category reports statistics when only households that report non-zero durable consumption are considered. Quarter-on-quarter and Two-quarter growth rates defined as $\log(C_{i,t}/C_{i,t-1})$ and $\log(C_{i,t+1}/C_{i,t-1})$, respectively. Consumption variables are in constant 2001Q1 prices.

Table 3.5: Consumption response to the two-year rate: Nakamura-Steinsson shocks

Variable	(1) Dur	(2) Non-dur	(3) Dur	(4) Non-dur	(5) Dur	(6) Non-dur
r_t	-0.148**	-0.002	-0.497***	-0.026	-0.534***	-0.068***
	(0.063)	(0.007)	(0.185)	(0.025)	(0.136)	(0.020)
Age	0.004***	0.000***	-0.000	-0.001***	0.001	-0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
College education	0.028	0.010***	-0.007	0.011***	-0.031	0.005
	(0.020)	(0.002)	(0.028)	(0.003)	(0.032)	(0.004)
Race	0.120***	0.009***	0.072**	0.000	0.105***	0.008
	(0.025)	(0.003)	(0.032)	(0.004)	(0.036)	(0.005)
Marital	0.109***	0.008***	0.029	-0.003	0.064*	0.004
	(0.022)	(0.003)	(0.032)	(0.004)	(0.033)	(0.004)
Family size	0.020**	-0.001	0.047***	0.002**	0.035***	-0.000
	(0.008)	(0.001)	(0.010)	(0.001)	(0.011)	(0.001)
Income	-0.006	-0.004***	-0.001	-0.005***	0.007	-0.003**
	(0.004)	(0.001)	(0.007)	(0.001)	(0.008)	(0.001)
$\hat{cc} \cdot r_t$			1.379**	0.120		
			(0.617)	(0.083)		
$\hat{cc}$			-4.853***	-0.485**		
			(1.814)	(0.244)		
$I_{\hat{cc}} \cdot r_t$					1.339***	0.242***
					(0.362)	(0.056)
$I_{\hat{cc}}$					-4.209***	-0.750***
					(1.096)	(0.169)
Obs.	172,159	172,159	109,833	109,833	109,833	109,833

Notes: Regression results for CEX data from 1996Q1 to 2014Q1. The dependent variable is the two-quarter ahead consumption growth rate. r_t is the two-year rate instrumented with the Nakamura-Steinsson monetary policy shocks. Variables College education (yes or no), race (white or non-white), marital (married or not married) are dummies. Income is in logs. Standard errors are clustered by household. The standard errors for the regressions including $\hat{cc}$ or $I_{\hat{cc}}$ are bootstrapped. All regressions include year-quarter fixed effects. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 3.6: Consumption response to the two-year rate: Jarociński-Karadi shocks

Variable	(1) Dur	(2) Non-dur	(3) Dur	(4) Non-dur	(5) Dur	(6) Non-dur
r_t	-0.280**	-0.042***	-0.986***	-0.054*	-0.997***	-0.114***
	(0.124)	(0.014)	(0.246)	(0.030)	(0.215)	(0.027)
Age	0.004***	0.000***	0.000	-0.001***	0.001	-0.000**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
College education	0.031*	0.010***	-0.025	0.010***	-0.059*	0.001
	(0.019)	(0.002)	(0.027)	(0.003)	(0.031)	(0.004)
Race	0.084***	0.007**	0.040	-0.002	0.070*	0.004
	(0.024)	(0.003)	(0.033)	(0.004)	(0.037)	(0.005)
Marital	0.116***	0.008***	0.014	-0.001	0.052	0.004
	(0.021)	(0.002)	(0.033)	(0.004)	(0.035)	(0.004)
Family size	0.011	-0.001	0.034***	0.002	0.019	-0.001
	(0.008)	(0.001)	(0.011)	(0.001)	(0.012)	(0.002)
Income	-0.005	-0.004***	0.006	-0.005***	0.017**	-0.002*
	(0.004)	(0.001)	(0.007)	(0.001)	(0.008)	(0.001)
$\hat{cc} \cdot r_t$			2.332***	0.115		
			(0.644)	(0.085)		
$\hat{cc}$			-7.031***	-0.438*		
			(1.896)	(0.251)		
$I_{\hat{cc}} \cdot r_t$					1.947***	0.274***
					(0.396)	(0.059)
$I_{\hat{cc}}$					-5.578***	-0.779***
					(1.199)	(0.179)
Obs.	192,887	192,887	123,034	123,034	123,034	123,034

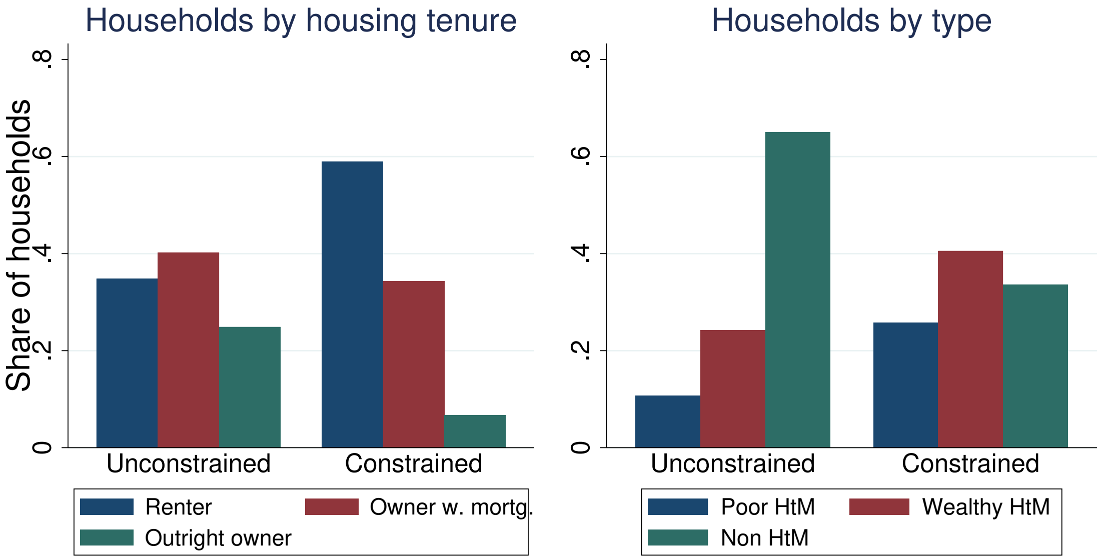
Notes: Regression results for CEX data from 1996Q1 to 2016Q4. The dependent variable is the two-quarter ahead consumption growth rate. r_t is the two-year rate instrumented with the Jarociński-Karadi monetary policy shocks. Variables College education (yes or no), race (white or non-white), marital (married or not married) are dummies. Income is in logs. Standard errors are clustered by household. The standard errors for the regressions including $\hat{cc}$ or $I_{\hat{cc}}$ are bootstrapped. All regressions include year-quarter fixed effects. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 3.7: Calibrated parameters

	Description	Value	Source/target
Preferences			
$1/\gamma$	Intertemporal elasticity of subst.	1	Kaplan et al. (2018)
$1/\phi_1$	Frisch elasticity of labor supply	1	Kaplan et al. (2018)
ϕ_2	Labor effort	3	Hours worked $= 1/3$
ρ	Discount rate (annualized)	2.1%	$\bar{r} = 2\%$ (annualized)
Production			
ε	Demand elasticity	10	Kaplan et al. (2018)
θ	Price adjustment cost	100	Kaplan et al. (2018)
Government			
τ	Proportional labor tax	0.2	Ahn et al. (2018)
T	Lump-sum transfer as $\%$ of GDP	0.06	Ahn et al. (2018)
Monetary policy			
ϕ_π	Taylor rule coefficient	1.25	Kaplan et al. (2018)
$\bar{r}$	Steady state real liquid return	2%	Kaplan et al. (2018)

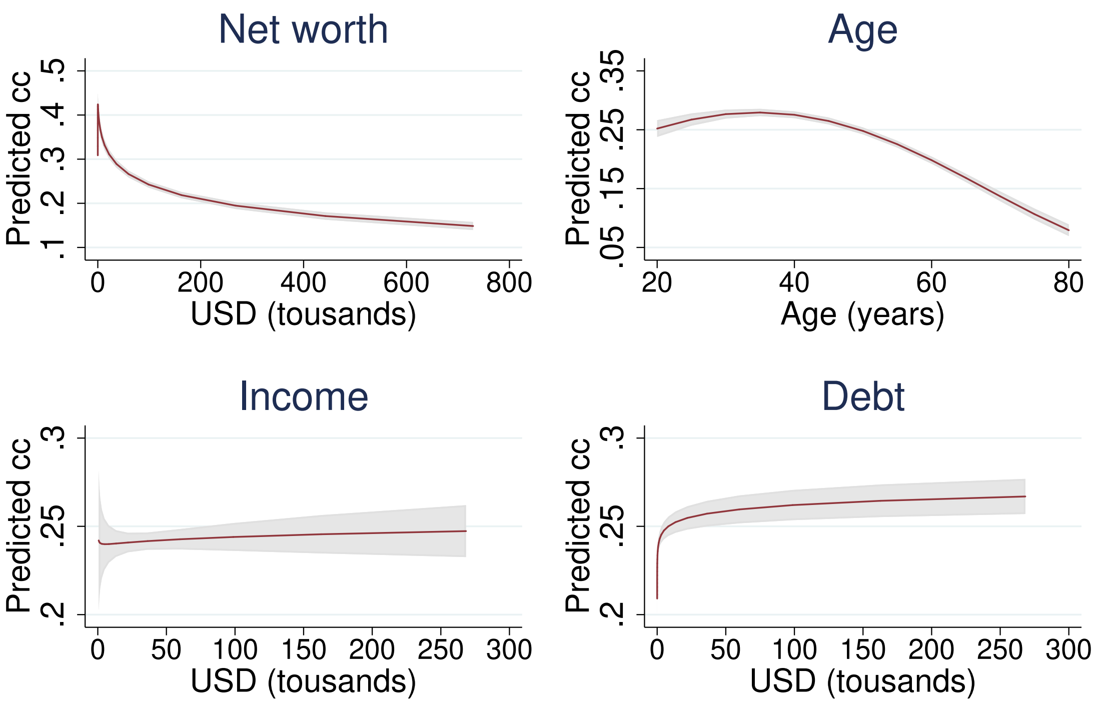
3.6 Figures

Figure 3.1: Households by housing tenure and Hand-to-Mouth type



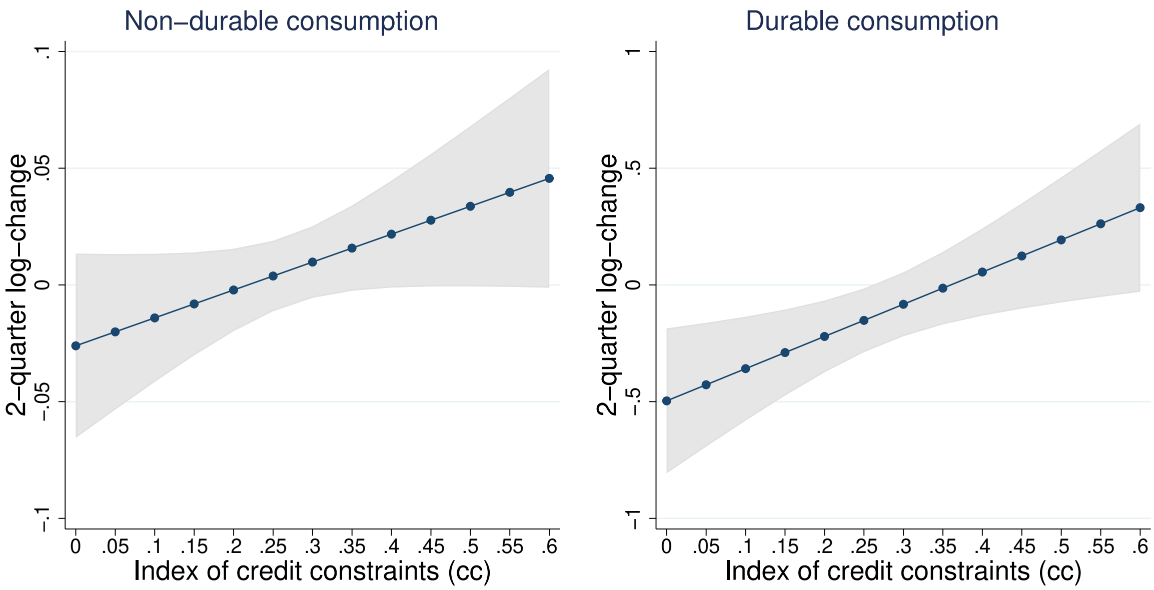
Notes: Data from SCF survey waves from 1995 to 2016. Hand-to-Mouth (HtM) types computed as in Kaplan and Violante (2014). Poor HtM: households with negative or zero illiquid wealth and liquid wealth lower than half their monthly labor income. Wealthy HtM: households with positive illiquid wealth and liquid wealth lower than half their monthly labor income. Non HtM: households that are neither poor HtM nor wealthy HtM.

Figure 3.2: Predicted probability of credit constraints across variables



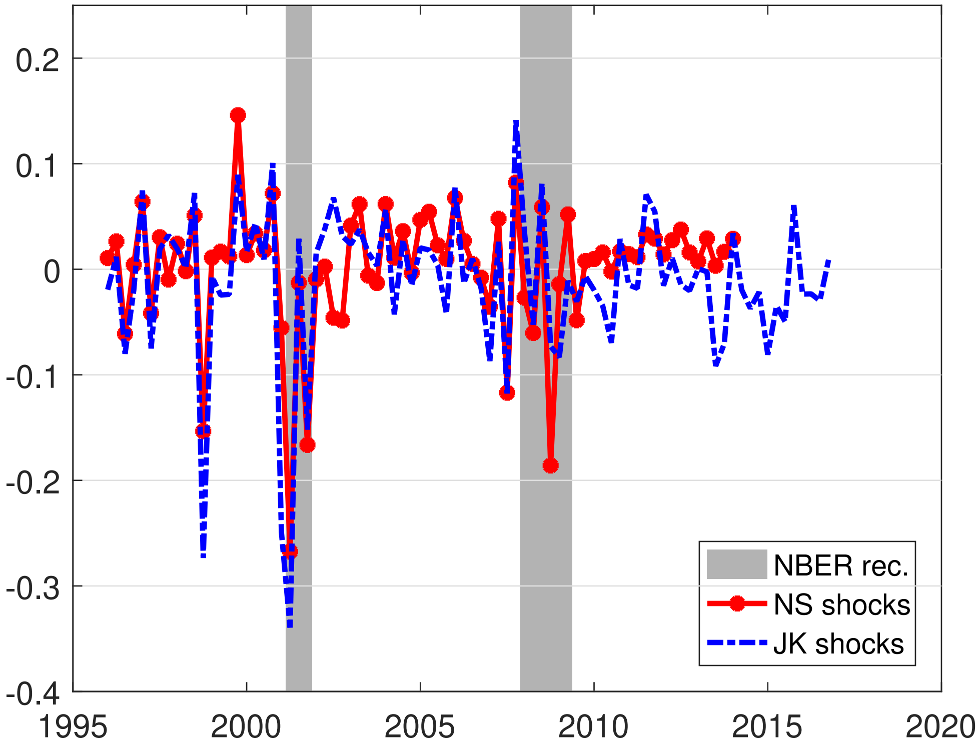
Notes: Predicted probabilities based on the estimated model in equation (3.2). Each plot shows the predicted probability across one variable, with all remaining variables at their sample means. Shaded areas depict 95% confidence intervals.

Figure 3.3: Consumption response to a 1% increase in the two-year yield across $\hat{cc}_{i,t}$: Nakamura-Steinsson shocks



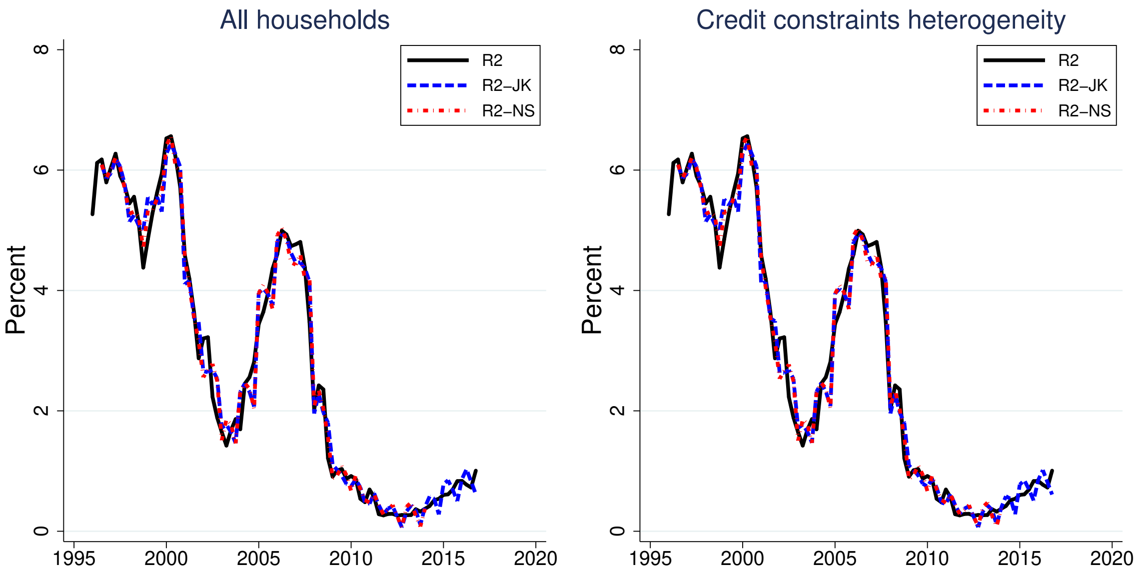
Notes: Dependent variable is the two-quarter log-change in consumption. Two-year yield instrumented with the Nakamura-Steinsson monetary policy shocks. Shaded areas depict 90% confidence intervals.

Figure 3.4: Monetary policy shocks: Nakamura-Steinsson & Jarociński-Karadi



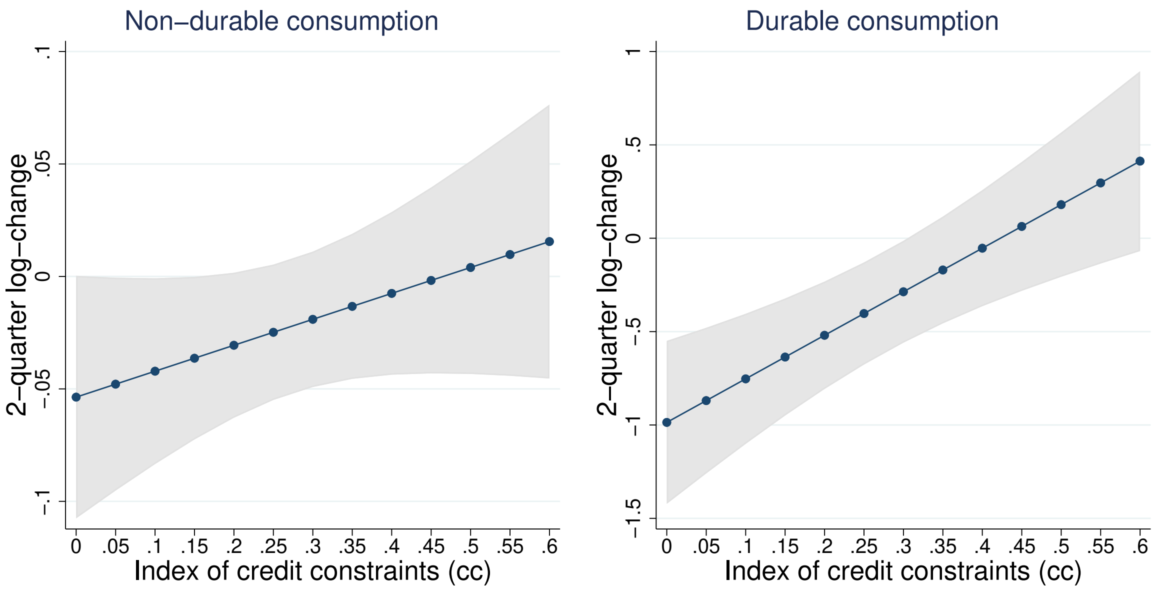
Notes: Monetary policy shocks computed by Nakamura and Steinsson (2018) in the red circled line and Jarociński and Karadi (2020) in the blue dashed line. Grey shaded areas indicate NBER recessions.

Figure 3.5: Two-year Treasury yield: data and predicted values from first-stage regressions



Notes: Two-year Treasury yield (black solid line) and predicted two-year yield from the first-stage regressions from the instrumental variable estimation using the Nakamura and Steinsson (2018) shocks (red dash-dotted line) and the Jarociński and Karadi (2020) shocks (blue dashed) as instruments. The left panel shows the first-stage regression results for regression (3.4), and the right panel shows the corresponding results for regression (3.5).

Figure 3.6: Consumption response to a 1% monetary policy shock across $\hat{cc}_{i,t}$: Jarociński-Karadi shocks



Notes: Dependent variable is the two-quarter log-change in consumption. Two-year yield instrumented with the Jarociński-Karadi monetary policy shocks. Shaded areas depict 90% confidence intervals.

Figure 3.7: MPCs and consumption policy functions across assets

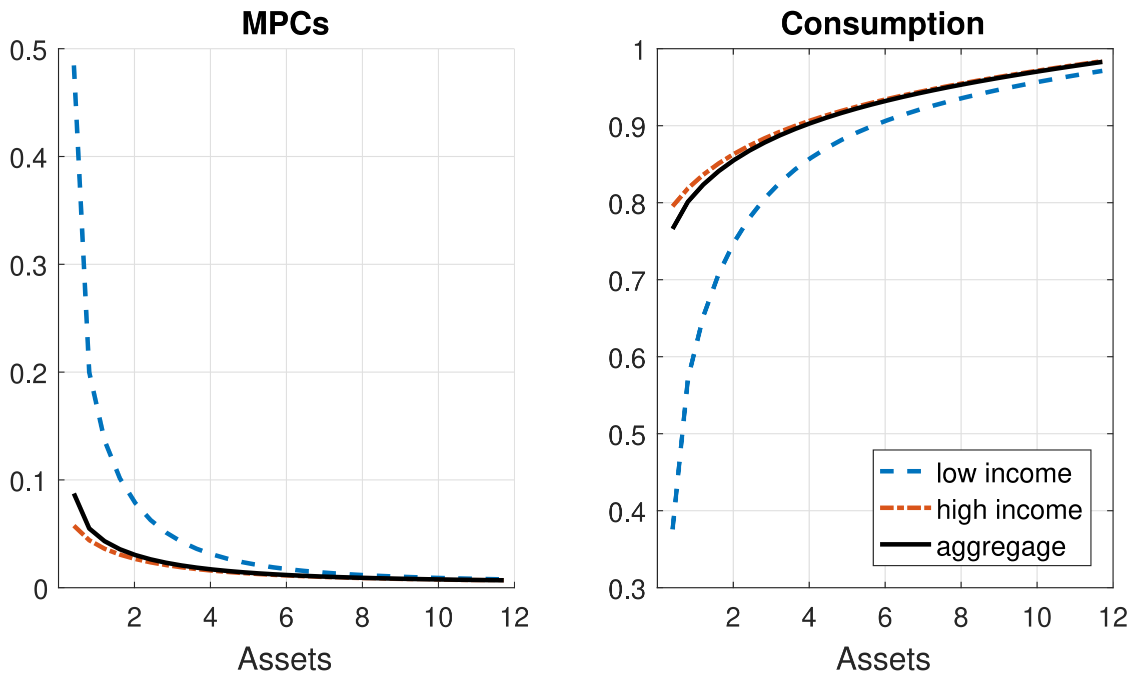
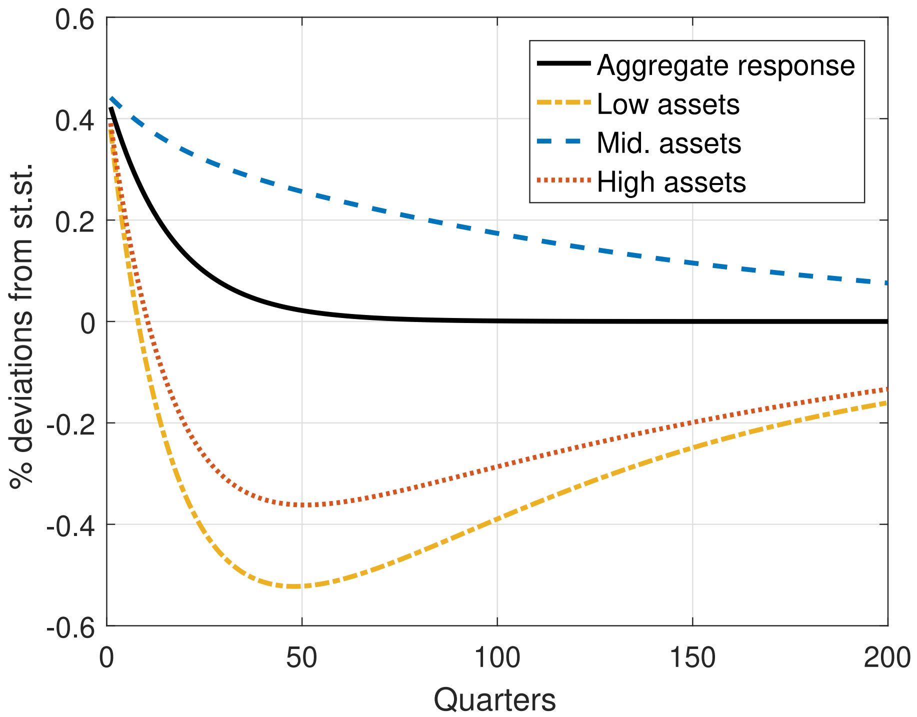
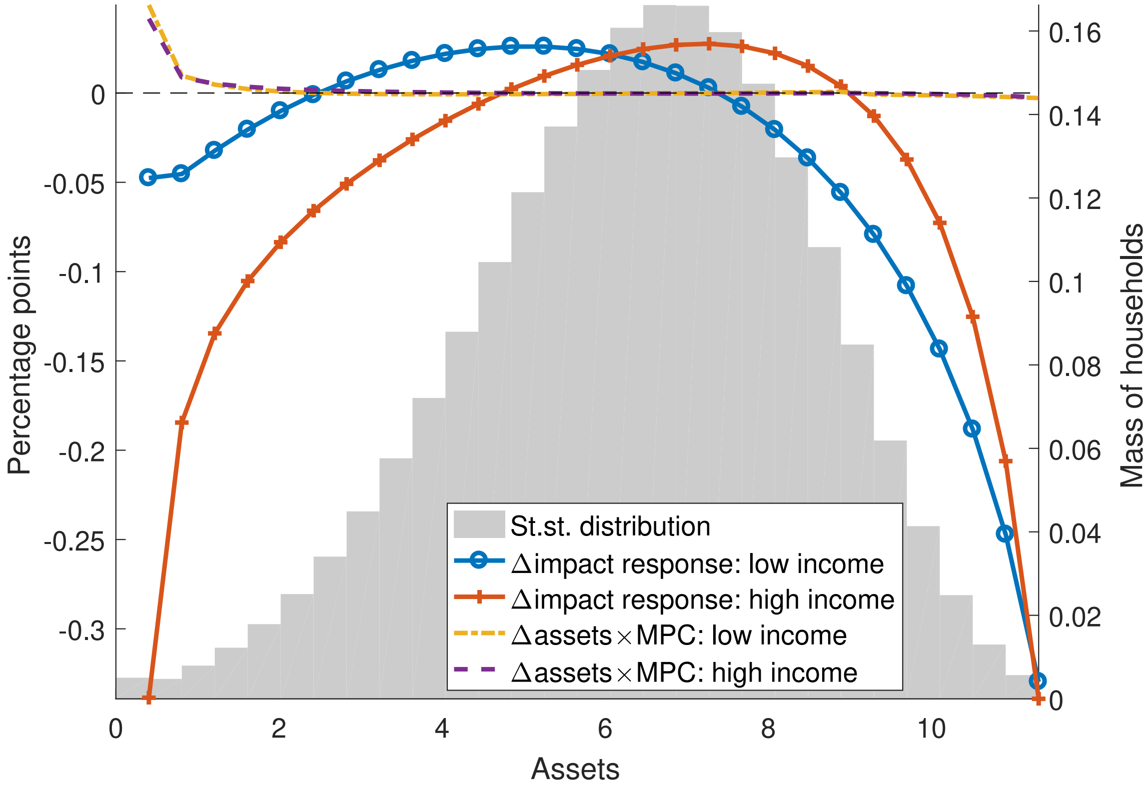


Figure 3.8: Consumption response to a 1% monetary policy shock



Notes: Asset groups (low-middle-high) stand for the lowest, middle, and highest thirds of the asset distribution, respectively. The plot reports the average response for each group and the aggregate response of the economy (black solid line), as percentage deviations from the respective steady states

Figure 3.9: Impact consumption response to a 1% monetary policy shock: difference between responses across asset distribution and aggregate response



Notes: The circled and crossed lines show the difference in the on-impact response for specific bins of the asset distribution and the aggregate consumption response. The yellow and purple lines show the change in assets triggered by the shock times the MPCs.

A Appendix to Chapter 1

A.1 Data

- GDP: Gross domestic product (FRED code: GDP), divided by the GDP deflator (FRED code: GDPDEF) and by the total population (FRED code: POPTOTUSA647NWDB), transformed into log-first differences minus the sample mean. Source: BEA.

- Consumption: Personal consumption expenditures of services (FRED code: PCESV) and nondurable goods (FRED code: PCND), divided by the GDP deflator and by the total population, transformed into log-first differences minus the sample mean. Source: BEA.

- Investment: Gross private domestic investment (FRED code: GPDI) and consumption expenditures of durable goods (FRED code: PCDG) divided by the GDP deflator and by the total population, transformed into log-first differences minus the sample mean. Source: BEA.

- Real wage: Nonfarm business sector compensation per hour (FRED code: COMPNFB), divided by the GDP deflator, transformed into log-first differences minus the sample mean. Source: US Bureau of Labor Statistics.

- Hours worked: Nonfarm business sector hours of all persons (FRED code: HOANBS), divided by the total population, transformed to log-levels minus the sample mean. Source: US Bureau of Labor Statistics.

- Relative price of investment goods: Relative price of investment goods (FRED code: PIRIC), transformed into log-first differences minus the sample mean. Source: DiCecio (2009).

- Inflation: Implicit price deflator for GDP, percent change from preceding period, annualized percent divided by 400. (FRED code: A712RI1Q225SBEA). Source: BEA.

- Nominal interest rate: Effective Federal Funds Rate (FRED code: FEDFUNDS), converted to quarterly by taking monthly averages, annualized percent divided by 400. Source: Board of Governors of the Federal Reserve System.

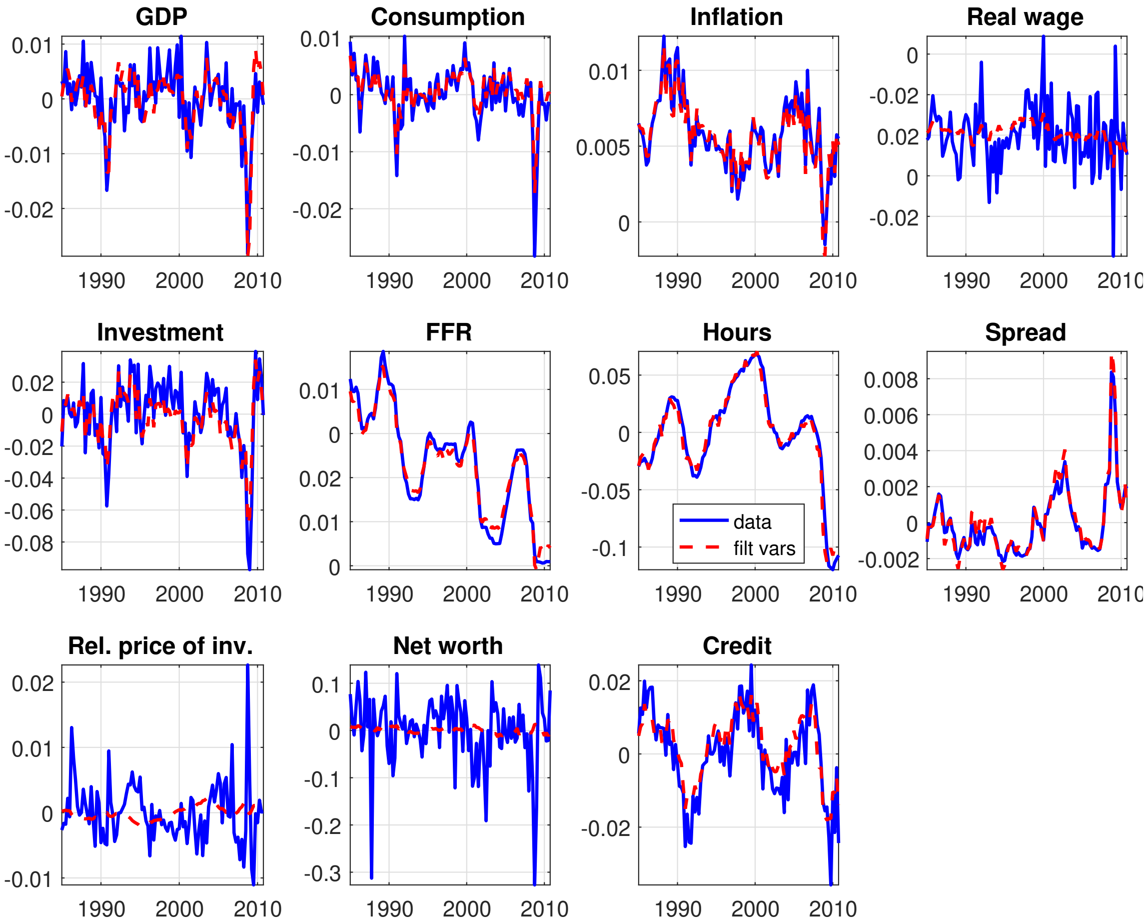
- Spread: Moody's seasoned Baa corporate bond yield relative to yield on 10-Year Treasury at constant maturity (FRED code: BAA10YM), converted to quarterly by taking monthly averages, annualized percent divided by 400 minus the sample mean. Source: Federal Reserve Bank of St. Louis.

- Net worth: Wilshire 5000 Total Market Full Cap Index (FRED code: WILL-5000INDFC), divided by the total population, transformed into log-first differences minus the sample mean. Source: Wilshire Associates.

- Firm credit: Nonfinancial business, debt securities and loans, liability, divided by the GDP deflator, divided by the total population, transformed into log-first differences minus the sample mean. Source: Financial Accounts of the United States - Z1/FA14

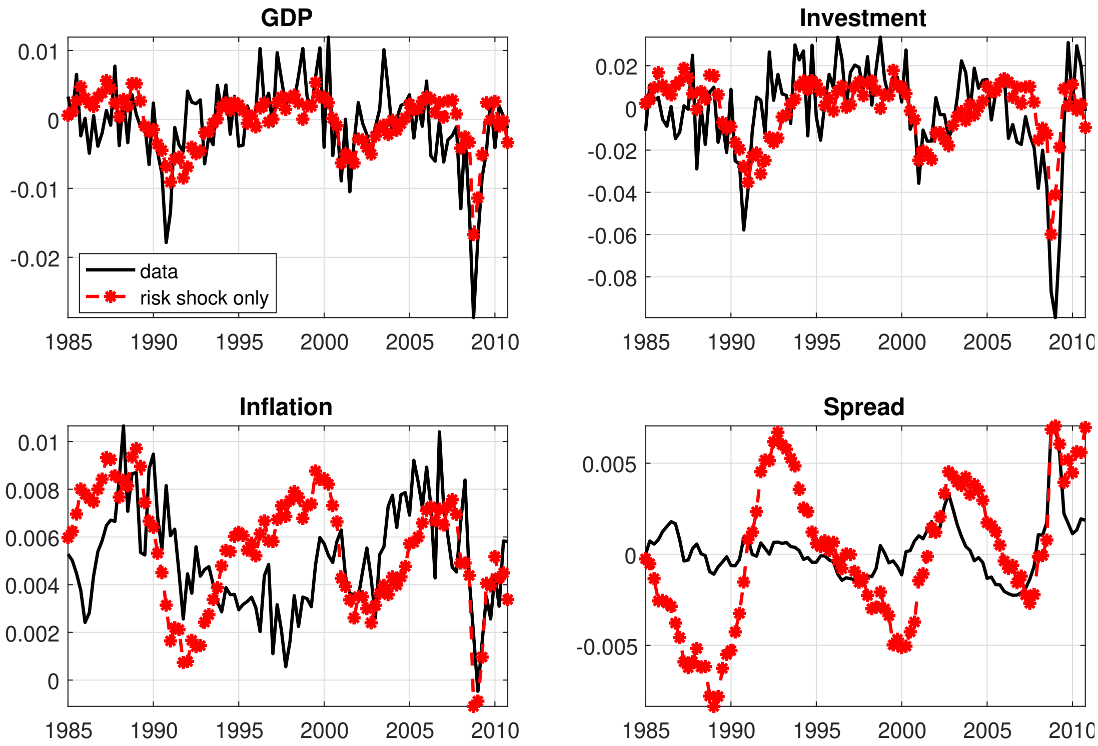
A.2 Additional Figures

Figure A.1: One-step-ahead model forecasts and data



Notes: The blue (solid) line shows the data and the red (dashed) line shows the one-step-ahead forecasts of the DSGE model.

Figure A.2: Data and the Risk Shock



The black (solid) line shows the data and the red (starred) line shows the smoothed series for each variable when only feeding the anticipated and unanticipated components of the risk shock to the model.

Figure A.3: Leverage-spread schedule: second- and third-order

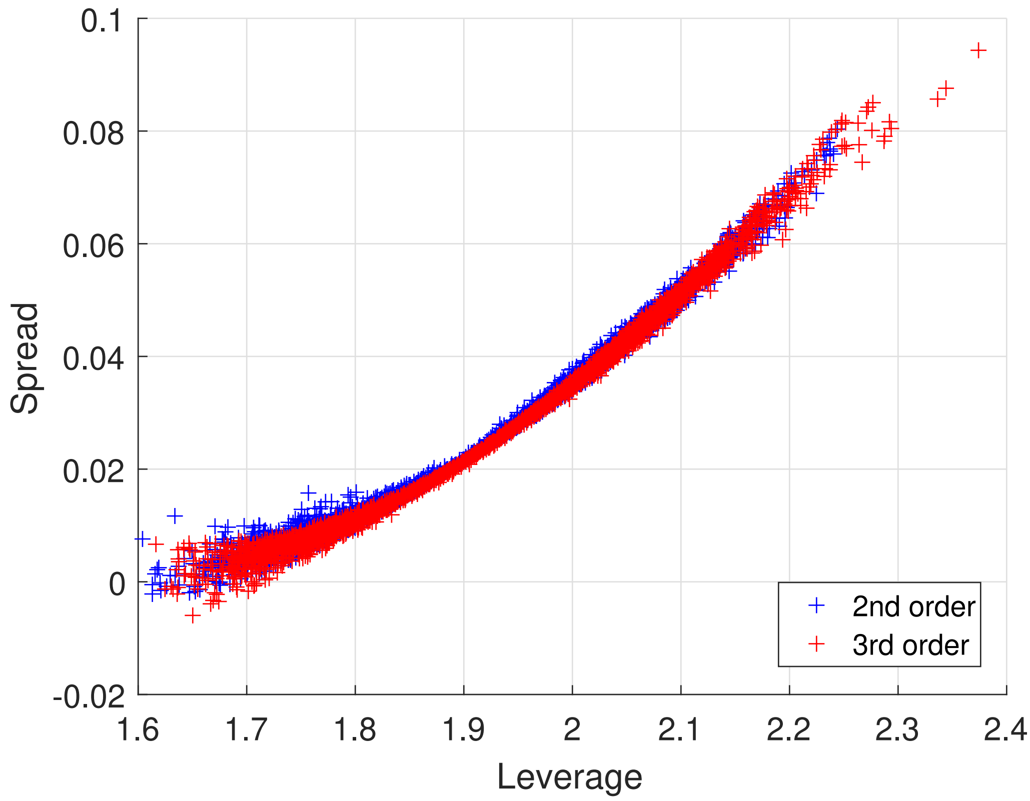
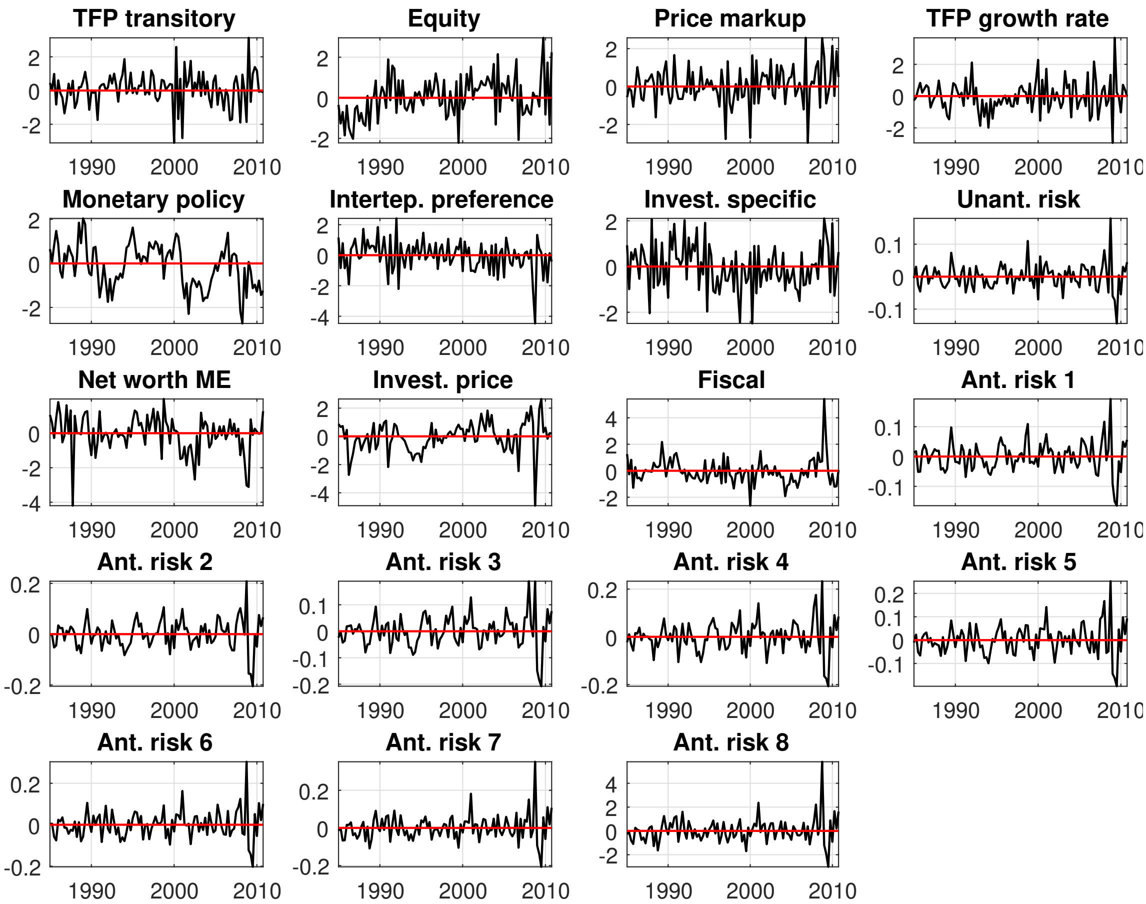
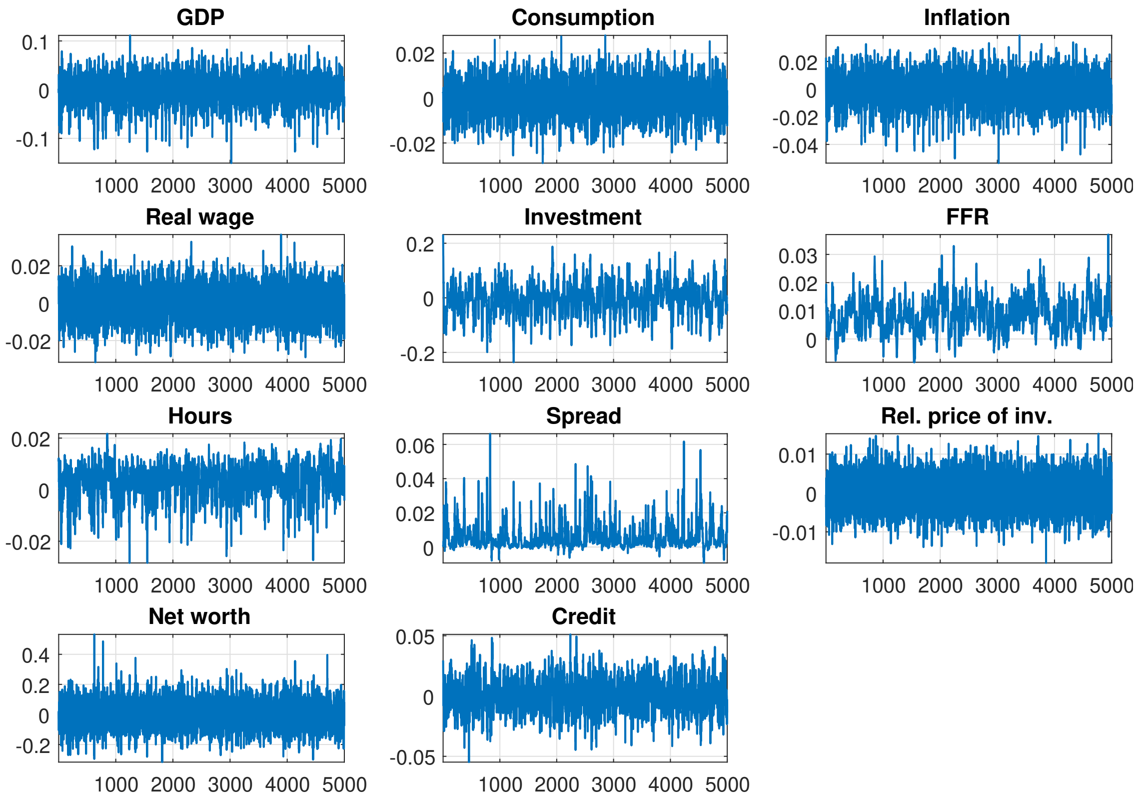


Figure A.4: Smoothed shocks



Notes: Smoothed shocks of the estimated DSGE model, normalized such that the units of the y-axis is standard deviations of each shock. The panels ant. risk 1-8 show the anticipated component of the risk shock from 1 to 8 quarters ahead.

Figure A.5: Simulated data from the third-order model



A.3 The Financial Contract and the Sensitivity Spread-leverage

The derivations and properties of the functional forms under the log-normal distribution are discussed in detail in BGG and can be found in many other sources; here we focus on the derivation of the spread-leverage sensitivity, which plays an important role for our analysis. As stated in equation (1.12), the expected returns for entrepreneurs can be written as

$$E_t \int_{\varpi_{t+1}}^{\infty} \left[R^k_{t+1}\omega Q_{\bar{K},t}\bar{K}_{t+1} - R^L_{t+1}B_{t+1}\right] dF(\omega,\sigma) = E_t[1-\Gamma_t(\bar{\omega}_{t+1})]R^k_{t+1}L_tN, \quad \text{(A.1)}$$

with $\Gamma_t(\bar{\omega}_{t+1}) \equiv [1-F(\bar{\omega}_{t+1})]\bar{\omega}_{t+1} + G_t(\bar{\omega}_{t+1})$, $G_t \equiv \int_0^{\bar{\omega}_{t+1}} \omega dF_t(\omega)$. We can combine equations (1.11) and (1.13) to derive the participation constraint of banks and formulate the optimization problem of entrepreneurs. From equation (1.11), $R^L_{t+1}B^N_{t+1} = R^k_{t+1}Q_{\bar{K},t}\bar{K}_{t+1}\bar{\omega}_{t+1}$. Plugging this into equation (1.13) we obtain

$$[1-F(\varpi_{t+1})]\, R^k_{t+1}Q_{\bar{K},t}\bar{K}_{t+1}\bar{\omega}_{t+1} + (1-\mu)\int_0^{\varpi_{t+1}} \omega dF_t(\omega) R^k_{t+1}Q_{\bar{K},t}\bar{K}_{t+1} = R_tB^N_{t+1}, \quad \text{(A.2)}$$

where we have used the fact that this equation holds with equality in equilibrium. We can use the definitions of $\Gamma_t(\bar{\omega}_{t+1})$ and $G_t(\bar{\omega}_{t+1})$ to simplify this expression as follows:

$$\left([1-F(\varpi_{t+1})]\,\bar{\omega}_{t+1} + (1-\mu)G_t(\bar{\omega}_{t+1})\right) R^k_{t+1}Q_{\bar{K},t}\bar{K}_{t+1} = R_tB^N_{t+1} \quad \text{(A.3)}$$

$$\left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right] R^k_{t+1}Q_{\bar{K},t}\bar{K}_{t+1} = R_tB^N_{t+1} \quad \text{(A.4)}$$

and divide by N

$$\left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right] R^k_{t+1}L_t = R_t\frac{B^N_{t+1}}{N}. \quad \text{(A.5)}$$

Rearranging and noting that $\frac{B^N_{t+1}}{N} = L_t - 1$

$$\frac{R^k_{t+1}}{R_t} = \frac{1}{\left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right]}\left(1-\frac{1}{L_t}\right), \quad \text{(A.6)}$$

which is equation (1.14). Then, the problem of the entrepreneur is:

$$\max_{L_t, \bar{\omega}_{t+1}} \quad E_t[1-\Gamma_t(\bar{\omega}_{t+1})]R^k_{t+1}L_t N \tag{A.7}$$

$$\text{s.t. } \left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right] R^k_{t+1}L_t N = R_t(L_t-1)N, \tag{A.8}$$

where we have replaced $L_t = (Q_{\bar{K},t}\bar{K}_{t+1})/N$ and $B^N_{t+1} = (L_t-1)N$ in equation (A.4). The first order conditions associated to the problem are

$$L_t: \quad (1-\Gamma_t(\bar{\omega}_{t+1}))s_t + \lambda_t\left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right]s_t - \lambda_t = 0 \tag{A.9}$$

$$\bar{\omega}_{t+1}: \quad -\Gamma'_t(\bar{\omega}_{t+1}) + \lambda_t\left[\Gamma'_t(\bar{\omega}_{t+1}) - \mu G'_t(\bar{\omega}_{t+1})\right] = 0 \tag{A.10}$$

$$\lambda_t: \quad \left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right]s_t L_t - (L_t-1) = 0, \tag{A.11}$$

where we have replaced $s_t = R^k_{t+1}/R_t$. Now we can express λ_t, s_t and L_t as a function of $\bar{\omega}_{t+1}$. Specifically, from equations (A.10), (A.9), and (A.11) we get, respectively

$$\lambda_t = \frac{\Gamma'_t(\bar{\omega}_{t+1})}{\Gamma'_t(\bar{\omega}_{t+1}) - \mu G'_t(\bar{\omega}_{t+1})} \tag{A.12}$$

$$s_t = \frac{\lambda_t}{1-\Gamma_t(\bar{\omega}_{t+1}) + \lambda_t\left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right]} \tag{A.13}$$

$$L_t = \frac{1}{1-\left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right]s_t}. \tag{A.14}$$

Equation (A.14) establishes the equilibrium relation between the leverage ratio and the spread that we have defined as $s(\cdot)$ in section 1.2. With these expressions at hand we can now compute the steady state sensitivity spread-leverage as a function of $\bar{\omega}$. We simply drop all the time indices, so that the value will be pinned down by the steady state value of $\bar{\omega}$ along with the parameter values of the financial contract. We define this sensitivity as

$$\eta_{s,L} = \frac{d\log s(\bar{\omega})}{d\log L(\bar{\omega})}. \tag{A.15}$$

Define $\Psi(\bar{\omega}) \equiv 1 - \Gamma_t(\bar{\omega}_{t+1}) + \lambda_t \left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right]$ so that equation (A.13) can be rewritten as $s_t = \lambda(\bar{\omega})/\Psi(\bar{\omega})$. Plugging this into equation (A.14) we obtain $L(\bar{\omega}) = \Psi(\bar{\omega})/(1 - \Gamma(\bar{\omega}))$. And now we can compute the following derivatives:

$$\frac{d \log s(\bar{\omega})}{d\bar{\omega}} = \frac{\lambda'(\bar{\omega})}{\lambda(\bar{\omega})} - \frac{\Psi'(\bar{\omega})}{\Psi(\bar{\omega})} \tag{A.16}$$

$$\frac{d \log L(\bar{\omega})}{d\bar{\omega}} = \frac{\Psi'(\bar{\omega})}{\Psi(\bar{\omega})} + \frac{\Gamma'(\bar{\omega})}{1 - \Gamma(\bar{\omega})}, \tag{A.17}$$

where

$$\lambda'(\bar{\omega}) = \frac{\mu \left[\Gamma'(\bar{\omega})G''(\bar{\omega}) - \Gamma''(\bar{\omega})G'(\bar{\omega})\right]}{\left[\Gamma'(\bar{\omega}) - \mu G'(\bar{\omega})\right]^2} \tag{A.18}$$

$$\Psi'(\bar{\omega}) = \lambda'(\bar{\omega}) \left[\Gamma(\bar{\omega}) - \mu G(\bar{\omega})\right] + \lambda(\bar{\omega}) \left[\Gamma'(\bar{\omega}) - \mu G'(\bar{\omega})\right] - \Gamma'(\bar{\omega}). \tag{A.19}$$

So that the expression for the steady state spread-leverage sensitivity becomes

$$\eta_{s,L} = \frac{\frac{\lambda'(\bar{\omega})}{\lambda(\bar{\omega})} - \frac{\Psi'(\bar{\omega})}{\Psi(\bar{\omega})}}{\frac{\Psi'(\bar{\omega})}{\Psi(\bar{\omega})} + \frac{\Gamma'(\bar{\omega})}{1-\Gamma(\bar{\omega})}}. \tag{A.20}$$

B Appendix to Chapter 2

B.1 DSGE Model Equation Details

This section provides additional details on the model equations.

B.1.1 Patient Households

The patient household budget constraint is given by

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

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

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

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 (B.1) and (B.2).

B.1.2 Wholesale Firms

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. They solve

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

subject to the production technology

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

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 (2.4).

B.2 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

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

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

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

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. When the model implied notional rate is above zero, that rate is the observed rate and the monetary policy shock is reinstated. Note that this allows for active expansionary (but not contractionary) monetary policy when the observed rate is at the lower bound.

The likelihood of the model takes the form

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

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 (B.7) to obtain the posterior.

B.3 Data

Here we present a summary of the data definitions, transformations and sources for the theoretical and empirical analysis.

B.3.1 Local Projections

Table B.1: Data definitions and sources

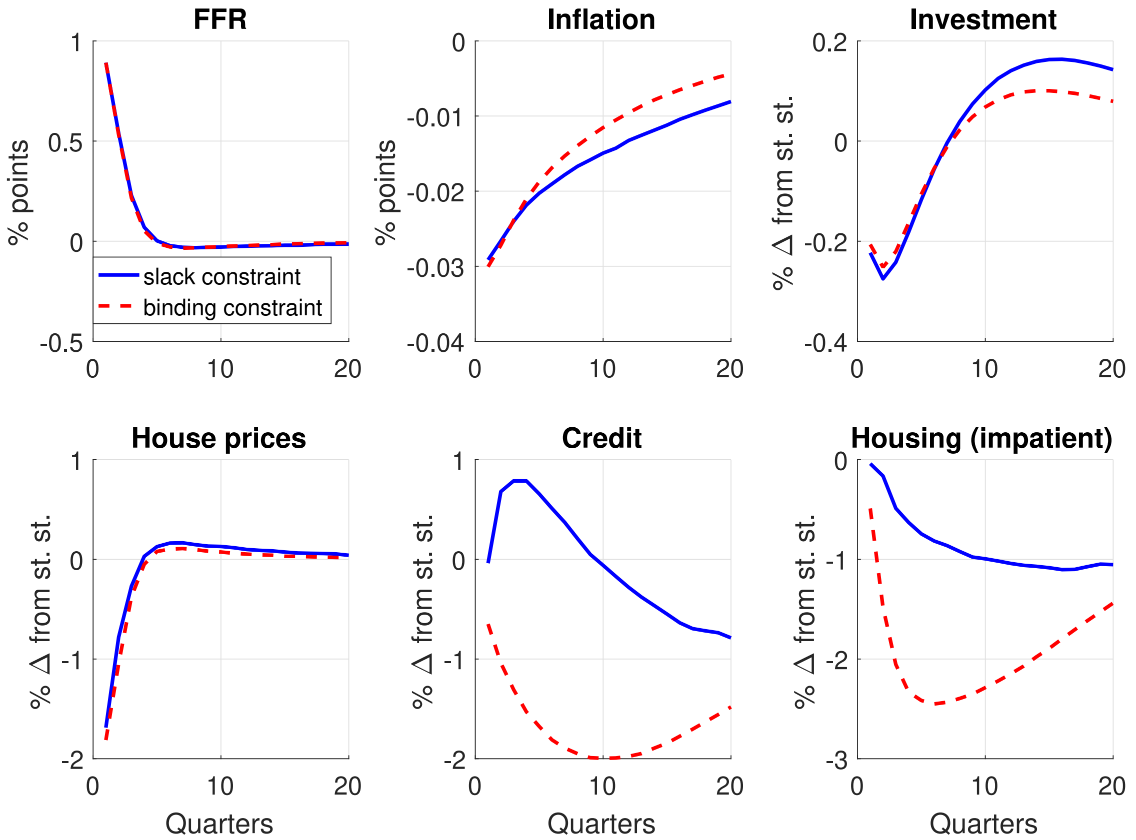
Variable	Description	Source
GDP	Real GDP	BEA
CPI	Price index personal consumption expenditures	BEA
PGDP	GDP deflator	BEA
Wu and Xia shadow rate	Shadow federal funds rate	Atlanta FED website
Consumption	Nominal personal consumption expenditures	BEA
Investment	Nominal fixed private investment	BEA
Romer and Romer shocks	Extended narrative series	Silvia Miranda-Agrippino's website
Household net worth	Households and nonprofit organizations net worth	Flow of Funds Tables
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
Financial stress	Financial Conditions: Bank Leverage	Chicago FED website

B.3.2 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).

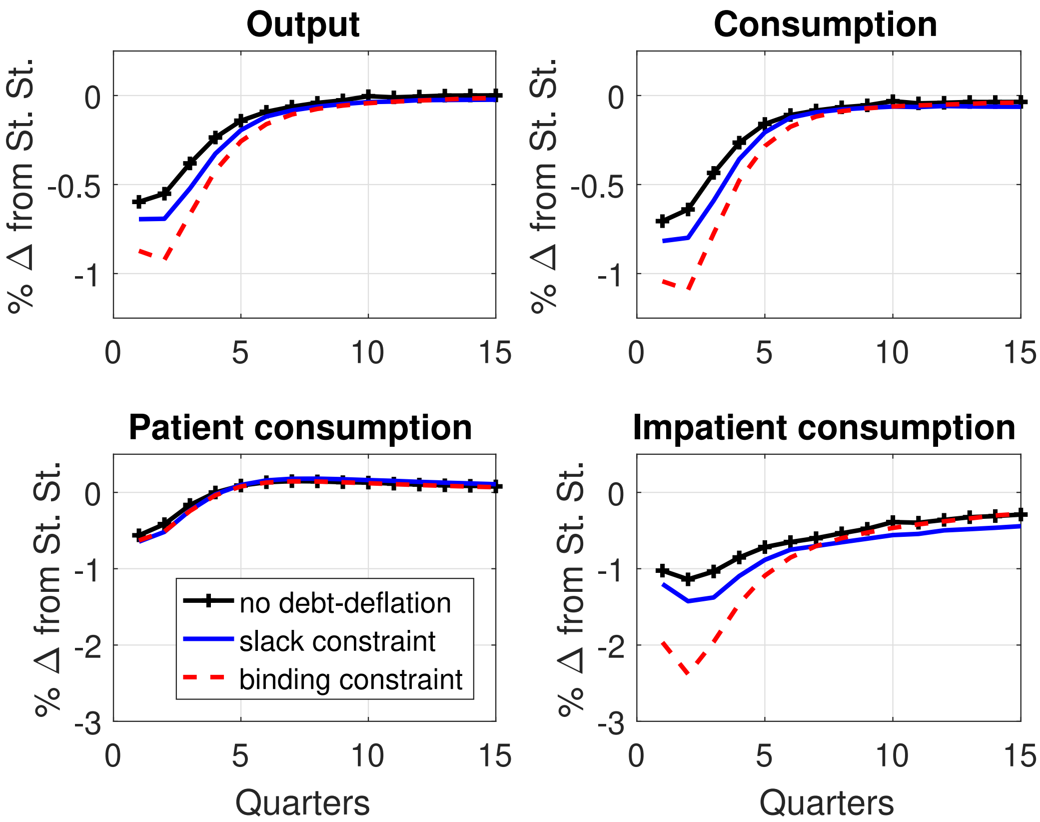
B.4 Additional Figures

Figure B.1: IRFs to a 1% contractionary monetary policy phock



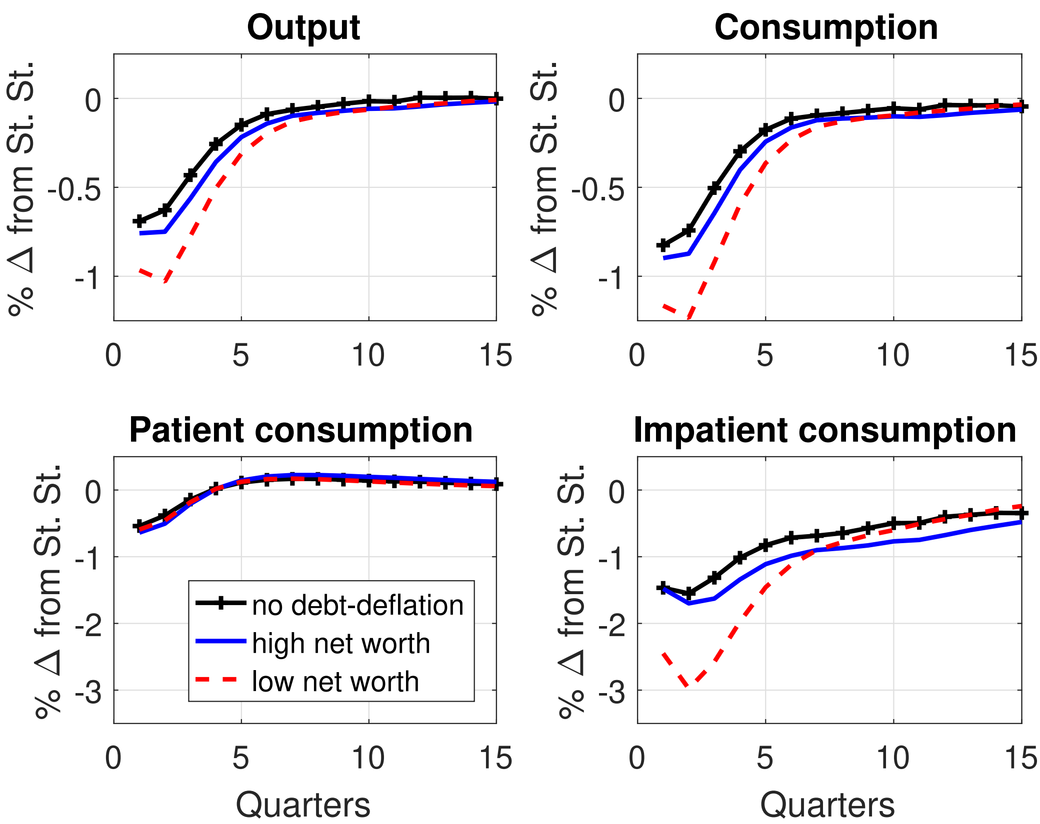
Notes: Generalized IRFs to an (annualized) 100 basis points monetary policy shock under binding and slack collateral constraints. GIRFs are computed by simulating the model for 600 periods, once with all shocks evaluated at their estimated standard deviations and a second time where, on top of that, 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).

Figure B.2: IRFs to a 1% contractionary monetary policy shock, $M = 0.8$



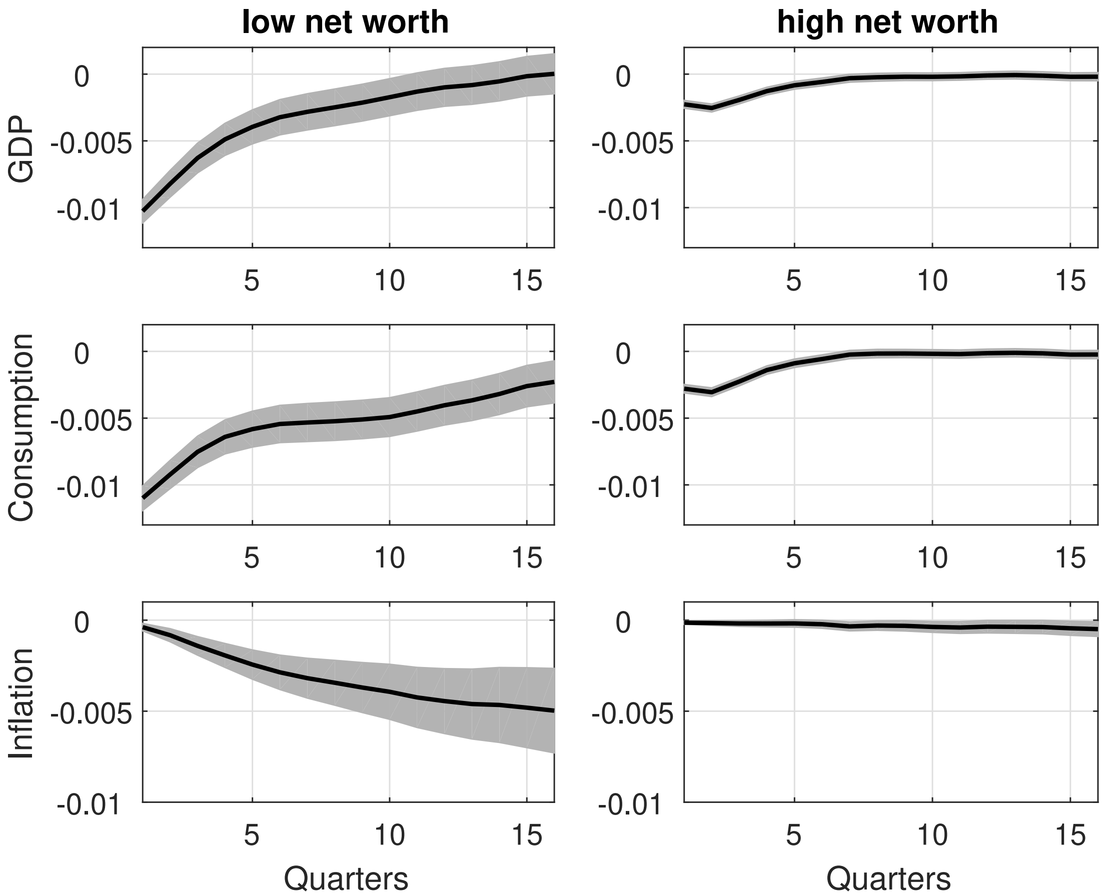
Notes: Generalized IRFs to an (annualized) 100 basis points monetary policy shock under binding and slack collateral constraints. GIRFs are computed by simulating the model for 600 periods, once with all shocks evaluated at their estimated standard deviations and a second time where, on top of that, 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 B.3: IRFs to a 1% contractionary monetary policy shock, net worth states



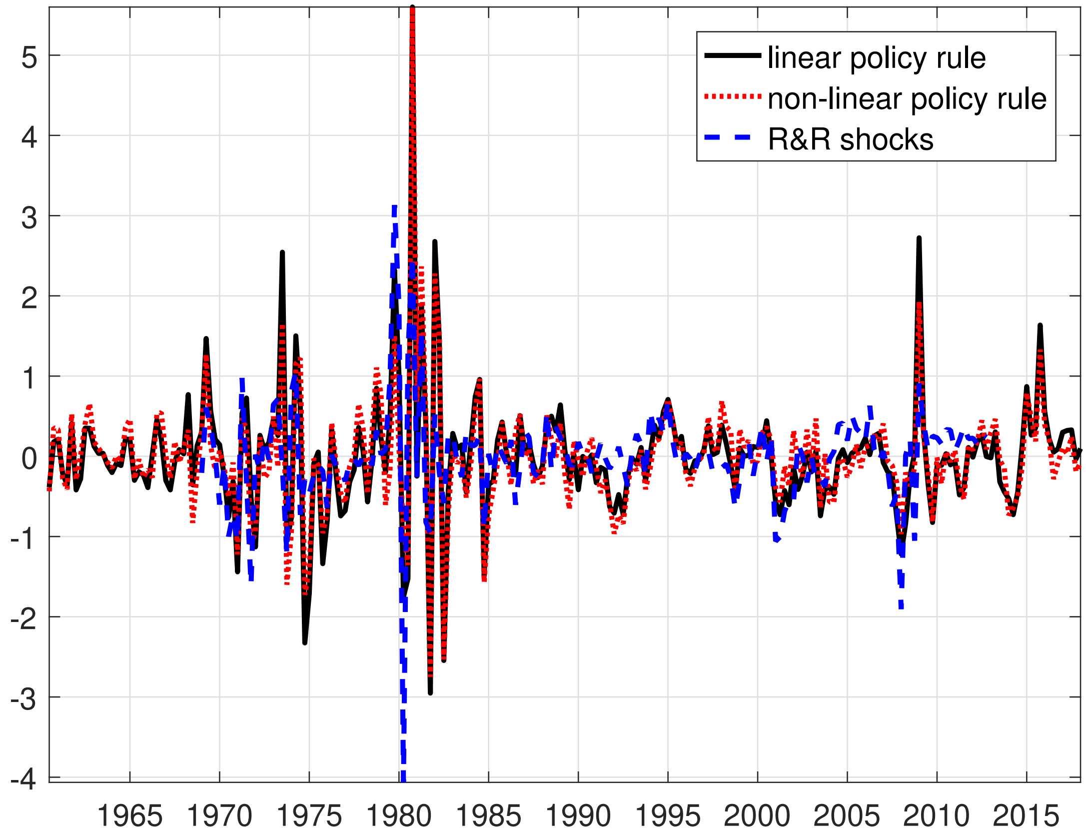
Notes: Generalized IRFs to an (annualized) 100 basis points monetary policy shock under low and high net worth states, defined as the realizations below the 15th percentile and above the 85th percentile of the net worth distribution, respectively. GIRFs are computed by simulating the model for 600 periods, 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 B.4: Local projections with simulated data from the DSGE model: IRFs to a 1% contractionary monetary policy shock



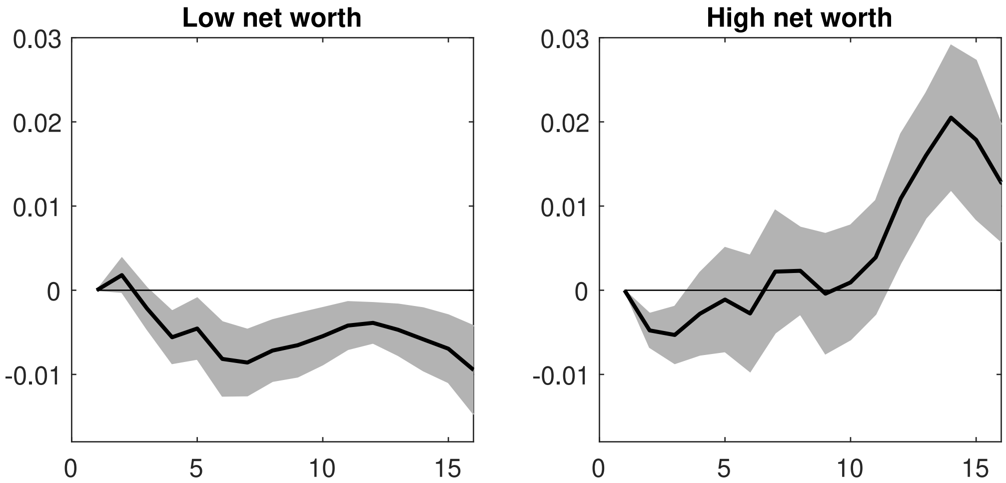
Notes: Local projection impulse responses to a 1% monetary policy shock computed on a simulated sample of 10,000 periods from the DSGE model. The monetary policy shock is the shock in the Taylor rule of the DSGE model. Low and high net worth states are defined as periods when the level of net worth is below and above its steady state value, respectively. The shaded areas indicate 90% confidence bands based on Newey and West (1987) standard errors.

Figure B.5: Monetary policy shocks



Notes: Monetary policy shocks from the extended Romer&Romer series by Miranda-Agrippino and Rey (2015) (blue-dashed line), the baseline linear specification from equation (2.9) (black-solid line), and the baseline nonlinear specification from equation (2.10) (red-dotted line).

Figure B.6: Nonlinear Romer and Romer (2004) Shocks (GDP responses)



Notes: The first column shows the impulse responses of a 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.

Figure B.7: DSGE model smoothed shocks

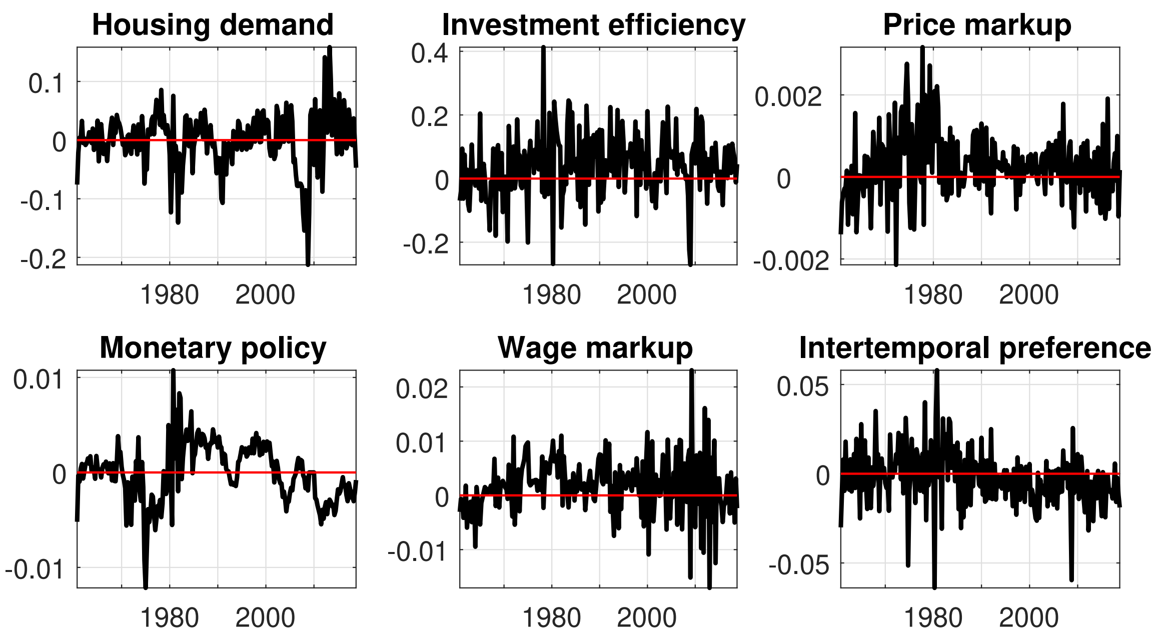
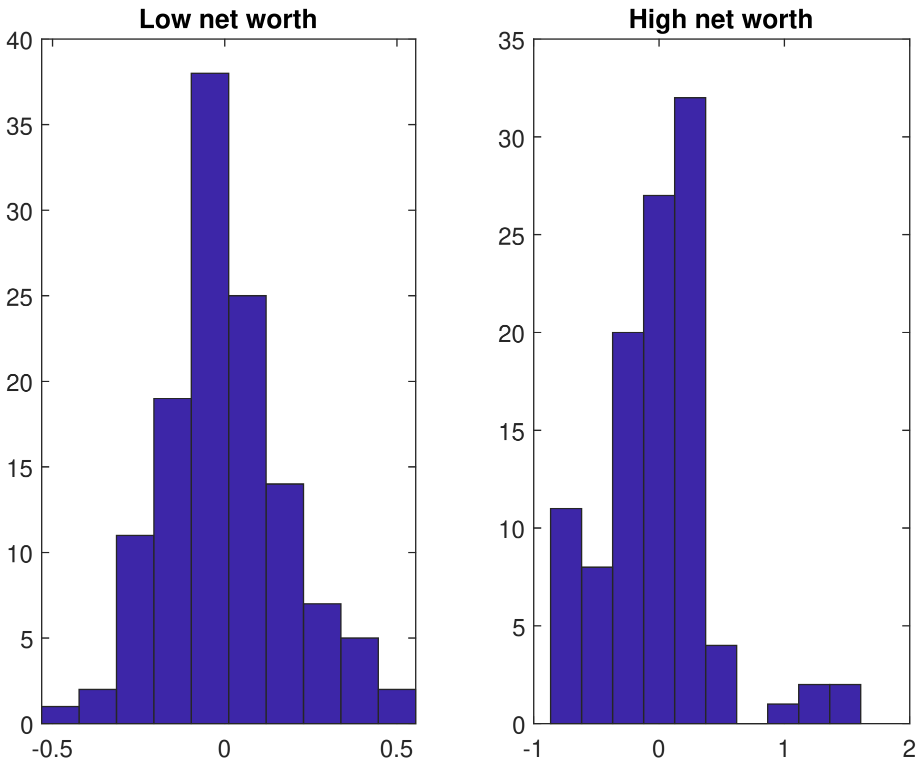


Figure B.8: Distribution of Monetary Policy Shocks



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

B.5 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 2.2.3.1. Table B.2 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) 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 B.2: Prediction analysis: alternative simulation approach

	Levels		Growth rates		HP cycle	
	IS	OOS	IS	OOS	IS	OOS
Net worth	0.85	0.83	0.44	0.44	0.67	0.64
Leverage	0.81	0.81	0.53	0.53	0.64	0.60
Credit	0.61	0.57	0.62	0.61	0.66	0.64
House prices	0.63	0.62	0.52	0.52	0.66	0.65
Credit gaps	0.56	0.56	0.54	0.54	0.53	0.53

Notes: Prediction analysis with simulated sample of size $N = 20,000$. We estimate the probit regressions described in equation (2.8) 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 B.3 repeats the analysis of table 2.3 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 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 B.3: 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	0.88	0.91	0.89	0.84	0.68	0.59	0.56	0.52	0.79	0.75	0.71	0.67
Leverage	0.72	0.81	0.83	0.80	0.61	0.58	0.55	0.51	0.68	0.68	0.66	0.63
Credit	0.64	0.65	0.63	0.62	0.91	0.79	0.70	0.61	0.71	0.70	0.68	0.66
House prices	0.65	0.66	0.66	0.66	0.75	0.62	0.56	0.48	0.76	0.74	0.71	0.66
Credit gaps	0.61	0.59	0.57	0.56	0.56	0.53	0.52	0.44	0.58	0.53	0.51	0.45

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 (2.8) 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.

C Appendix to Chapter 3

C.1 Data

C.1.1 SCF Data

The SCF data used in this paper includes the SCF waves of 1995, 1998, 2001, 2004, 2007, 2010, 2013, and 2016. Income is defined as income from all sources received in a given year, before taxes and other deductions. It is recorded in variable X5729 across all waves. Liquid assets include checking and savings accounts, mutual funds, bonds, stocks, and cash or call money accounts, net of revolving credit card debt. Illiquid assets include retirement and pension accounts, certificates of deposits, saving bonds, life insurance policies, and owned property net of total mortgage debt. Net worth is defined as the sum of liquid and illiquid assets. Debt is defined as total mortgage debt plus revolving credit card debt. The data is deflated by CPI and presented at constant 2001Q1 prices.

C.1.2 CEX Data

Data cleaning.– I drop households that do not report information for all 4 quarters of the survey and those that report negative consumption. The CEX consumption data is not necessarily recorded during the quarter where the expenses took place, because households are asked to report their consumption expenditures for the past three months at any given month when the interview takes place. Hence, these past three months reported do not necessarily coincide with calendar quarters in a year. Thus, I make the necessary adjustments such that the consumption data reflects the calendar quarters when the expenses took place.

Consumption data.– Durable and non-durable consumption is constructed by adding the expenses registered by households in the following categories (survey variables in parentheses):

- Durable consumption: House furnishings and equipment (HOUSEQ), cars and trucks, new (CARTKN), cars and trucks, used (CARTKU), and other vehicles (OTHVEH).

- Non-durable consumption: Food (FOOD), alcoholic beverages (ALCBEV), tobacco and smoking supplies (TOBACC), household operations (HOUSOP), utilities, fuels and public services (UTIL), gasoline and motor oil (GASMO), public and other transportation (PUBTRA), personal care (PERSCA), reading (READ), entertainment (ENTERT), apparel and services (APPAR), health (HEALTH), and education (EDUCA).

Income and financial data.– Income is defined as after-tax income (FINCATAX) before 2004, and imputed after-income tax (FINCATXM) from 2004 onwards. Liquid assets include all checking, savings, money market accounts, and certificates of deposit. These balances are recorded in variables CKBKACTX and SAVACCTX until 2012Q4, and in variable LIQUIDX thereafter. Illiquid assets are measured with the value of owned property (PROPVALX), net of mortgage debt. The mortgage outstanding balance is calculated using the variables QBLNCM1X, QBLNCM2X, and QBLNCM3X. Debt is measured as credit card debt (CREDITX) plus the mortgage balance and other loans (OTHLONX). Net worth is defined as the sum of liquid and illiquid assets. The data is deflated by CPI and presented at constant 2001Q1 prices.

C.1.3 Aggregate Data

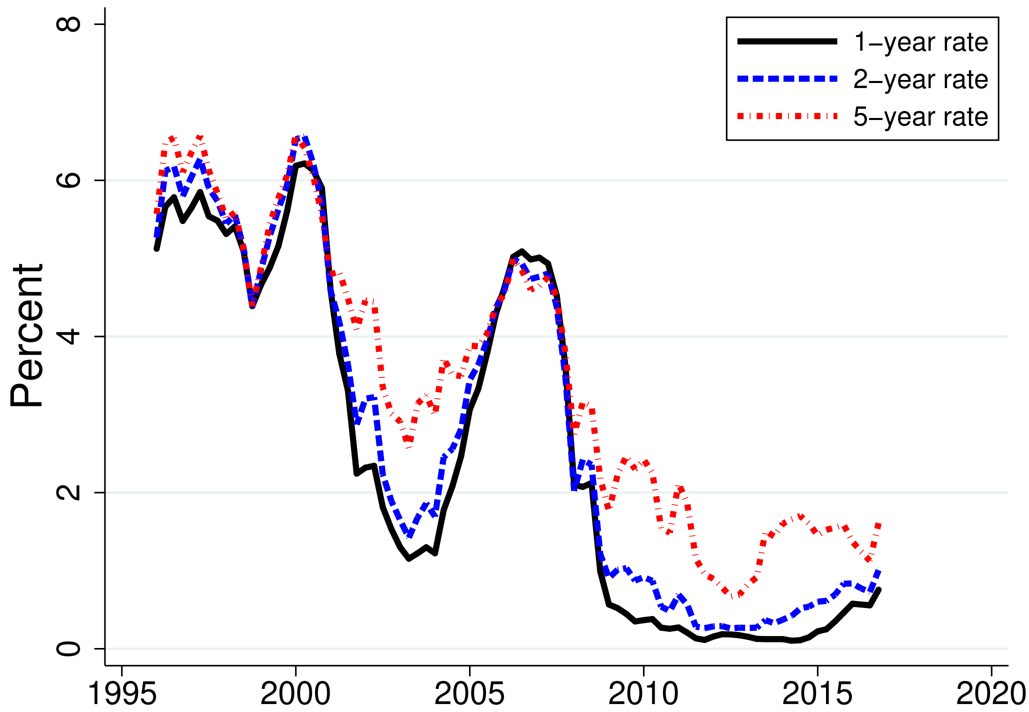
Aggregate data is obtained from FRED Economic Data. The following table describes the data on prices and interest rates used for the empirical analysis.

Table C.1: FRED data

Variable	Description	FRED code
CPI	Consumer Price Index (all urban consumers), seasonally adjusted	CPIAUCSL
One-year rate	1-Year Treasury Constant Maturity Rate	GS1
Two-year rate	2-Year Treasury Constant Maturity Rate	GS2
Five-year rate	5-Year Treasury Constant Maturity Rate	GS5

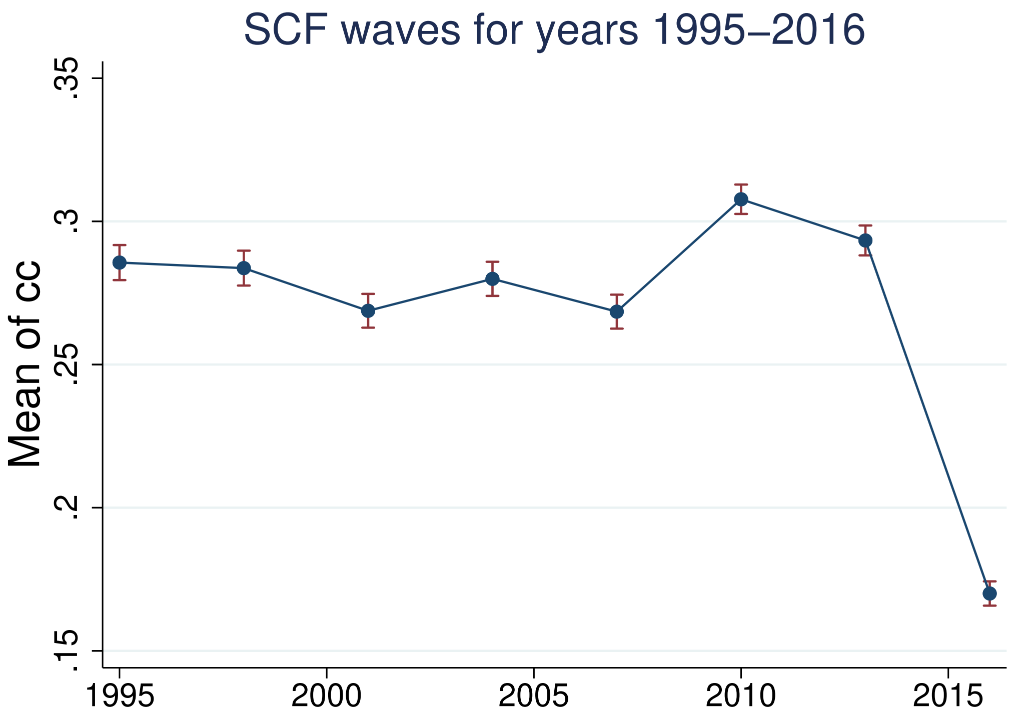
The data is reported at monthly frequency and transformed to quarterly frequency.

Figure C.1: US Treasury Constant Maturity Rates.



C.2 Appendix to Section 3.2.2

Figure C.2: Share of constrained households.



Notes: Estimated share of constrained households for all SCF waves from 1995 to 2016. Dots depict the estimated population mean for each survey wave with 95% confidence intervals. For the 2016 wave the horizon over which households are asked about loan rejections changed from 5 years (as in all previous surveys) to 1 year, which explains the sharp drop for the 2016 data.

Table C.2: Logit regression results and implied probabilities at sample means

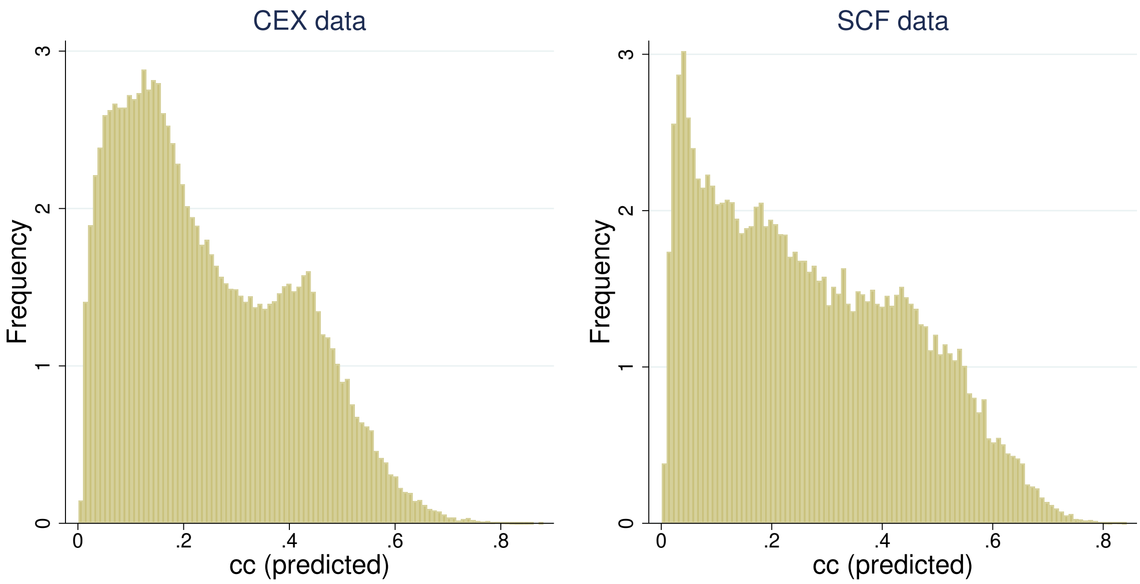
	1995		1998		2001		2004	
Variable	β	dy/dx	β	dy/dx	β	dy/dx	β	dy/dx
Income	-0.847 ***	-0.008	0.134	0.003	0.145	0.019**	-0.390***	0.017**
	(0.133)	(0.008)	(0.176)	(0.008)	(0.142)	(0.008)	(0.135)	(0.008)
Income ^{2}	0.029 ***		-0.018		-0.007		0.027***	
	(0.007)		(0.012)		(0.008)		(0.008)	
Net worth	0.320 ***	-0.023 ***	0.276***	-0.023***	0.415***	-0.026***	0.542***	-0.025***
	(0.041)	(0.004)	(0.072)	(0.003)	(0.059)	(0.003)	(0.054)	(0.003)
Net worth ^{2}	-0.018 ***		-0.021***		-0.024***		-0.024***	
	(0.001)		(0.002)		(0.001)		(0.001)	
Income*Net worth	-0.017 ***		-0.003		-0.015**		-0.031***	
	(0.004)		(0.010)		(0.006)		(0.006)	
Neg net worth	-0.117	-0.017	0.455***	0.066	0.166*	0.022	0.349***	0.048
	(0.092)	(0.038)	(0.153)	(0.042)	(0.097)	(0.034)	(0.087)	(0.035)
Age	-0.073 ***	-0.003 ***	-0.036**	-0.003***	-0.034**	-0.003***	0.029**	-0.003***
	(0.012)	(0.001)	(0.014)	(0.001)	(0.014)	(0.001)	(0.012)	(0.000)
Age ^{2}	-0.000 ***		-0.001***		-0.001***		-0.001***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Age*Income	0.008 ***		0.007***		0.007***		0.005***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Age*Net worth	0.001 **		-0.000		-0.001**		0.001**	
	(0.000)		(0.000)		(0.000)		(0.000)	
Debt	0.044 ***	0.006 ***	0.043***	0.006***	0.035***	0.005**	0.019***	0.003
	(0.005)	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.005)	(0.002)
Marital status	-0.572 ***	-0.086 ***	-0.445***	-0.066***	-0.311***	-0.042**	-0.314***	-0.044**
	(0.040)	(0.019)	(0.039)	(0.018)	(0.039)	(0.017)	(0.041)	(0.017)
Race	-0.541 ***	-0.084 ***	-0.341***	-0.051***	-0.287***	-0.040***	-0.327***	-0.046***
	(0.032)	(0.017)	(0.031)	(0.015)	(0.036)	(0.014)	(0.031)	(0.014)
Sex	0.210 ***	0.030 *	0.027	0.004	-0.085**	-0.011	-0.139***	-0.019
	(0.038)	(0.017)	(0.039)	(0.017)	(0.041)	(0.016)	(0.038)	(0.016)
Family size	0.178 ***	0.026 ***	0.136***	0.020***	0.115***	0.015***	0.113***	0.015***
	(0.011)	(0.005)	(0.011)	(0.005)	(0.012)	(0.005)	(0.011)	(0.005)
Outright owner	-0.180 ***	-0.026	-0.278***	-0.039	-0.161**	-0.021	-0.293***	-0.039
	(0.068)	(0.026)	(0.067)	(0.027)	(0.065)	(0.026)	(0.068)	(0.027)
Renter	0.356 ***	0.053 **	0.415***	0.062***	0.526***	0.073***	0.547***	0.079***
	(0.052)	(0.022)	(0.050)	(0.022)	(0.058)	(0.021)	(0.051)	(0.023)
College education	-0.002	-0.000	0.031	0.004	0.130***	0.017	-0.119***	-0.016
	(0.030)	(0.013)	(0.034)	(0.014)	(0.031)	(0.013)	(0.030)	(0.013)
Unemployed	0.067	0.010	-0.191***	-0.027	0.016	0.002	0.098*	0.014
	(0.059)	(0.033)	(0.059)	(0.027)	(0.060)	(0.029)	(0.059)	(0.027)
Positive savings	-0.401 ***	-0.061 ***	-0.450***	-0.068***	-0.731***	-0.107***	-0.614***	-0.089***
	(0.038)	(0.017)	(0.050)	(0.018)	(0.049)	(0.018)	(0.038)	(0.016)

Logit regression results and implied probabilities at sample means (cont.)

	2007		2010		2013		2016	
Variable	β	dy/dx	β	dy/dx	β	dy/dx	β	dy/dx
Income	-0.537***	0.003	-0.082	0.006	0.325**	0.005	-0.118	-0.001
	(0.140)	(0.009)	(0.130)	(0.009)	(0.129)	(0.008)	(0.143)	(0.007)
Income^2	0.027***		-0.003		-0.021***		-0.003	
	(0.008)		(0.007)		(0.007)		(0.008)	
Net worth	0.435***	-0.028***	0.384***	-0.022***	0.269***	-0.023***	0.545***	-0.009***
	(0.044)	(0.003)	(0.045)	(0.003)	(0.040)	(0.003)	(0.043)	(0.002)
Net worth^2	-0.028***		-0.025***		-0.018***		-0.020***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Income*Net worth	-0.014***		-0.009*		-0.011**		-0.028***	
	(0.004)		(0.005)		(0.005)		(0.005)	
Neg net worth	-0.143	-0.018	0.436***	0.076**	0.083	0.014	0.683***	0.078***
	(0.118)	(0.036)	(0.122)	(0.038)	(0.086)	(0.033)	(0.084)	(0.026)
Age	0.032**	-0.002***	0.005	-0.002***	0.029**	-0.002***	-0.027**	-0.001***
	(0.012)	(0.000)	(0.012)	(0.000)	(0.011)	(0.000)	(0.012)	(0.000)
Age^2	-0.001***		-0.001***		-0.001***		-0.001***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Age*Income	0.003**		0.006***		0.005***		0.009***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Age*Net worth	-0.000		0.000		0.001*		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)	
Debt	0.038***	0.005**	0.040***	0.007***	0.031***	0.005**	0.023***	0.003
	(0.006)	(0.002)	(0.006)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)
Marital status	-0.343***	-0.045***	-0.325***	-0.058***	-0.201***	-0.033**	-0.438***	-0.050***
	(0.039)	(0.016)	(0.039)	(0.017)	(0.039)	(0.016)	(0.039)	(0.012)
Race	-0.206***	-0.027**	-0.203***	-0.036***	-0.372***	-0.064***	-0.338***	-0.040***
	(0.033)	(0.013)	(0.030)	(0.013)	(0.030)	(0.013)	(0.030)	(0.010)
Sex	-0.200***	-0.026	-0.116***	-0.020	-0.049	-0.008	0.021	0.002
	(0.038)	(0.016)	(0.038)	(0.017)	(0.038)	(0.015)	(0.038)	(0.012)
Family size	0.169***	0.022***	0.134***	0.023***	0.115***	0.019***	0.187***	0.021***
	(0.011)	(0.004)	(0.011)	(0.004)	(0.011)	(0.004)	(0.011)	(0.003)
Outright owner	0.068	0.009	0.039	0.007	0.123*	0.021	0.077	0.009
	(0.069)	(0.028)	(0.070)	(0.029)	(0.065)	(0.026)	(0.065)	(0.021)
Renter	0.355***	0.047**	0.436***	0.078***	0.423***	0.072***	0.284***	0.033**
	(0.062)	(0.023)	(0.050)	(0.022)	(0.049)	(0.021)	(0.049)	(0.017)
College education	-0.134***	-0.017	-0.083***	-0.014	-0.021	-0.003	-0.200***	-0.022
	(0.031)	(0.013)	(0.030)	(0.012)	(0.030)	(0.012)	(0.030)	(0.014)
Unemployed	-0.097	-0.012	0.447***	0.082***	0.168***	0.029	0.123**	0.015
	(0.059)	(0.026)	(0.059)	(0.023)	(0.059)	(0.022)	(0.059)	(0.021)
Positive savings	-0.676***	-0.093***	-0.518***	-0.094***	-0.474***	-0.083***	-0.716***	-0.090***
	(0.046)	(0.016)	(0.036)	(0.016)	(0.037)	(0.016)	(0.041)	(0.014)

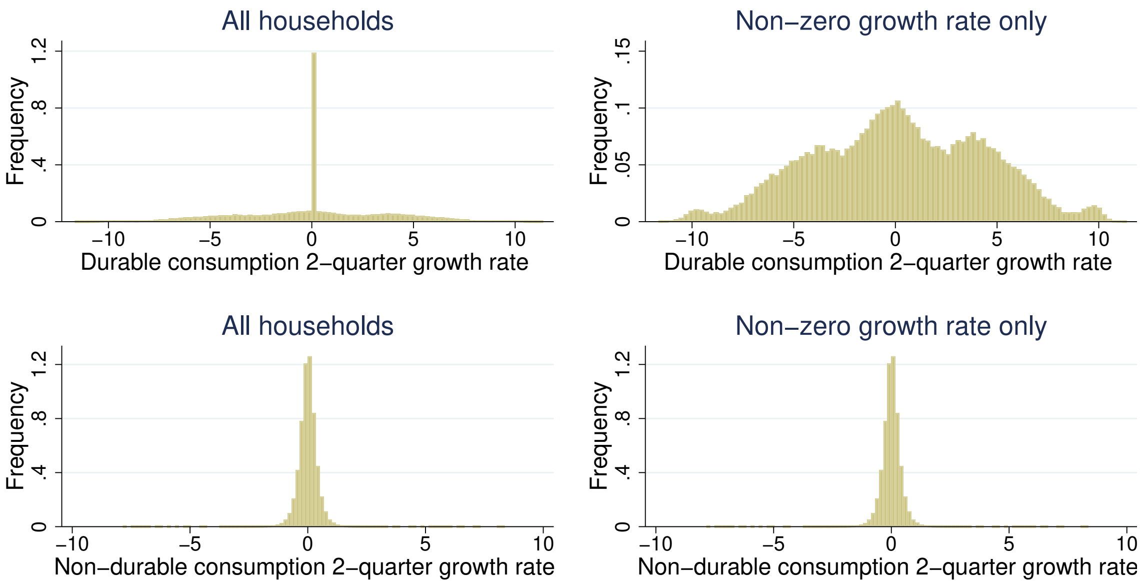
C.3 Appendix to Section 3.2.3

Figure C.3: Distribution of predicted $\hat{cc}_{i,t}$ across surveys.



Notes: Predicted $\hat{cc}$ computed as fitted value of the estimated logit model of the determinants of credit constraints, as in equation (3.3), for CEX data and SCF data, respectively.

Figure C.4: Distribution of durable and non-durable consumption growth rates.



Notes: Distribution of the two-quarter growth rates for durable and non-durable consumption. Growth rates are computed as: $\log\left(C_{i,t+1}/C_{i,t-1}\right)$. The left panels plot the distribution for all households, irrespective of whether there is variation in consumption in a given two-quarter window. The right panels plot the growth rates only for those households that exhibit a non-zero variation in consumption in a given two-quarter window.

C.3.1 Estimation Details

All regressions are estimated using an IV-GMM procedure as implemented in Stata. Let ε_t^{mp} denote the high frequency monetary policy shocks (from Nakamura and Steinsson (2018) or Jarociński and Karadi (2020), depending on the specification) in quarter t. Then, in equation (3.4) the two-year rate r_t is instrumented using the monetary policy shocks ε_t^{mp}, ε_{t-1}^{mp}, and ε_{t-2}^{mp}. The vector $Z_{i,t}$ includes the continuous variables "age", "family size", and "income"; and the dummy variables "college education", "race", and "marital". These variables take the value of one if the household head has college education/is white/is married, respectively, and zero otherwise. The vector $\lambda_{(t)}$ includes year-quarter fixed effects.

Equation (3.5) shares the same baseline elements as equation (3.4) but here the instrumented variables are r_t and the interaction $\hat{cc}_{i,t} \cdot r_t$. As before, the high-frequency monetary policy shocks ε_t^{mp}, ε_{t-1}^{mp}, and ε_{t-2}^{mp} are used as instruments, but in addition, household net worth is used as an instrument in order to disentangle variation in r_t and $\hat{cc}_{i,t}$. For the estimation of equation (3.6) the same logic applies: r_t and the interaction $I_{\hat{cc}} \cdot r_t$ are instrumented with the monetary policy shocks ε_t^{mp}, ε_{t-1}^{mp}, and ε_{t-2}^{mp}, and household net worth.

In estimating regressions in equations (3.5) and (3.6), one has to take the additional uncertainty generated from the fact that $\hat{cc}_{i,t}$ is predicted from an estimated model –and not a fixed regressor– into account. To take this additional uncertainty into account, standard errors are computed using a bootstrap procedure that involves the following steps: (i) generate N independent bootstrap samples by sampling with replacement from the CEX data; (ii) for each sample n, predict $\hat{cc}_{i,t}$ using the estimated logit model from equation (3.3); (iii) for each sample n, estimate the parameters of interest, $\hat{\theta}^{(n)}$; (iv) estimate the bootstrapped standard errors as

$$se(\hat{\theta}) = \sqrt{\frac{1}{(N-1)} \sum_{n=1}^{N} \left(\theta^{(n)} - \bar{\theta}\right)^2}, \tag{C.1}$$

with $\bar{\theta} = \left(\sum_{n=1}^{N} \theta^{(n)}\right) / N$. I set $N = 1,000$ for the computations, which is considered standard in the literature, and results are robust to using a larger N.

Table C.3: Consumption response to the one-year rate

Variable	(1) Dur	(2) Non-dur	(3) Dur	(4) Non-dur	(5) Dur	(6) Non-dur
r_t	-0.121**	-0.002	-0.476**	-0.029	-0.524***	-0.073***
	(0.053)	(0.006)	(0.186)	(0.024)	(0.147)	(0.020)
Age	0.004***	0.000***	-0.000	-0.001***	0.001	-0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
College education	0.028	0.010***	-0.006	0.011***	-0.032	0.004
	(0.020)	(0.002)	(0.028)	(0.003)	(0.032)	(0.004)
Race	0.120***	0.009***	0.073**	0.000	0.109***	0.009
	(0.025)	(0.003)	(0.034)	(0.004)	(0.038)	(0.005)
Marital	0.109***	0.008***	0.029	-0.003	0.063*	0.004
	(0.022)	(0.003)	(0.031)	(0.004)	(0.033)	(0.004)
Family size	0.020**	-0.001	0.048***	0.003**	0.037***	0.000
	(0.008)	(0.001)	(0.011)	(0.001)	(0.011)	(0.002)
Income	-0.006	-0.004***	-0.001	-0.005***	0.006	-0.003**
	(0.004)	(0.001)	(0.007)	(0.001)	(0.008)	(0.001)
$\hat{cc} \cdot r_t$			1.393**	0.124		
			(0.636)	(0.084)		
$\hat{cc}$			-4.538***	-0.468**		
			(1.716)	(0.226)		
$I_{\hat{cc}} \cdot r_t$					1.390***	0.254***
					(0.413)	(0.061)
$I_{\hat{cc}}$					-4.008***	-0.721***
					(1.147)	(0.168)
Obs.	172,159	172,159	109,833	109,833	109,833	109,833

Notes: Regression results for CEX data from 1996Q1 to 2014Q1. The dependent variable is the two-quarter ahead consumption growth rate. r_t is the one-year rate instrumented with the Nakamura-Steinsson monetary policy shocks. Variables College education (yes or no), race (white or non-white), marital (married or not married) are dummies. Income is in logs. Standard errors are clustered by household. The standard errors for the regressions including $\hat{cc}$ or $I_{\hat{cc}}$ are bootstrapped. All regressions include year-quarter fixed effects. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

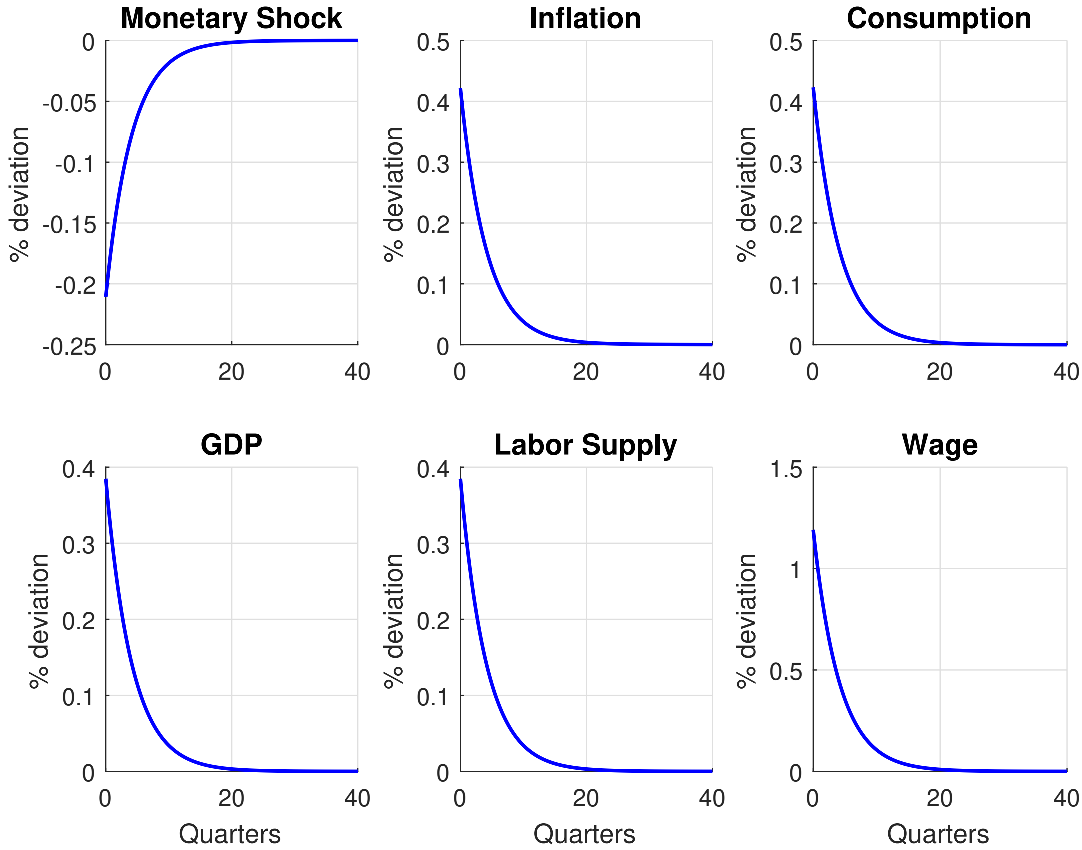
Table C.4: Consumption response to the five-year rate

Variable	(1) Dur	(2) Non-dur	(3) Dur	(4) Non-dur	(5) Dur	(6) Non-dur
r_t	-0.229**	0.003	-0.644***	-0.025	-0.692***	-0.076***
	(0.097)	(0.011)	(0.230)	(0.029)	(0.187)	(0.025)
Age	0.004***	0.000***	-0.000	-0.001***	0.001	-0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
College education	0.028	0.010***	-0.007	0.011***	-0.030	0.005
	(0.020)	(0.002)	(0.028)	(0.003)	(0.031)	(0.004)
Race	0.119***	0.009***	0.070**	0.000	0.100***	0.007
	(0.025)	(0.003)	(0.034)	(0.004)	(0.037)	(0.005)
Marital	0.109***	0.008***	0.029	-0.002	0.066**	0.005
	(0.022)	(0.003)	(0.031)	(0.004)	(0.032)	(0.004)
Family size	0.020**	-0.001	0.047***	0.002**	0.033***	-0.000
	(0.008)	(0.001)	(0.011)	(0.001)	(0.011)	(0.001)
Income	-0.006	-0.004***	-0.001	-0.005***	0.007	-0.003***
	(0.004)	(0.001)	(0.007)	(0.001)	(0.008)	(0.001)
$\hat{cc} \cdot r_t$			1.617**	0.132		
			(0.712)	(0.094)		
$\hat{cc}$			-6.571***	-0.605*		
			(2.545)	(0.337)		
$I_{\hat{cc}} \cdot r_t$					1.533***	0.270***
					(0.430)	(0.061)
$I_{\hat{cc}}$					-5.740***	-1.000***
					(1.567)	(0.224)
Obs.	172,159	172,159	109,833	109,833	109,833	109,833

Notes: Regression results for CEX data from 1996Q1 to 2014Q1. The dependent variable is the two-quarter ahead consumption growth rate. r_t is the five-year rate instrumented with the Nakamura-Steinsson monetary policy shocks. Variables College education (yes or no), race (white or non-white), marital (married or not married) are dummies. Income is in logs. Standard errors are clustered by household. The standard errors for the regressions including $\hat{cc}$ or $I_{\hat{cc}}$ are bootstrapped. All regressions include year-quarter fixed effects. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

C.4 Appendix to Section 3.3

Figure C.5: IRFs to a 1% monetary policy shock



Bibliography

Adrian, Tobias and Nina Boyarchenko. (2012). "Intermediary leverage cycles and financial stability". Staff Reports 567. Federal Reserve Bank of New York.

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. (2019). "Vulnerable growth". *American Economic Review 109* (4), 1263–89.

Ahn, SeHyoun, Greg Kaplan, Benjamin Moll, Thomas Winberry, and Christian Wolf. (2018). "When inequality matters for macro and macro matters for inequality". *NBER macroeconomics annual 32* (1), 1–75.

Alessandri, Piergiorgio and Haroon Mumtaz. (2017). "Financial conditions and density forecasts for US output and inflation". *Review of Economic Dynamics 24*, 66–78.

Alpanda, Sami, Eleonora Granziera, Sarah Zubairy, et al. (2019). "State dependence of monetary policy across business, credit and interest rate cycles".

Alpanda, Sami and Sarah Zubairy. (2019). "Household Debt Overhang and Transmission of Monetary Policy". *Journal of Money, Credit and Banking 51*, 1265–1307.

Angrist, Joshua D, Òscar Jordà, and Guido M Kuersteiner. (2018). "Semiparametric estimates of monetary policy effects: string theory revisited". *Journal of Business & Economic Statistics 36* (3), 371–387.

Aruoba, S Borağan, Luigi Bocola, and Frank Schorfheide. (2017). "Assessing DSGE model nonlinearities". *Journal of Economic Dynamics and Control 83*, 34–54.

Auclert, Adrien. (2019). "Monetary policy and the redistribution channel". *American Economic Review 109* (6), 2333–67.

Auclert, Adrien, Matthew Rognlie, and Ludwig Straub. (2020). "Micro Jumps, Macro Humps: Monetary Policy and Business Cycles in an Estimated HANK Model". NBER Working Papers 26647. National Bureau of Economic Research, Inc.

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

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

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

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

Barnichon, Regis, Christian Matthes, and Alexander Ziegenbein. (2018). “Are the Effects of Financial Market Disruptions Big or Small?” *working paper*.

Beraja, Martin, Andreas Fuster, Erik Hurst, and Joseph Vavra. (2019). “Regional heterogeneity and the refinancing channel of monetary policy”. *The Quarterly Journal of Economics 134* (1), 109–183.

Bernanke, Ben S., Mark Gertler, and Simon Gilchrist. (1999). “The financial accelerator in a quantitative business cycle framework”. In: *Handbook of Macroeconomics*. Ed. by J. B. Taylor and M. Woodford. Vol. 1. Handbook of Macroeconomics. Elsevier. Chap. 21, 1341–1393.

Bilbiie, Florin O. (2019). “The new Keynesian cross”. *Journal of Monetary Economics*.

Bloom, Nicholas. (2009). “The impact of uncertainty shocks”. *econometrica 77* (3), 623–685.

Bluwstein, Kristina. (2017). “Asymmetric Macro-Financial Spillovers”. Working Paper Series 337. Sveriges Riksbank (Central Bank of Sweden).

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

Brunnermeier, Markus K. (2009). “Deciphering the liquidity and credit crunch 2007-2008”. *Journal of Economic perspectives 23* (1), 77–100.

Brunnermeier, Markus K. and Yuliy Sannikov. (2014). “A Macroeconomic Model with a Financial Sector”. *American Economic Review 104* (2), 379–421. DOI: 10.1257/aer.104.2.379.

Brzoza-Brzezina, Michał and Marcin Kolasa. (2013). "Bayesian evaluation of DSGE models with financial frictions". *Journal of Money, Credit and Banking 45* (8), 1451–1476.

Cai, Michael, Marco Del Negro, Marc Giannoni, Abhi Gupta, Pearl Li, and Erica Moszkowski. (2018). "DSGE forecasts of the lost recovery". Staff Reports 844. Federal Reserve Bank of New York.

Chang, Yoosoon, Junior Maih, and Fei Tan. (2018). "State Space Models with Endogenous Regime Switching". Working Paper 2018/12. Norges Bank.

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

Christiano, Lawrence J., Martin S. Eichenbaum, and Mathias Trabandt. (2018). "On DSGE Models". *Journal of Economic Perspectives 32* (3), 113–40. DOI: `10.1257/jep.32.3.113`.

Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno. (2014). "Risk Shocks". *American Economic Review 104* (1), 27–65. DOI: `10.1257/aer.104.1.27`.

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

Cloyne, James, Clodomiro Ferreira, and Paolo Surico. (2020). "Monetary policy when households have debt: new evidence on the transmission mechanism". *The Review of Economic Studies 87* (1), 102–129.

Coenen, Günter, Christopher J. Erceg, Charles Freedman, Davide Furceri, Michael Kumhof, René Lalonde, Douglas Laxton, Jesper Lindé J., Annabelle Mourougane, Dirk Muir, Susanna Mursula, Carlos de Resende, John Roberts, Werner Roeger, Stephen Snudden, Mathias Trabandt, and Jan in't Veld. (2012). "Effects of Fiscal Stimulus in Structural Models". *American Economic Journal: Macroeconomics 4* (1), 22–68. DOI: `10.1257/mac.4.1.22`.

Del Negro, Marco, Marc P. Giannoni, and Frank Schorfheide. (2015). "Inflation in the Great Recession and New Keynesian Models". *American Economic Journal: Macroeconomics 7* (1), 168–96. DOI: `10.1257/mac.20140097`.

Del Negro, Marco, Raiden B Hasegawa, and Frank Schorfheide. (2016). "Dynamic prediction pools: an investigation of financial frictions and forecasting performance". *Journal of Econometrics 192* (2), 391–405.

Del Negro, Marco and Frank Schorfheide. (2013). "DSGE model-based forecasting". In: *Handbook of economic forecasting*. Vol. 2. Elsevier, 57–140.

Dewachter, Hans and Raf Wouters. (2014). "Endogenous risk in a DSGE model with capital-constrained financial intermediaries". *Journal of Economic Dynamics and Control 43* (C), 241–268. DOI: 10.1016/j.jedc.2013.12.00.

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

DiCecio, Riccardo. (2009). "Sticky wages and sectoral labor comovement". *Journal of Economic Dynamics and Control 33* (3), 538–553.

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

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

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

Eichenbaum, Martin, Sergio Rebelo, and Arlene Wong. (2018). "State dependent effects of monetary policy: The refinancing channel". Tech. rep. National Bureau of Economic Research.

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

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

Gertler, Mark and Simon Gilchrist. (2018). "What Happened: Financial Factors in the Great Recession". *Journal of Economic Perspectives 32* (3), 3–30. DOI: 10.1257/jep.32.3.3.

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

Gilchrist, Simon and Egon Zakrajšek. (2012). "Credit Spreads and Business Cycle Fluctuations". *American Economic Review 102* (4), 1692–1720. DOI: 10.1257/aer.102.4.1692.

Guerrieri, Luca and Matteo Iacoviello. (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.

Gürkaynak, Refet S, Brian Sack, and Eric Swanson. (2005). "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements". *International Journal of Central Banking 1* (1).

Gust, Christopher, Edward Herbst, David López-Salido, and Matthew E. Smith. (2017). "The Empirical Implications of the Interest-Rate Lower Bound". *American Economic Review 107* (7), 1971–2006.

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

Harding, Martin and Mathias Klein. (2019). "Monetary Policy and Household Deleveraging". Discussion Papers of DIW Berlin 1806. DIW Berlin, German Institute for Economic Research.

He, Zhiguo and Arvind Krishnamurthy. (2014). "A Macroeconomic Framework for Quantifying Systemic Risk". Working Paper 19885. National Bureau of Economic Research. DOI: 10.3386/w19885.

Holden, Tom D., Paul Levine, and Jonathan M. Swarbrick. (2018). "Credit crunches from occasionally binding bank borrowing constraints". Discussion Papers 57/2018. Deutsche Bundesbank.

Holm, Martin Blomhoff, Pascal Paul, and Andreas Tischbirek. (2020). "The Transmission of Monetary Policy under the Microscope". In: Federal Reserve Bank of San Francisco.

Hubrich, Kirstin and Robert J Tetlow. (2015). "Financial stress and economic dynamics: The transmission of crises". *Journal of Monetary Economics 70*, 100–115.

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

Iacoviello, Matteo. (2015). “Financial Business Cycles”. *Review of Economic Dynamics 18* (1), 140–164.

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

Jarociński, Marek and Peter Karadi. (2020). “Deconstructing Monetary Policy Surprises-The Role of Information Shocks”. *American Economic Journal: Macroeconomics 12* (2), 1–43. DOI: 10.1257/mac.20180090.

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

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

——— (2017). “Large and State-Dependent Effects of Quasi-Random Monetary Experiments”. Working Paper Series 2017-2. Federal Reserve Bank of San Francisco.

Kaplan, Greg, Benjamin Moll, and Giovanni L Violante. (2018). “Monetary policy according to HANK”. *American Economic Review 108* (3), 697–743.

Kaplan, Greg and Giovanni L. Violante. (2014). “A Model of the Consumption Response to Fiscal Stimulus Payments”. *Econometrica 82* (4), 1199–1239.

——— (2018). “Microeconomic Heterogeneity and Macroeconomic Shocks”. *Journal of Economic Perspectives 32* (3), 167–94. DOI: 10.1257/jep.32.3.167.

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

Kocherlakota, Narayana R. (2000). “Creating business cycles through credit constraints”. *Quarterly Review* (Sum), 2–10.

Lindé, Jesper, Frank Smets, and Rafael Wouters. (2016). “Challenges for Central Banks’ Macro Models”. Working Paper Series 323. Sveriges Riksbank (Central Bank of Sweden).

Lindé, Jesper and Mathias Trabandt. (2018). “Resolving the missing deflation puzzle”. *Manuscript, Sveriges Riksbank.*

Luetticke, Ralph. (2018). “Transmission of Monetary Policy with Heterogeneity in Household Portfolios”. Discussion Papers 1819. Centre for Macroeconomics (CFM).

Maih, Junior. (2015). “Efficient perturbation methods for solving regime-switching DSGE models”. *Norges Bank Working Paper* (No. 2015/1).

Maria, José R. and Paulo Júlio. (2018). "An integrated financial amplifier: the role of defaulted loans and occasionally binding constraints in output fluctuations". Working Papers w201813. Banco de Portugal, Economics and Research Department.

McKay, Alisdair, Emi Nakamura, and Jón Steinsson. (2016). "The power of forward guidance revisited". *American Economic Review 106* (10), 3133–58.

Mendoza, Enrique G. (2010). "Sudden Stops, Financial Crises, and Leverage". *American Economic Review 100* (5), 1941–66. DOI: 10.1257/aer.100.5.1941.

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

Mian, Atif R. and Amir Sufi. (2012). "What explains high unemployment? The aggregate demand channel". NBER Working Papers 17830. National Bureau of Economic Research, Inc.

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

Miranda-Agrippino, Silvia and Giovanni Ricco. (2018). "The Transmission of Monetary Policy Shocks". CEPR Discussion Papers 13396. C.E.P.R. Discussion Papers.

Nakamura, Emi and Jón Steinsson. (2014). "Fiscal Stimulus in a Monetary Union: Evidence from US Regions". *American Economic Review 104* (3), 753–92.

Nakamura, Emi and Jón Steinsson. (2018). "High-frequency identification of monetary non-neutrality: the information effect". *The Quarterly Journal of Economics 133* (3), 1283–1330.

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

Ottonello, Pablo and Thomas Winberry. (2018). "Financial heterogeneity and the investment channel of monetary policy". Tech. rep. National Bureau of Economic Research.

Pietrunti, Mario. (2017). "Financial Frictions and the Real Economy". *ESRB Working Paper Series* (No 41).

Prieto, Esteban, Sandra Eickmeier, and Massimiliano Marcellino. (2016). "Time Variation in Macro-Financial Linkages". *Journal of Applied Econometrics 31* (7), 1215–1233.

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

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

Ravn, Morten O. and Harald Uhlig. (2002). “On adjusting the Hodrick-Prescott filter for the frequency of observations”. *The Review of Economics and Statistics 84* (2), 371–375.

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

Rotemberg, Julio J. (1982). “Sticky prices in the United States”. *Journal of Political Economy 90* (6), 1187–1211.

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

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

Swanson, Eric T. and John C. Williams. (2014). “Measuring the Effect of the Zero Lower Bound on Medium- and Longer-Term Interest Rates”. *American Economic Review 104* (10), 3154–85. DOI: 10.1257/aer.104.10.3154.

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

Werning, Iván. (2015). “Incomplete markets and aggregate demand”. Tech. rep. National Bureau of Economic Research.

Wong, Arlene. (2019). “Refinancing and The Transmission of Monetary Policy to Consumption”. Tech. rep. Mimeo.

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

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Hiermit erkläre ich, dass ich die vorgelegte Dissertation auf Grundlage der angegebenen Quellen und Hilfsmittel selbstständig verfasst habe. Alle Textstellen, die wörtlich oder sinngemäß aus veröffentlichten oder nicht veröffentlichten Schriften entnommen sind, sind als solche kenntlich gemacht. Die vorgelegte Dissertation hat weder in der gleichen noch einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule zum Promotionsverfahren vorgelegen.

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Berlin, 31. Mai 2020

Liste verwendeter Hilfsmittel

- MATLAB Version: 9.1.0.441655 (R2016b)
  - Econometrics Toolbox
  - Global Optimization Toolbox
  - Optimization Toolbox
  - Parallel Computing Toolbox
  - Symbolic Math Toolbox
  - Statistics Toolbox
- Dynare 4.5.4
- Stata 15
- Rationality In Switching Environments (RISE) Toolbox
- PHACT Toolbox
- Microsoft Excel
- LaTeX
- Siehe auch Literatur- und Quellenangaben