JOINT PHD PROGRAM IN ECONOMICS

UNIVERSITIES OF FLORENCE, PISA AND SIENA

ESSAYS IN APPLIED MACROECONOMICS

SUBMITTED BY

GIACOMO RELLA

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY IN ECONOMICS

SUPERVISED BY
PROF. MARCO P. TUCCI

PROGRAM COORDINATOR
PROF. MICHELANGELO VASTA

ACADEMIC YEAR 2020-2021

XXXIII CYCLE

ACKNOWLEDGMENTS

I experienced some of the best years during my time as PhD student and many people contributed to that, both inside and outside academia.

I would like to express my gratitude to my supervisor Marco P. Tucci for his continuous guidance, encouragement and insights. I am thankful to the members of the examination committee, Gert Peersman, Sarah Zubairy and Alberto Dalmazzo, for providing detailed and thoughtful comments and suggestions on the thesis. I would like to thank all the Board of the joint PhD Program in Economics of the Universities of Siena, Pisa and Florence, Directors Ugo Pagano and Michelangelo Vasta, Francesca Fabbri for academic support, and Regione Toscana for financial support. I am thankful to Serena Sordi whose lectures and supervision during my master studies sparked me the desire to research in macroeconomics.

I wrote the second and third chapters of this thesis during the periods I spent as a visiting PhD student in Gent and Boston. I would like to thank Gert Peersman for welcoming me as visiting student at Gent University from September 2019 to February 2020. I am grateful to the staff of the Department of Economics that ensured a smooth arrival and stay. The research period in Gent represented a real shift in my research interests and skills. I am grateful to many people from which learned a lot, and which made my stay pleasant and funny. In particular, I would like to thank Marco Onofri, Wouter Van der Veken, Andrzej Szczepaniak, Lara Coulier, Frederic Opitz and Martin Iseringhausen.

I am grateful to Yun K. Kim for welcoming me as visiting PhD student at the Department of Economics at UMass Boston from February to September 2020, for making my stay in Boston smooth despite the tough times, for welcoming me into his family, and for continuous encouragement and support. The visiting period in Boston represented a further shift in my research path. I had the honor to co-author a paper with Yun K. Kim, Leila E. Davis and Joao Paulo A. de Souza. Thank you for giving me this opportunity and for constantly supervising my work. I want to to thank Riccardo Sangermano, Sara Piccinelli, Carmen Marsico and Björn Wennås for the nice months in Boston, the sunsets on the Charles River, the hikes and their friendship.

I am grateful to my fellow students Andrea Borsato, Andrea Galeotti, Asya Bellia, Chandni Dwarkasing, Erubiel Ordaz Cuevas, Giovanna Scarchilli, Leonarda Spiranec and Mehmet Ulug and fellow students from other cohorts - a special mention goes to Gabriele Lombardi - for their friendship and unforgettable days in Siena.

The chapters contained in this thesis have benefited from the inputs and comments of several people. I received helpful comments on the first chapter from Antonella Palumbo and Marwil Davila Fernández and seminar participants at Pontignano Annual Meeting (Siena, 2019), YSI@Storep conference (Siena, 2019), 2020 FMM Conference (Berlin, 2020). I received decisive inputs on the second chapter of the thesis from Wouter Van der Veken and Martin Iseringhausen and seminar participants at the Internal Seminar of the Department of Economics

(Gent, 2019) and Scottish Economic Society Annual Conference (2021). I am grateful to Daniele Girardi and seminar participants at the Pontignano Annual Meeting (2020) for comments on the third chapter of the thesis. It would not have been possible to write part of this thesis without open science and without the possibility of accessing codes and data for learning and replication. I am thankful to Dimistris Korobilis, Silvia Miranda-Agrippino, Ambrogio Cesa-Bianchi, Atif Mian and Amir Sufi, among others, for sharing their code and data with the research community.

I dedicate this work to my mother, father, sister and brother for their endless support and love.

Introduction

> *The monetary history of the last four hundred years has been replete with financial crises. The pattern was that investor optimism increased as economies expanded, the rate of growth of credit increased and economic growth accelerated, and an increasing number of individuals began to invest for short-term capital gains rather than for the returns associated with the productivity of the assets they were acquiring. The increase in the supply of credit and more buoyant economic outlook often led to economic booms as investment spending increased in response to the more optimistic outlook and the greater availability of credit, and as household spending increased as personal wealth surged.*
>
> *Kindleberger and Aliber (2011, p. 275)*

This dissertation consists of three chapters in applied macroeconomics. Although each chapter is independent and self-contained, they are linked by the common goal of shedding light on the macroeconomic implications of household and non-financial corporate debt.

Household debt expansions and macroeconomic stability

For many years, until the outbreak of the Great Financial Crisis, the mainstream view of the role of private debt in macroeconomic fluctuations was essentially a positive one. Although private debt-to-GDP ratios have grown almost everywhere in advanced countries, such a rise was generally interpreted as a by-product of economic growth. Ultimately, rising economic activity stimulates the development of credit markets or, as Joan Robinson (1952) put it, "where enterprise leads, finance follows." An alternative strand of research view credit and the development of financial markets as determining factors of economic development. This view, which dates back to Walter Bagehot (1873), Joseph A. Schumpeter (1911), John G. Gurley and E. S. Shaw (1955) and Raymond W. Goldsmith (1969), can be succinctly summarized in the following statement by John G. Gurley and E. S. Shaw (1955): "development involves finance as well as goods." Regardless of whether credit causes growth or vice-versa, both views envisage that credit-to-income ratios increase together with economic growth.

The outbreak of the Great Financial Crisis in 2007, however, shook this consensus. A substantial amount of post-crisis empirical work suggests that episodes of strong growth in private debt relative to income, especially when backed by real estates, foreshadow future contractions in economic activity. This new strand of literature, of which Atif Mian and Amir Sufi and Òscar Jordà, Moritz Schularick and Alan M. Taylor are leading authors, has essentially overturned the sign of the correlation between debt-to-income ratios and economic growth. The impressive boom-and-bust in household debt in the United States, Spain and Greece, together with the release of popular books and movies (e.g. *Inside Job* and *The Big Short*) helped to establish this view as the main narrative on the macroeconomic effects of private debt in the public opinion.

The new empirical literature on the macroeconomic effects of private debt, however, echoes an illustrious tradition in macroeconomics that views swings in credit as the determining factor in aggregate fluctuations. In writing on the role of balance sheet deterioration during the Great Depression Irving Fisher (1933) argued that:

> "I venture the opinion [...] that, in the great booms and depressions, each of the above named factors [over-production, under-consumption, over-capacity, price-dislocation, maladjustment between agricultural prices and industrial prices, over-confidence, over-investment, over-saving, over-spending, and the discrepancy between saving and investment] has played a subordinate role as compared with two dominant factors, namely over-indebtedness to start with and deflation following soon after." (Fisher, 1933, pp. 340-341)

Similarly, Charles E. Persons (1930) and Albert G. Hart (1938) wrote about the way in which the credit expansion of the 1920s led to defaults and foreclosures among household and small businesses and to generalized credit crunches in the following decade. Ben Bernanke (1983) and Frederic S. Mishkin (1978) later argued that incomplete credit contracts and imperfect credit markets likely magnified the adverse effects of the credit expansion prior to the Great Depression.

No scholar has perhaps focused on credit booms and their interaction with asset prices as Charles P. Kindleberger (1978) and Hyman P. Minsky (1986) did. Financial systems, it is argued, are inherently fragile as the supply of credit and expectations are pro-cyclical. Lenders and borrowers become greedier in lending and borrowing during expansions while they retreat from credit markets as the economy contracts. In Charles P. Kindleberger own's words:

> "[...] cycle of manias and panics results from the pro-cyclical changes in the supply of credit; the credit supply increases relatively rapidly in good times, and then when economic growth slackens, the rate of growth of credit has often declined sharply. A mania involves increases in the prices of real estate or stocks or a currency or a commodity [...] During the economic expansions investors become increasingly optimistic and more eager to pursue profit opportunities that will pay off in the distant future while the lenders become less risk-averse. Rational exuberance morphs into irrational exuberance, economic euphoria develops and investment spending and consumption spending increase. There is a pervasive sense that it is 'time to get on the train before it leaves the station' and the exceptionally profitable opportunities disappear. Asset prices increase further. An increasingly large share of the purchases of these assets is undertaken in anticipation of short-term capital gains and an exceptionally large share of these purchases is financed with credit". (Kindleberger and Aliber, 2011, p. 12)

The Great Financial Crisis induced numerous economists to rethink the issue of how private debt, in particular household debt, influences macroeconomic fluctuations. In many instances, this new literature re-elaborates the original ideas of Irving Fisher (1933), Charles P. Kindleberger (1978) and Hyman P. Minsky (1986) on the interaction between borrowing, asset prices and expectations.

Because much has been written about this topic since 2008, in the first chapter, titled MACROECONOMIC EFFECTS OF HOUSEHOLD DEBT: A SURVEY OF THE EMPIRICAL LITERATURE, I provide a systematic survey of the most influential contributions and categorize them in three main groups. The first group consists of papers that estimate the macroeconomic effects of household debt using cross-country panel data models. Papers in the second group employ cross-sectional regressions to explore the implications of the massive increase in household debt that preceded the contraction in consumption in the US during the Great Recession. The third and last group includes specifications that embrace vector autoregressions to explore the dynamic interaction between credit, output, prices and monetary policy in the US. The surveyed literature concurs that household debt expansions are followed by contractions in economic activity, after short periods of economic growth. Studies employing single-equation regressions suggest that this negative correlation can be explained by increased financial fragility during the expansions. Rising leverage increases spending and financial fragility, thus making aggregate demand more sensitive to exogenous shocks and to endogenous reversals in credit sentiment, as was foreseen by Irving Fisher (1933), Charles P. Kindleberger (1978) and Hyman P. Minsky (1986). In contrast, according to vector autoregression models the slowdown in economic activity that follows household debt expansions can be largely attributed to a tightening in monetary policy which endogenously responds to inflationary pressures. The two channels through which credit expansions lead to a disappointing growth performance in the future are not necessarily in contrast with each other. The disagreement might be due to the fact that vector autoregressions model the endogenous rise in interest rates elicited by household debt expansions. Instead, such endogenous response of interest rates is usually omitted in the single-equation regression framework.

MONETARY POLICY AND THE HOUSING FINANCE SYSTEM

Research on the macroeconomic effects of household debt suggests that monetary policy in the US has likely reacted, directly or indirectly, to household debt expansions. Although there is much debate on whether central banks should tame potentially unstable credit expansions with tighter monetary policy ("leaning against the wind"), the transmission of (conventional) monetary policy massively involves the response of both the housing sector and households' borrowing to changes in short-term interest rates. In a textbook depiction of the monetary policy transmission mechanism through housing, rising short-term interest rates may increase the cost of borrowing for prospective homeowners and depress housing demand. Because housing and construction activity is thought to be an important component of the business cycle in the US, lower housing demand may slowdown general economic activity.

Other mechanisms may however be quantitatively more relevant. For instance, since many US homeowners borrow at rates that are close to that set by the central bank, rising short-term interest rates may increase the debt service, squeeze discretionary income and reduce consumption of homeowners with adjustable-rate mortgages. On the contrary, interest rate cuts may stimulate spending of these same homeowners via lower interest payments. An expansionary monetary policy that lowers interest rates benefits homeowners with fixed-rate mortgages through mortgage refinancing. Regardless of the prevailing interest rate structure in the mortgage market, because higher short-term rates are associated with falling asset prices, tighter monetary policy may lead to a decline in house prices and consequently reduce the collateral value and raise the external finance premium of prospective homeowners. These examples show that the institutional features of the housing finance system (e.g. the prevailing structure of mortgage interest rates, the size of down-payments, the possibility to refinance and borrow against rising home equity) matter for the monetary policy transmission mechanism and for the responses to the policy shocks of household borrowing and of the housing sector.

The central topic of the second chapter, THE FED, HOUSING AND HOUSEHOLD DEBT OVER TIME, is the interplay between the sensitivity of the economy to monetary policy shocks and the institutional features of the housing finance system. In the US, the housing finance system underwent waves of institutional and regulatory changes between the 1970s and the 1980s. Some of these changes centered on the repeal of ceilings on lending rates, the cancellation of Regulation Q which capped interest rates payable on deposits, the entrance of less regulated financial institutions in the mortgage market and the growth of a market for mortgage-backed securities. As a consequence, the response of household borrowing and that of housing to monetary policy shocks may have changed over time. In order to assess whether this is the case, I estimate a medium-scale vector autoregression model of the US economy. The model includes ten variables covering real GDP, prices, construction activity, monetary policy and the financial liabilities of the household sector from 1960 to 2018. Since the relationship between these variables is potentially time-varying, the vector autoregression model has parameters and volatility that vary over time.

Time-varying parameter models are now widely used in macroeconometrics. Time variation in the transmission of monetary policy implies that the parameters describing the relation between a policy instrument and some real variable has changed over time. Such changes can either be gradual or sudden at specific dates. The modeling approach to which I adhere favors the former type. Parameters that vary gradually over time imply that the response of the economy to monetary policy shocks changed slowly as the housing finance system swung between different regulatory regimes. Giorgio Primiceri (2005) emphasizes that continuously evolving parameters are compatible with agents in the private sector learning about regime changes rather than immediately responding to them, as would be the case with discrete shifts. In estimating the model I deviate from the purely Bayesian framework that is traditionally used for time-varying parameter models. The computational complexity of this framework, in fact, poses an upper bound on how many variables (and parameters) a model can consider. Instead, I follow recent contributions that advocate for the use of approximation methods, such as forgetting factors and variance discounting estimators, which dramatically reduce the computational complexity associated with the estimation of medium- and large-scale time-varying parameter models.

The model provides some interesting insights on how the relationship between monetary policy, housing sector and household debt changed over time. Firstly, construction activity has become slightly more sensitive to monetary policy shocks despite reacting slower in most recent periods. In general, the effects of contractionary monetary policy shocks on household debt diminished over time except in some periods during which they have increased. Tight monetary policy led to large contractions in home mortgages and consumer credit during the credit crunches of the late 1960s. On the contrary, the reaction of all components of household debt to monetary policy shocks weakened during the Great Moderation. However, home mortgages were very sensible to monetary policy in the early 2000s but by less than what was in the late 1960s. The most striking result regards the dramatic increase in the responsiveness of house prices to monetary policy shocks.

In the last part of the chapter, I attempt a preliminary interpretation of these results. The exceptionally high responsiveness of mortgages and construction activity to monetary policy contractions in the 1960s and 1970s may suggest that the transmission of monetary policy worked through both Regulation Q and the maturity mismatch of thrift institutions (which were major lenders in the mortgage markets). Because of ceilings on lending rates and on interest rates that thrifts could offer to depositors, tight monetary policy in response to rising inflation was likely to be disruptive for the balance sheets of thrift institutions. Limits on the offered deposits rates at thrift institutions led to numerous disintermediation episodes whenever inflation was pushing interest rates beyond the ceiling. Indeed, with rising inflation, new saving products (e.g. certificate of deposits sold by commercial banks, and Treasury bills) offered higher yields than what the thrift industry could afford to pay on deposits. In this period, nonprice credit rationing was crucial in determining large fluctuations in credit flowing to the housing sector whenever interest rates rose beyond the ceilings. The interpretation based on nonprice credit rationing mechanisms is even more plausible in light of the extremely low responsiveness of house prices to monetary policy shocks during the same period. However, with the advent of the Great Moderation the relative importance of quantity rationing over price mechanisms likely decreased. Starting from the early 1980s, tighter monetary policy led to higher-and-higher contractions in house prices, while the sensitiveness of household debt in response to tightening policy shocks decreased. This suggests that after the late 1980s while Regulation Q was gradually lifted and the mortgage market was progressively integrated in capital markets, monetary policy shocks may have transmitted through the housing sector via house prices (and eventually mortgage rates) rather than through the quantity of mortgages supplied.

Non-financial corporate debt and the macroeconomy: a missing link?

Theories of credit-driven business cycles in the spirit of Hyman P. Minsky (1986) and Charles P. Kindleberger (1978) emphasize that the expansions in investment and household spending during *manias* are to some extent fueled by the greater availability of credit. Credit expansions toward households are indeed associated with temporary increases in economic activity, as showed in Chapter 1, whereas credit expansions toward non-financial corporations are not correlated with short-run growth in aggregate demand.

Against the backdrop of rising non-financial corporate debt-to-income ratios in advanced economies, the weak correlation between corporate debt expansions and aggregate demand is puzzling. Studies in corporate finance consider debt as an important source of finance of capital investment, besides internal funds and equity. For example, the *pecking order theory* of Stewart C. Myers and Nicholas S. Majluf (1984) suggests that the accumulation of corporate debt should mirror the need for external finance in financing investment. However, if increased borrowing is not associated neither with higher GDP nor with investment booms, then what is the non-financial corporate sector borrowing for?

In the third chapter, titled Real and financial effects of non-financial corporate debt, co-authored with Leila E. Davis, Joao Paulo A. de Souza and Yun K. Kim, we investigate the potential determinants of the weak correlation between non-financial corporate debt and aggregate demand. Our interpretation of this correlation rests on two main observations. On the one hand, new borrowing (the flow of credit to firms) provides funds which can be given alternative uses besides the financing of capital investment in the domestic economy. These alternative uses include the repayment of existing debts and the accumulation of a portfolio of financial assets. If firms channels a substantial part of borrowed funds into one of these uses, the relationship between debt expansions and aggregate demand is not straightforward. On the other hand, large non-financial corporations, which contribute to the bulk of aggregate financial flows, operate in global markets. With loose constraints on international capital movements, part of new borrowing may leak from the domestic economy in form of investment abroad and this would reduce the observed correlation between non-financial corporate debt expansions and aggregate demand in the domestic economy.

The empirical analysis in Chapter 3 supports these interpretations of the weak correlation between non-financial corporate debt expansions and aggregate demand. Using flow of funds data for the non-financial corporate sector in sixteen advanced economies over the 1970-2018 period, we show that new borrowing is strongly associated with a rise in holdings of financial assets net of non-debt liabilities, while being only weakly associated with an increase in capital expenditure. We find moreover that the initial infusion of cash that follows upon the settlement of a borrowing transaction accounts only for a small fraction of the increase in financial assets holdings, with the majority of the increase being accounted for non-cash assets. When we combine sector-level flow of funds data with country-level balance of payment data, we estimate a sizable relationship between new borrowing and the accumulation of large-stake equity holdings against foreign entities by resident units.

To conclude, this research explores the different facets of the macroeconomic consequences of private debt. In a broad sense, it highlights that recognizing the (often evolving) institutional setting, in which economic relations take place, matters for our understanding of the economy. For instance, considering that the housing finance system has dramatically changed is essential for a proper evaluation of the aggregate effects of monetary policy through housing and household debt. Moreover, recognizing that non-financial corporations are complex organizations, often operating in international financial and goods markets, is crucial in order to understand the relationship between corporate debt and the overall economy. The questions concerning the macroeconomic consequences of household and non-financial corporate debt are certainly not new. This dissertation is a preliminary attempt to inform this literature. For every potential answer provided in this dissertation new questions will arise. I hope to address these and others in future research.

Table of contents

List of Tables

LIST OF FIGURES

Chapter 1

MACROECONOMIC EFFECTS OF HOUSEHOLD DEBT: A SURVEY OF THE EMPIRICAL LITERATURE*

ABSTRACT

What are the macroeconomic effects of household debt? A recent empirical literature flourished after the Great Financial Crisis argues that household debt expansions have been historically followed by boom-and-bust cycles in economic activity. I survey this literature and organize it according to three main branches: panel data, cross-sectional, and vector autoregression models. I show that while different strands of literature concur that there is a significant correlation between household debt expansions and subsequent contractions in economic activity, they point to different underlying mechanisms. On the one hand, single-equation regressions favor explanations based on household financial fragility. On the other hand, vector autoregression models identify a role for monetary policy in generating the negative correlation between household debt and future economic activity.

Keywords: survey, household debt, macroeconomics
JEL codes: E32, E44, G51

1.1 Introduction

Since the Great Financial Crisis interest has grown in researching the links between household debt expansions and the macroeconomy. Researchers and policy makers are now more concerned about the macroeconomic consequences of household debt than they were before 2008. This concern partly mirrors the emblematic role that the accumulation of household debt had for the large imbalances that led to the Great Financial Crisis in the US.[1]

*I am grateful to Marco P. Tucci, Gert Peersman, Antonella Palumbo and Marwil J. Dàvila-Fernández for suggestions and comments on an early draft of this chapter. An earlier version of this chapter has been presented at the 2019 Pontignano PhD Annual Meeting (Siena), 2019 INET/YSI at STOREP Conference (Siena) and 2019 FMM Conference: The Euro at 20 (Berlin). The VAR model in the chapter has been estimated with the VAR Toolbox by Ambrogio Cesa-Bianchi to which I am grateful for making the toolbox available for the research community. In the Appendix of this chapter I replicate the findings in Mian et al. (2017) to which I am grateful for sharing codes and data.

[1] Along the chapter I use the words "household credit" and "household debt" interchangeably. In all case I refer to households' financial liabilities such as mortgages, consumer credit, other loans.

Credit cycles and financial crises, however, are not recent phenomena. Economic history records many episodes of boom-and-bust cycles in credit activity followed by deep recessions. The 1720 bubble of the South Sea Company, the 1790s credit expansion and the 1792 financial panic in Europe, the explosion of commercial papers backed by claims on the North America Western Lands and the subsequent panic in 1796-1797 are clear historical examples. In the most recent history, the late 1980s Japanese crisis, the early 1990s Scandinavian banking crises and the 2008-2011 financial crisis in Iceland provide vivid examples of business cycles induced by boom-and-bust cycles in private debt. To quote Charles P. Kindleberger, details proliferate, structure abides. Notwithstanding the post-2008 renewed interest, credit cycles were central in earlier macroeconomic theories of the real-financial interaction (Gertler, 1988). Leading authors, such as Fisher (1933), Kindleberger (1978) and Minsky (1986), formulated original theories of aggregate fluctuations driven or amplified by credit.

The growing importance of private debt reflects a long-term transformation in finance. Jordà et al. (2017) argue that as one looks at the financial history of advanced economies in the last 140 years, the *financial hockey stick* emerges as metaphor for the extraordinary acceleration in the growth of private debt-to-income ratios since the 1980s. As shown in Figure 1.1, the rise in total loans to the non-financial private sector accelerates starting from the 1980s. However, most of this acceleration has been driven by rising credit to household and by growing mortgage credit. The literature on the finance-growth nexus generally interprets the long-term rise of debt-to-income ratios as a growing of *financial depth* which is argued to be beneficial for economic growth (Levine, 2005; Rajan and Zingales, 1998).[2] In contrast, a recent literature focuses on the cyclical component of debt-to-income ratios and argues that episodes of large private debt expansions are generally followed by long and deep recessions.

In this chapter, I survey the recent literature on the macroeconomic effects of household debt and take a stock of its main results. Because much has been written on this topic, I narrow my attention to the post-2008 papers which explicitly address the consequences of household debt from a macroeconomic standpoint. To have a better mapping of the literature, I organize it in three branches or strands. The first strand of literature consists of papers that estimate the macroeconomic effects of household debt using cross-country panel data models. Papers in the second branch of literature employ cross-sectional regression models (generally at county/state level) to ask whether the large increase in household debt in the early 2000s was responsible for the large drop in consumption during the Great Recession in the US. The third strand of literature adopts multivariate vector autoregression (VAR) models to study the joint dynamics of credit, macroeconomic aggregates and monetary policy in the US.

[2] Recent studies on the finance-growth nexus suggest that the relationship between private debt-to-income ratios and economic growth is non-linear, namely debt becomes detrimental for growth after debt-to-income ratios reach some threshold level (Arcand et al., 2015).

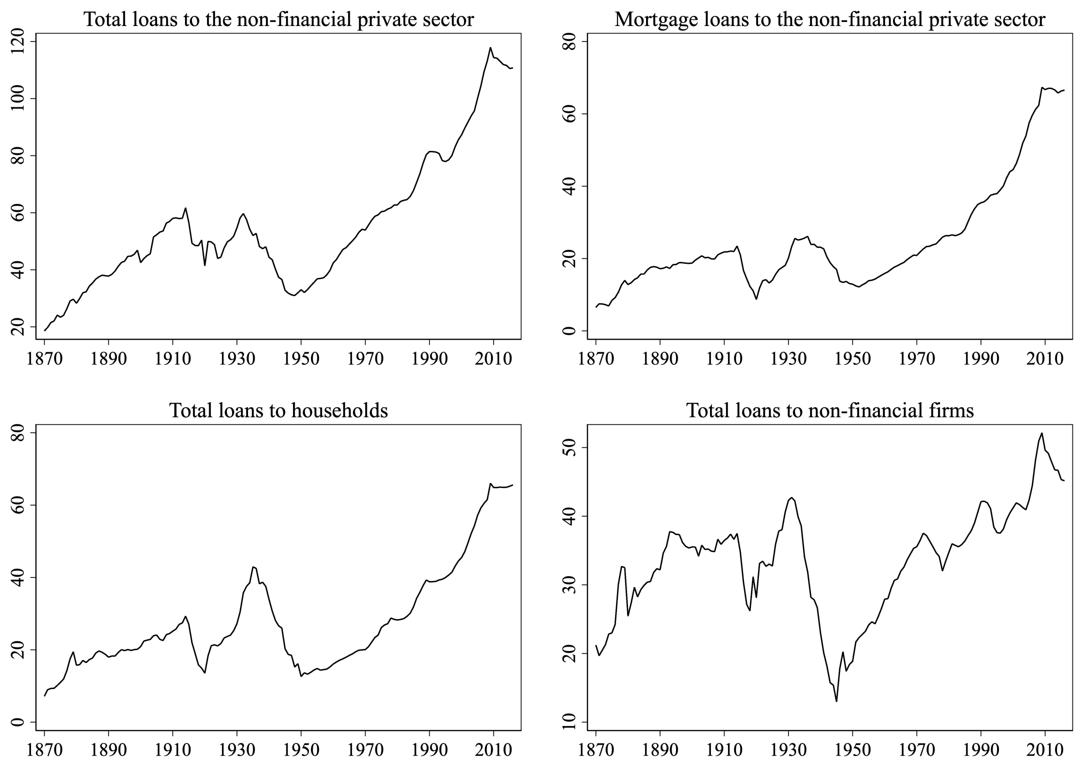


FIGURE 1.1: CREDIT TO NON-FINANCIAL SECTOR, 1870-2015, AVERAGE OF 17 COUNTRIES

Notes: this figure plots average debt-to-GDP ratios using annual data from the Jordà-Schularick-Taylor Macrohistory Database (Jordà et al., 2017). Both debt and GDP are nominal and in local currency. The y-axis measure debt as percentage of GDP. Country are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States.

The papers included in this survey consider very diverse indicators of aggregate activity and of household debt. To fix ideas on which are the key variables, I present a series of general or nested model for each of the surveyed strands of literature. These models nest the various empirical specifications proposed in the papers that I survey. The nested models serve the purpose of allowing the reader to easily move through the literature, quickly identify empirical specifications, outcome variables, key household debt indicators and the main macroeconomic controls that have been considered.[3]

The surveyed literature suggests that household debt expansions are followed by contractions in economic activity. However, there is some disagreement on which is the economic mechanism that better explains this correlation. Single-equation regressions (panel data and

[3] The nested models are only used as conceptual framework to help the organization of the literature. To gain familiarity with this framework, I introduce an example borrowed from Brooks (2019). Suppose that two researchers are independently working on measuring the variation in some variable y. Each researcher has a different theory about which explanatory variable to choose. Alice selects the model $y = \alpha_1 + \alpha_2 x_1 + u$ while Bob selects the model $y = \beta_1 + \beta_2 x_2 + v$. Bob's model can not be viewed as a restricted version of Alice's model, and vice-versa. They are non-nested models. However, the two non-nested models can be compared by nesting them into a more general model. The nested model is $y = \gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \varepsilon$ and contains both Bob and Alice's models as special case when γ_2 and γ_1 are restricted to zero, respectively. This is the philosophy that has inspired the construction of nested models to sum-up the literature in this survey.

cross-sectional models) suggest that large financial imbalances during the credit expansion lead to increased financial fragility and are responsible for the subsequent contraction in economic activity. The emphasis on expectations and financial innovations as endogenous forces driving the interaction between credit and real activity makes this interpretation descendant of Minsky (1986) and Kindleberger (1978). An influential version of this interpretation is the *credit-driven household demand channel* (Mian and Sufi, 2018). According to this channel, many business cycles in advanced economies are ultimately generated by an exogenous expansion in the supply of credit which, most of the time, is not motivated by prospects of future income growth. During the expansion, economic growth is driven by debt-financed household demand rather than by increases in the productive capacity of firms. The expansion ultimately leads to a contraction when aggregate demand starts to decline due to exogenous shocks or to endogenous reversal in credit sentiment. The household debt overhang and the imbalances during the credit expansion amplify the contraction in economic activity.

Multivariate (VAR) models cast doubt on the relevance of the household financial fragility hypothesis. Instead, this strand of literature favors an explanation of the negative correlation between household debt expansions and subsequent economic activity that hinges on the endogenous reaction of interest rates. Household debt expansions stimulate output growth in the short- and medium-run but they also lead to a rise in inflation. Rising inflation elicits a tightening in monetary policy and the resulting increase in interest rates slows down output growth. In other words, the VAR literature suggests that the contractions in economic activity following (inflationary) household debt expansions are caused by the automatic increase in interest rates they cause.

ROAD MAP. The chapter is organized as follows. In Section 1.2, I survey the strand of literature that uses single-equation regressions, namely cross-country panel data and cross-sectional models. Section 1.3 surveys the macro-financial VAR models on the interaction between credit, macroeconomic aggregates and monetary policy in the US. In Section 1.4, I delve into some unresolved issues highlighted by the survey. These issues concern the choice and interpretation of the household debt indicators, the mechanisms proposed to explain the correlation between household debt and real activity, and the comparison between the macroeconomic effects of household and non-financial firm debt expansions. Section 1.5 concludes.

1.2 Evidence from single-equation regressions

I begin by surveying the evidence on the macroeconomic effects of household debt arising from single-equation regressions. I start by looking at panel-data models estimated for large cross-sections of mostly advanced economies. Then, I explore the relationship between household debt and consumption during the Great Recession in the US.

1.2.1 Patterns of household debt and business cycles across time and space

An influential strand of research in applied macroeconomics shows a systematic relationship between household debt expansions and future downturns in economic activity. This result is supported by a number of studies using panel data models for large cross-sections of countries. Equation 1.1 combines some of the most influential empirical specifications in this literature. In particular, the panel data model in equation 1.1 nests the baseline models in Mian et al. (2017), Drehmann et al. (2018), Jordà et al. (2016) and Müller and Verner (2020):

$$\Delta y_{it+h} = \alpha_i^h + \beta^h D_{it}^{HH} + \textbf{Credit}_{it}'\gamma^h + \textbf{Financial}_{it}'\theta^h + \textbf{Housing}_{it}'\delta^h \\ + \textbf{Real Activity}_{it}'\lambda^h + \textbf{Openness}_{it}'\psi^h + u_{it+h} \quad (1.1)$$

where i and t index countries and time (years or quarters), respectively. Equation 1.1 suggests that the macroeconomic effects of household debt can be estimated by regressing a measure of economic activity (Δy_{it+h}) on an indicator of household debt (D_{it}^{HH}). Since many other factors may influence economic activity independently of household debt, a wide set of control variables is generally included in the models. Panel A in Table 1.1 groups the household debt indicators, outcome variables and other information about the non-nested models. In equation 1.1, I add the subscript/superscript h because all non-nested models estimate the macroeconomic effects of household debt using local projections (Jordà, 2005). With local projections, the sequence of estimated coefficients $\left\{\partial \Delta y_{it+h}/\partial D_{it}^{HH} = \beta^h\right\}_{h=1}^{H}$ traces out an impulse response function, namely the impact of a unit change in D_{it}^{HH} on the dependent variable at time $t+h$.

Outcome. The outcome variable is generally a measure of economic activity. More specifically, the dependent variable can be the 3-year growth of log real GDP (Mian et al., 2017), the h-year growth of log real GDP (Drehmann et al., 2018), the h-year change of log real GDP per capita during the economic recovery (Jordà et al., 2016), or alternatively the change of log real GDP from $t-3+h$ to $t+h$ (Müller and Verner, 2020).

Household debt indicator. The non-nested models in equation 1.1 proxy household debt growth using slightly different indicators. For example, the main proxy of household debt growth in Mian et al. (2017) is the 3-year change in household debt-to-GDP in $t-1$. Their main source of data for the stock of household debt is the Bank of International Settlements (BIS) "Long series of total credit to the nonfinancial sector." In BIS data, debt is defined as total borrowing by households and nonprofit institutions serving households from banks and other non-bank lenders. Müller and Verner (2020) employ substantially the same measure of household debt growth, namely the contemporaneous 3-year change in household debt-to-GDP. The household debt indicator in Jordà et al. (2016) is mortgage debt accumulated during the expansion. The accumulation of mortgage debt is calculated at annual rate in percentage points per year and in deviations from its historical mean. They focus on the accumulation of mortgage debt before a crisis occurs and measure economic activity after each crisis. Drehmann et al. (2018) explicitly focus on the flow of household debt rather that on changes in debt-to-income ratios. Their indicator of household debt growth is new borrowing-to-GDP in $t-1$ and new borrowing is measured by the change in the stock of debt plus amortizations.

MACROECONOMIC CONTROLS. The macroeconomic controls represent factors which are likely to influence current and future economic activity, independently of household debt. Table 1.2 provides a detailed list of the control variables organized in blocks. The Credit block comprehends leverage measures of other sectors in the economy, e.g. non-financial firms, government, tradable and non-tradable sector. The Financial block includes factors that capture general credit conditions in the economy, e.g. changes in interest rates on the stock of household debt, spreads and changes in loan loss provision. The Housing block includes variables that control for the value of collateral and house prices. The Real Activity block encompasses conventional macroeconomic indicators such as various measures of inflation, the unemployment rate and productivity growth. The Openness block consists of control variables related to the current account and to exchange rates. In addition, all non-nested models include country fixed effects in order to account for country-level unobserved heterogeneity.[4]

Household debt expansions predict negative GDP growth

In Mian et al. (2017), Drehmann et al. (2018), Jordà et al. (2016) and Müller and Verner (2020), household debt growth is positively correlated with contemporaneous and short-term GDP growth ($\beta^h > 0$ for small values of h), while the correlation turns negative as GDP growth is projected further into the future ($\beta^h < 0$ for large values of h). In other words, household debt expansions predict short-run growth but future contractions in economic activity.

It is important to highlight that this correlation does not necessarily implies that household debt expansions are *the* cause of future economic contractions. However, some studies take a number of strategies to exclude that the correlation is driven by confounding factors. For example, Mian et al. (2017) show impulse responses from a proxy-VAR in which mortgage spreads are used to instrument household debt expansions. In a two-stage least squares exercise, they use the convergence of sovereign spreads over 10-year US Treasuries to instrument household

[4]The nested model in equation 1.1 does not include time fixed effects since they are not considered by the non-nested models. Omitting time fixed effects amounts to exclude the autonomous influence that unobserved time-varying global factors may have on country-level GDP growth. In order to assess whether the exclusion of time fixed effects leads to an omitted variable problem I replicate Figure II in Mian et al. (2017, p. 1770) using their replication kit. In that figure, Mian et al. (2017) use local projections to show that household debt expansions predict significant boom-and-busts cycles in GDP. However, when I replicate their impulse responses after adding time fixed effect I find that the boom-and-bust cycles in GDP induced by household debt expansions become not significant. Moreover, time fixed effects attenuates the real effects of household debt expansions. I show and compare these results in Appendix A. Mian et al. (2017) acknowledge that time fixed effects would reduce both magnitude and significance of their estimates. At the same time, they provide an economic interpretation of time fixed effects. They argue that the global unobserved factor that matters the most for country-level GDP growth is the global change in the household debt-to-GDP ratio. This motivates their choice of excluding *generic* time dummies from their baseline models. Time fixed effects, it is argued, would lead to underestimate the effects of global household debt cycles. To the best of my knowledge, only Mian et al. (2017) discuss the implications of omitting time fixed effects for their results.

debt expansions in the euro zone. Jordà et al. (2016) provide estimates of β^h using using synthetic controls methods. Moreover, in many specifications, the household debt indicator is lagged relative to the outcome variable in order to avoid simultaneity.

The specifications included in equation 1.1 represent a small though rather influential subset of cross-country panel data models on the macroeconomic effects of household debt growth. Other studies find similar results using slightly different specifications, e.g. threshold models and logistic regressions. Lombardi et al. (2017) and Cecchetti et al. (2011) find that household debt may slow down economic growth when it reaches 80 to 85% of GDP. Gourinchas and Obstfeld (2012) show that domestic credit expansions together with a real currency appreciation robustly predict financial crises in both advanced and emerging economies. Anundsen et al. (2016) find that bubbles in house prices and high household debt are strong predictors of the probability of observing financial crises. In a sample of advanced and emerging economies, Büyükkarabacak and Valev (2010) find that household debt expansions increase the probability of banking crises without any long-term positive effect on income growth. Similarly, Alter et al. (2018) confirm the findings in Mian et al. (2017) for a larger set of countries.

Why do household debt expansions predict future recessions?

The model in equation 1.1 can be used to shed light on the different channels through which household debt expansions can influence future economic activity.

THE CREDIT-DRIVEN HOUSEHOLD DEMAND CHANNEL. Mian et al. (2017) and Mian and Sufi (2018) argue that the negative correlation between household debt expansions and future economic activity can be explained through the *credit-driven household demand channel*. This view of the business cycle conceives an outward shift in the supply of credit as the ultimate force generating expansions and contractions in economic activity. Potential drivers of the initial shift can be an influx of foreign capital in the country, financial liberalizations, or financial innovations. The credit supply shock can materialize as a relaxation of lending standards with lenders being more willing to lend to marginal borrowers as the economy starts to boom. A favorable credit market sentiment may induce an endogenous shift in the supply of credit, possibly detached from market fundamentals.[5] As the supply of credit shifts, credit spreads fall and house prices rise. Over the boom, credit-induced increases in house prices encourage the growth of the construction sector with amplification effects on aggregate demand. The crucial prediction of the *credit-driven household demand channel* is that the credit expansion spills over into the real economy by supporting household demand in contrast to business investment.[6] During household debt booms consumption-to-GDP rises, expenditure for tradable

[5] As in Kindleberger (1978) and Minsky (1986), this view stresses that the supply of credit is pro-cyclical and that this features is among the main factors that make the financial system fragile. Pro-cyclic means that lenders and borrowers become more greedy in lending and borrowing during expansions and less when the economy contracts. It follows that waves of optimism and pessimism are pro-cyclical too.

[6] Mian et al. (2020) provide a test for this prediction using cross-country panel data and the US banking deregulation in the 1980s.

goods and services increases, imports of consumption goods grow, while business investment-to-GDP remains flat. The expansion turns into a recession when household demand contracts. The shortfall in demand may be triggered by *events* that increase the real burden of debt, e.g. unemployment or a halt in house prices growth. These *events* do not necessarily reflect exogenous shocks. Indeed, a reversal in lenders expectations or a tightening of lending standards may arise endogenously as a consequence of the credit expansion. Just like overoptimism may drive the expansion in the supply of credit and lower spreads, unexpected news may lead lenders to revise their expectations downward and to increase spreads. These swings in expectations and credit may produce credit crunches and a slowdown in aggregate demand. The household debt overhang amplifies the response of the economy to these shocks. Heterogeneous marginal propensities to consume, the zero lower bound on nominal interest rates, fixed exchange rate regimes, defaults, foreclosures, credit crunches induced by losses at financial institutions make the recession following a debt expansion harsher and longer.

PRODUCTIVITY AND CAPITAL MISALLOCATION. Müller and Verner (2020) suggest that a potential reason for which household debt expansions are followed by recessions is that debt-financed household demand stimulates the growth of the non-tradable sector while leaving the productive capacity of the economy unaltered.[7] Non-tradable industries are characterized by lower productivity relative to tradable ones and household debt expansions are associated with the reallocation of resources toward low productivity sectors. This misallocation of resources from high to low productivity sectors may amplify the effects of the recession when it arrives. Moreover, household debt expansions may reduce the future level of productivity through a demand channel. For example, Bridges et al. (2017) suggest that large contractions in aggregate demand observed after household debt booms may be such that to reduce the productive capacity of the economy. In sum, the contractions in economic activity following household debt expansions may leave permanent scars on the economy.

EXTERNAL IMBALANCES. During household debt booms, the current account mirrors the reallocation of production and employment from tradable toward non-tradable industries. Mian et al. (2017) show that household debt expansions coincide with shrinking net exports and growing imports, mostly of consumption goods. However, net exports improve in the future but this improvement is driven by a drop in imports of consumption goods rather than by an increase in exports. Moreover, they find that the negative effects on output growth of household debt expansions are sharper when the country is running increasing current account deficits.

[7] Tradable and non-tradable are sub-sectors of the non-financial corporate sector. The tradable sector consists of firms producing goods and services that can be sold in the home economy and abroad, e.g. manufacturing. In contrast, the non-tradable sector consists of firms producing goods and services that can be only be consumed in the home economy, e.g. real estate and restaurants firms. Hence, the latter, differently from the former, is constrained by domestic demand. See also Mian and Sufi (2014) and Mian et al. (2020) on the importance of non-tradable sectors during household debt expansions.

THE OTHER SIDE OF THE COIN: RISING DEBT SERVICE. Debt expansions are persistent and mortgages (the bulk of household debt) have long maturities. Hence, new borrowing, i.e. the change in the stock of debt plus amortization, entails a particular schedule for the debt service, i.e. the sum of interest payments and amortization. According to Drehmann et al. (2018), new borrowing stimulates the expansion but also pushes up the debt service on the outstanding stock of debt. As a result, the rise in debt service reduces discretionary income and depresses output growth. Drehmann et al. (2018) argue that the observed medium-run downturn can be completely attributed to the delayed increase in debt service implied by the initial boom in new borrowing.

TABLE 1.1: MACROECONOMIC EFFECTS OF HOUSEHOLD DEBT: SUMMING UP THE LITERATURE

	Household debt indicator, D^{HH}	**Dependent variable**	**When**	**Where**
Panel A: cross-country panel data models (equation 1.1)				
Mian et al. (2017)	3-year change in debt-to-GDP	3-year growth in log real GDP	1960-2012 annual data	30 advanced and emerging economies
Drehmann et al. (2018)	new borrowing -to-GDP	h-year growth in log real GDP	1980-2015 annual data	16 advanced economies
Jordà et al. (2016)	mortgage credit accumulated in the expansion	h-year cumulative change in log real GDP per capita	1870-2015 annual data	17 advanced economies
Müller and Verner (2020)	3-year change in debt-to-GDP	3-year change in log real GDP	1940-2014 annual data	116 advanced and emerging economies
Panel B: cross-sectional model of the Great Recession in the US (equation 1.2)				
Mian and Sufi (2010)	2002Q2-2006Q4 change in debt-to-income	2006Q4-2009Q2 change in auto sales	Great Recession, quarterly data	450 US counties
Mian et al. (2013)	2006 housing leverage ratio	2006-2009 change in auto sales	Great Recession, annual data	6,182 US ZIP codes
Dynan (2012)	2007 mortgage debt-to-assets ratio	2007-2009 change in non-housing consumption	Great Recession, two survey waves	About 8,000 households from PSID
	Household debt indicator (D^{HH})	**Identification strategy**	**Shock**	**Where and When**
Panel C: macro-financial VAR model of the US economy (equation 1.3)				
Brunnermeier et al. (2019)	real bank credit for real estate and consumer loans	identification -through -heteroskedasticity	shock to D^{HH}	US 1973-2015 monthly data
Guerini et al. (2018)	real mortgage debt outstanding	independent component analysis	shock to D^{HH}	US 1966-2015 quarterly data
Peersman and Wagner (2015)	mortgage and consumer loans outstanding	zero and sign restrictions	Bank lending shock: it moves outstanding, retained and securitized loans in the same direction	US 1970-2008 quarterly data
Bachmann and Rüth (2020)	mortgages loan-to-value ratio	zero (Cholesky) restrictions	shock to D^{HH}	US 1973-2008 quarterly data

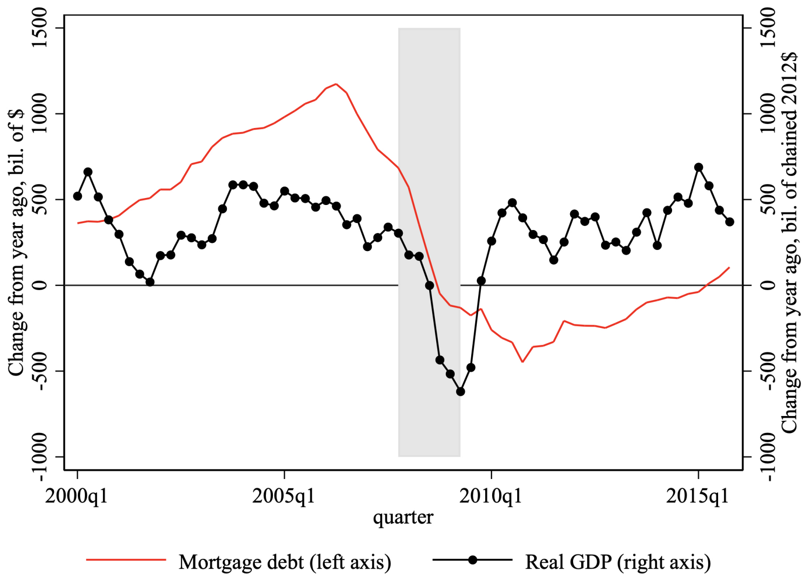


FIGURE 1.2: MORTGAGE DEBT AND THE GREAT RECESSION IN THE US

Notes: this figure plots the dynamics of mortgage debt and real GDP around the Great Recession in the US. Mortgage debt is the level (liability) of one-to-four-family residential mortgages. Both series are seasonally adjusted. The shaded area is the (NBER) Great Recession.

1.2.2 Household debt during the Great Recession in the United States

Although the correlation between household debt and subsequent contractions in economic activity is interesting in its own right, the interpretation of this result as a causal relationship may be threatened by the existence of an omitted factor that explains changes in both debt and activity. In contrast, the Great Recession provides a *natural experiment* that may be used to measure the effect of household debt expansions and explore the mechanisms at work.

From 2000 to 2009, the US experienced a dramatic boom-and-bust in household debt and the largest contraction in economic activity since the Great Depression. These credit and business cycles are clearly visible in Figure 1.2 which plots the year-over-year changes in mortgage debt and real GDP. The household debt expansion and the Great Recession unevenly hit the country. House prices and household debt grew more in some counties and metropolitan areas relative to other areas. Analogously, the drop in employment at the beginning of the crisis was not homogeneous across the country. Atif Mian and Amir Sufi collected a large amount of evidence on the causes and consequences of the boom-and-bust cycle in household debt in their influential book *House of Debt* (Mian and Sufi, 2015).

The cross-sectional variation in household debt growth led many researchers to employ very disaggregated datasets to identify and measure the consequences of the household debt expansion of the early 2000s. The cross-sectional units in these datasets are states, counties, metropolitan areas, ZIP-codes, or alternatively households. The effects of household debt expansions are generally estimated by regressing some proxy of economic activity (ΔC_i) observed during the crisis on a household debt indicator (D_i^{HH}) measured just before the onset of the recession. Equation 1.2 nests the models in Mian and Sufi (2010), Mian et al. (2013) and Dynan (2012) which may be considered among the most influential studies on the role of household debt during the Great Recession:

$$\Delta C_i = \alpha_i + \beta D_i^{HH} + \mathbf{Credit}_i' \boldsymbol{\gamma} + \mathbf{Housing}_i' \boldsymbol{\delta} + \mathbf{Real\ Activity}_i' \boldsymbol{\lambda} + u_i \tag{1.2}$$

The unit i can be a county (Mian and Sufi, 2010), a ZIP code (Mian et al., 2013), or alternatively a household from the Panel Study of Income Dynamics (Dynan, 2012). Additional details on the key household debt and outcome variables are provided in Panel B of Table 1.1.

OUTCOME. The dependent variable is a measure of spending between the beginning and the end of the Great Recession. More specifically, ΔC_i can be the change in auto sales in county i between 2006Q4 and 2009Q2 (Mian and Sufi, 2010), the change in auto sales in ZIP code i between 2006 and 2008 (Mian et al., 2013), or alternatively the change in non-housing consumption of household i between 2007 and 2009 (Dynan, 2012). Non-housing consumption is consumption for non-durable and durable non-housing goods. Mian and Sufi (2010) use a model similar to the one in equation 1.2 to estimate the effects of household debt expansions on household defaults, house prices, unemployment and residential investment.

HOUSEHOLD DEBT INDICATOR. The outcome variable is regressed on a measure of household debt, D_i^{HH}. Mian and Sufi (2010) focus on household debt growth and measure it as the change in the debt-to-income ratio in county i from 2002Q2 to 2006Q4. In contrast, Mian et al. (2013) use a proxy for the level of debt, namely the housing leverage ratio in 2006 at ZIP code-level. The housing leverage ratio is a stock-to-stock measure and is calculated as the sum of mortgages and home equity debt divided by home values. Hence, it is a measure of leverage akin to loan-to-value ratios. Using household-level data, Dynan (2012) measures household leverage as the ratio between mortgage debt and home value in 2007. In this context, the parameter β estimates if and to what extent the pre-2007 growth of household debt, or alternatively its level before the crisis, contributed to the slowdown in household spending during the Great Recession.

MACROECONOMIC CONTROLS. The nested model in equation 1.2 includes other variables which might have had an autonomous influence on household spending between 2007 and 2009. They are listed in Table 1.3. The controls in the Credit block capture local credit market conditions and the household-level cost of servicing debt. In fact, rising default rates or an increase in the share of income that is used for interest payments are likely to reduce consumption, independently of debt overhang problems. Analogously, the Real Activity block encompasses indicators of regional economic activity, as county- and state-level employment shares in selected sectors, unemployment rates and median income. The Housing block includes indicators of home values and wealth which might affect consumption through wealth effects.

Was household debt responsible for the Great Recession?

Mian and Sufi (2010), Mian et al. (2013) and Dynan (2012) estimate a negative relationship between the pre-crisis level or growth of household debt and the decline in various measures of household spending. In terms of the nested model, the parameter β is estimated to be negative and significant. In light of this, the literature suggests that the early 2000s household debt expansion, or alternatively the ex-ante level of household debt, was responsible for the downturn in spending during the Great Recession. The fact that these studies concur on the sign of the parameter β is noteworthy because they use very different data sources, definitions of leverage and cross-sectional aggregations. According to Mian and Sufi (2010, p. 96), "a one standard deviation increase in leverage growth from 2002 to 2006 in a county was associated with a one-half standard deviation decreases in auto sales from 2006 to 2009." Similarly, Dynan (2012, p. 330) finds that "an increase in a household's mortgage loan-to-value ratio from 1 to 1.1 would have reduced its consumption growth by 0.6 percentage point over this 2 year period, or 0.3 percentage point per year." The combination between high household debt and falling house prices weakened households' balance sheet and exacerbated the slowdown in spending. Interestingly, the combination of high leverage and house prices affected spending independently of wealth effects of falling house prices. For example, Mian et al. (2013, p. 1720) report that "ZIP codes with a housing leverage ratio below 30% cut spending on autos by $0.01 for every $1 decline in home value. However, the same effect is three times as large for ZIP codes with a housing leverage ratio of 90% or higher."[8] The result that households in highly leveraged areas reduced spending by more than households in other areas in response to the same fall in house prices is reminiscent of the *debt-deflation theory* (Fisher, 1933).

At first sight, the non-nested models in equation 1.2 suffers from the same identification problems that affect the panel data specifications from the previous section. However, Mian and Sufi (2010) and Dynan (2012) provide extensive evidence that the correlation between pre-crisis debt growth and spending during the Great Recession can be interpreted as a causal effect. Mian and Sufi (2010) present estimates resulting from an instrumental variable specification in which the growth of leverage is instrumented with county-level housing supply (in)elasticity. Since 2002, a nationwide credit supply shock boosted the demand for housing. However, the response of house prices to shifts in housing demand depends on the elasticity of

[8] A drawback of Mian et al. (2013) and Mian and Sufi (2010) is that they rely on proprietary data which are inaccessible if one wants to replicate their findings. For example, Mian et al. (2013) measure expenditure using proprietary data from Mastercard and proprietary data on auto sales. Auto sales can be though as a proxy of expenditure for durable goods. The same data on auto sales are used in Mian and Sufi (2010) although with a different time and spatial aggregation. Kaplan et al. (2020) replicate the estimates in Mian et al. (2013) using accessible county-level data on house prices and expenditure for non-durable goods. They find that the effect of leverage on expenditure is slightly softened relative to Mian et al. (2013) after controlling for the direct effect of house prices on expenditure (wealth effect). The smaller effect of leverage on expenditure in Kaplan et al. (2020) is likely to depend on the fact that they only observe spending for non-durable goods which tends to fall by less than spending for durable goods during recessions. For example, between 2007Q4 and 2008Q4 in the US, the personal consumption expenditure for durable goods fell by 15% while expenditure for non-durable goods fell *only* by 3%.

the local housing supply curve. In areas with less elastic housing supply curves, house prices responded more than in areas with more elastic housing supply curves to the same housing demand shock. The reason for this is that in areas with less elastic housing supply curves, natural or regulatory constraints prevented home builders to build new houses to meet the peak in demand. On the contrary, in areas with more elastic housing supply curves, supply adjusted to demand because the construction of new homes was not constrained. Therefore, in areas with less elastic housing supply curves, more expensive houses led households to take out larger mortgages and higher house prices stimulated home equity borrowing.

The nested model in equation 1.2 considers a limited set of contributions on household debt during the Great Recession. Mian and Sufi (2017) provide reference of other studies linking the early 2000s expansion of household debt to several measures of economic activity during the crisis. Using a panel of US states, Albuquerque and Krustev (2018) show that the 2007-2012 decline in consumption can be explained by a combination of household deleveraging and debt overhang effects. Petach (2020) finds evidence that US states where local financial sectors rapidly expanded during the housing boom also experienced the strongest growth in household indebtedness. Other studies find a significant correlation between the country-level growth or level of private debt-to-GDP ratios before 2007 and the poor performance of output growth during the Great Recession (Berkmen et al., 2012; Bezemer and Zhang, 2019; Glick and Lansing, 2010; Lane and Milesi-Ferretti, 2011).

The evidence of a negative correlation between household debt growth and contractions in household spending during the Great Recession is not limited to the US. In a study on the effect of a currency crisis in Hungary in 2008, Verner and Gyöngyösi (2020) estimate that a currency revaluation that raised the burden of debt caused large financial distresses for households who borrowed in foreign currency and a slowdown of the local economy. Using household-level data for Denmark, Andersen et al. (2016) show that the pre-crisis growth in leverage and spending growth during the crisis are negatively correlated. However, they interpret this result as arising from a normalization of spending rather than from a debt overhang. Bunn and Rostom (2014, 2015) show a similar correlation between household debt and changes in spending using household-level data for UK. It is important to stress that both Andersen et al. (2016) and Bunn and Rostom (2014, 2015) reject the interpretation of this correlation as reflecting a causal effect of high or growing household debt on the subsequent drop in spending. More specifically, they argue that the correlation is driven by a third factor which can be debt-financed over-consumption (Andersen et al., 2016), or alternatively over-optimism (Bunn and Rostom, 2014, 2015) which caused both the rise in debt and the reduction of spending to *normal* levels.

Competing views on the role of household debt during the Great Recession

Was high household debt the ultimate cause of the unprecedented contraction in economic activity between 2007 and 2009? Mian and Sufi (2015, 2017) argue that the negative relationship between rising household debt during the early 2000s and the severity of the Great Recession is consistent with the *credit supply view*. This narrative (which echoes the *credit-driven household demand channel* from the previous section) interprets the Great Financial Crisis and the Great Recession as ultimately induced by an unsustainable credit expansion. The credit expansion was not backed by any economic fundamental or prospect of future income growth. Misaligned incentives in the financial sector, frauds and expectations of continuous increases in house prices contributed to the unsustainable increase in lending. The *credit supply view*, which I detail below, gained traction in the popular narrative as the main cause of the Great Financial Crisis and of the harshness of the Great Recession.

THE CREDIT SUPPLY VIEW. According to the *credit supply view*, the shock that initiated the rise in mortgage debt between 2002 and 2005 was an expansion in the supply of mortgages towards marginal borrowers, namely toward households that before 2002 would have been rationed from obtaining mortgages. The mortgage debt expansion was more pronounced in areas with high shares of subprime borrowers and it was unrelated to prospects of higher future incomes. The expansion of mortgages fed the house price bubble. In areas with high shares of subprime borrowers, the mortgage debt expansion boosted housing demand and pushed house prices up. At the same time, rising house prices raised the collateral value and softened credit constrains. Between 2002 and 2007, the household debt-to-GDP ratio reached unprecedented levels in the US. However, the mortgage debt expansion toward marginal borrowers accounts only for a small part of the rise in household debt. Actually, most of household debt growth was driven by existing homeowners borrowing against rising values of their homes. The bottom 80% of the credit score distribution massively borrowed against rising home equity in this period (Mian and Sufi, 2011).[9] Ultimately, the combination of *(i)* rising mortgage lending toward subprime borrowers, *(ii)* the aggressive use of home-equity borrowing by homeowners, and *(ii)* speculations and frauds in the housing sector triggered the rise in defaults between 2006 and 2007 when the growth of house prices stopped. The rise in delinquency rates was initially concentrated among subprime borrowers living in areas where swings in house prices were larger. Only in 2008 and 2009, when the fall in house prices and the Great Recession spread across the country, delinquency rates rose also for borrowers at the high end of the credit score distribution. The decline in house prices mechanically caused many mortgages to go underwater. High leverage and the high marginal propensity to consume out of housing wealth by subprime borrowers magnified the response of spending to a drop in home values. The defaults eventually caused large losses for financial institutions, distressed their balance sheets and initiated the Great Financial Crisis.[10]

[9] In other words, the household debt expansion affected the extensive margin, through increased borrowing by households who were traditionally denied credit, as well as the intensive margin, through increased borrowing by households who were already indebted.

[10] Cynamon and Fazzari (2016) argue for a link between rising household debt and stagnating wages in the US. Kim (2020) provides a comparative perspective on the *credit supply view*. Mason and Jayadev (2014) highlight that the rise in household debt-to-GDP ratios is more likely to reflect changes in interest rates, GDP growth, and inflation

OTHER VIEWS. While the *credit supply view* is consistent with other studies (see Mian and Sufi, 2017, and references therein), its focus on the role of subprime lending in the events leading to the Great Financial Crisis has been disputed by other researchers. For example, a different narrative emphasizes the role of expectations of future house price gains as *the* primary force driving the mortgage debt expansion and downplays the importance of lending to subprime borrowers relative to middle- and upper-class borrowers (Adelino et al., 2016). Moreover, this alternative view implies that credit moved passively and only in reaction to rising house prices. Therefore, this interpretation clashes with the causal mechanism from credit to house prices identified by Mian and Sufi (2017).

Recently, Bernanke (2018) proposed a different though complementary analysis on why the crisis has been particularly severe. According to this analysis, rising defaults in the household sector caused large losses for financial institutions, mostly so for those institutions which had increased their leverage in mortgage-related securities in the years preceding the crisis. This triggered a financial panic in the wholesale funding markets and induced a credit crunch. Although Bernanke (2018) recognizes the importance of the contraction in demand driven by excessively indebted households, he argues that problems related to the supply of credit that originated in wholesale funding markets were responsible for the unprecedented contraction in economic activity at the start of the Great Recession.

1.3 Evidence from multivariate models

The survey from the previous section suggests that household debt expansions lead to predictable boom-and-bust cycles in economic activity. This result arises from panel data studies covering large cross-section of (mostly advanced) economies and from the *natural experiment* of the Great Recession in the US. Moreover, most of the literature surveyed concurs that leverage-induced household financial fragility is the key factor driving the observed correlation. However, the consensus on the strength of this channel is more nuanced as the debate over the causes of the Great Recession in the US shows.

The robustness of the predictive content of household debt for future economic activity has been recently challenged on two fronts. First, there is some ambiguity on how one should interpret the estimated parameter associated to the household debt indicators in equations 1.1 and 1.2. The cross-country panel data models are ambiguous on whether the relationship between household debt and subsequent recessions reflects a correlation or a causal effect of debt on economic activity. Svensson (2019), building on Andersen et al. (2016) and Bunn and Rostom (2014, 2015), argues that the relationship between household debt and economic contractions does not reflect any causal effects and that solving this ambiguity is of primary importance for the design of macroprudential policies. Second, and perhaps most important, the predictive content of household debt for boom-and-bust cycles in economic activity is a result of reduced-

than shifts in the supply and demand for credit.

form single-equation regressions. However, there is an established strand of literature that models credit and macroeconomic aggregates using structural multivariate models.

In this section, I survey the literature that uses VAR models to represent the joint macro-financial dynamics of the US economy with a special focus on the effects of household debt. I refer to this class of multivariate models as macro-financial VAR models. In the VAR literature, the directions of causality from credit to real activity are multiple. In addition, an important result of this literature is that many developments in credit markets respond to and influence the conduct of monetary policy. In contrast, the role of monetary policy is barely considered in the single-equation models.[11] This would suggests that the findings from the previous section on the role of household debt may be partial or biased because of an omitted variable problem.

1.3.1 Evidence from VAR models of the United States

Equation 1.3 represents a typical macro-financial (structural) VAR model of the US economy:

$$\mathbf{y}_t = \mathbf{a} + \sum_{j=1}^{p} \mathbf{A}_j \mathbf{y}_{t-j} + \mathbf{A}_0 \varepsilon_t \tag{1.3}$$

where $\mathbf{A}$ is matrix of contemporaneous relationships, namely the matrix that is generally restricted to identify the model, and $\mathbf{a}$ is a vector of constants. Equation 1.3 nests the VAR models in Brunnermeier et al. (2019), Guerini et al. (2018), Peersman and Wagner (2015) and Bachmann and Rüth (2020). The vector of endogenous variables is partitioned as follows: $\mathbf{y}_t = \left[D_t^{HH}, \mathbf{Credit}_t', \mathbf{Financial}_t', \mathbf{Real\ Activity}_t', \mathbf{Housing}_t', \mathbf{Policy}_t'\right]$. The Credit, Financial, Real Activity, Housing, and Policy blocks group together the macro-financial variables traditionally included in the VAR model (see Table 1.4).

HOUSEHOLD DEBT INDICATOR. The key household debt indicator (D_t^{HH}) can be real estate and consumer loans (Brunnermeier et al., 2019), real mortgage debt outstanding (Guerini et al., 2018), mortgage and consumer loans outstanding (Peersman and Wagner, 2015), or alternatively mortgage loan-to-value ratios (Bachmann and Rüth, 2020). I report these indicators in Panel C of Table 1.1 together with other information on the single specifications. There is substantial heterogeneity between the sources of data and definitions of household debt. For example, Brunnermeier et al. (2019) consider loans to household from weekly surveys of commercial banks in the US. On the contrary, Peersman and Wagner (2015) use quarterly Flow of Funds data which should provide a wider coverage of mortgages and consumer credit. Bachmann and Rüth (2020) obtain mortgage (single-family) loan-to-value ratios from the survey of the Federal Housing Finance Agency.

SHOCKS. The interpretation of shocks to household debt reflects the different identification strategies employed. The lending shock in Peersman and Wagner (2015) is a shock that raises

[11] Among the panel data models from the previous section, Drehmann et al. (2018) argue that monetary policy responds to household debt expansions through higher money market rates. However, the rise in money market rates has quantitatively small effects on the credit cycle.

outstanding, securitized and retained mortgage and consumer loans. This shock is interpreted as arising from changing costs of creating loans or from varying monitoring costs. A lending shock may also reflect a shift in credit demand that is independent of macroeconomic conditions. For example, an exogenous rise in home values automatically increases the collateral that households pledge when applying for a mortgage. Similarly, Bachmann and Rüth (2020) focus on shocks to mortgage loan-to-value ratios. They interpret these shocks as reflecting changes in lending standards in housing markets.[12]

In spite of the vast literature on macro-financial VAR models, I select only contributions that explicitly explore the real effects of shocks to household debt. This choice ensures that the models surveyed in this section are comparable to the single-equation models that I previously introduced. However, there is a large literature that uses VAR models to estimate the effects of financial shocks (Furlanetto et al., 2019) and credit shocks to non-financial firms using information contained in credit spreads (Gilchrist and Zakrajšek, 2012). In a similar vein, Walentin (2014) estimates the real and financial effects of a decline in mortgage spreads in the US. A different literature looks at the real effects of changing market sentiment (López-Salido et al., 2017) and credit standards (Bassett et al., 2014). However, these studies do not distinguish between households and non-financial firms. Another strand of research explores the effects of bank lending shocks but it does not distinguish between borrowing sectors (see for example Gambetti and Musso (2017) for the US and UK, and Peersman (2011) for the euro area). Last, Calza et al. (2013), Hofmann and Peersman (2017a,b), Den Haan and Sterk (2010), Alpanda and Zubairy (2019), McCarthy and Peach (2002) explore the interaction between monetary policy shocks and household debt.

1.3.2 Macroeconomic effects of shocks to household debt

What are the macroeconomic effects of shocks to household debt in a macro-financial VAR model? A shock to real estate and consumer loans granted by banks leads to an initial increase in industrial production, followed by a persistent decline (Brunnermeier et al., 2019). The response of consumption and real GDP to a shock to mortgage debt follows a similar path (Guerini et al., 2018). Similarly, Peersman and Wagner (2015) show that a lending shock that raises mortgage and consumer loans outstanding leads to an initial positive response of real GDP. However, GDP returns to the equilibrium level within five years. In addition, the lending shock provokes a small though not significant increase in prices.

So far, the response of real activity to shocks to household debt confirms the negative correlation between household debt expansions and subsequent economic activity. However, the

[12] The focus of Bachmann and Rüth (2020) on lending standards would suggest that their model is not comparable to other non-nested models included in equation 1.3. However, taking into consideration the *credit-driven household demand channel* (Mian and Sufi, 2018), it is possible to interpret an increase in loan-to-value ratios as an instrument for mortgage expansions. In fact, according to the this channel, a rise in household debt may be induced by financial innovations or changes in beliefs which relax credit standards.

interpretation provided by macro-financial VAR models for this relationship is different from the one proposed by single-equation models from the previous section.

A different picture on the macroeconomic effects of household debt?

In macro-financial VAR models, shocks to household debt are followed by boom-and-bust cycles in economic activity and moderate increases in inflation. The interpretation of this pattern downplays the role of household financial fragility. In particular, the macro-financial VAR literature argues that the downturn in economic activity observed after a shock to household debt can be completely attributed to the endogenous response of monetary policy.

The model in Brunnermeier et al. (2019) implies that a shock to household debt increases inflation and industrial production while leaving credit spreads unchanged. The rise in inflation induces an endogenous increase in interest rates driven by a monetary policy tightening. A counterfactual experiment shows that if the endogenous response of monetary policy is silenced, shocks to household debt lead to persistently high inflation and output. The fact that credit spreads do not move in any significant way after a household debt shock downplays the importance of household financial fragility in driving the negative correlation between debt and economic activity. On the contrary, a rise in credit spread leads to a contraction in both household and non-financial firm debt. Moreover, the predictive content of household debt expansions for future economic activity is challenged. In fact, the analysis of the forecast error variance decomposition shows that neither including credit variables nor credit spreads increases the forecasting performance of the model.

Bachmann and Rüth (2020) provide a full exploration of the systematic reaction of monetary policy to expansionary shocks in the housing market. In their model, a shock that raises mortgage loan-to-value ratios leads to a counterintuitive contraction in residential investment, after a small and temporary increase. They show that the decline in residential investment is caused by the endogenous response of monetary policy to looser lending standards. In fact, an expansionary shock to mortgage loan-to-value ratios implies a persistent increase of the federal funds rate which, in turn, raises mortgage rates. In a nutshell, the effect of the endogenous tightening of monetary policy dominates the expansionary effect of higher loan-to-value ratios on residential investment. As in Brunnermeier et al. (2019), Bachmann and Rüth (2020) shows that in a VAR model estimated by omitting the policy function or by silencing the response of the federal funds rate, a shock that raises mortgage loan-to-value ratios implies an positive and long-lasting response of residential investment.

It is important to stress that Brunnermeier et al. (2019) and Bachmann and Rüth (2020) provide different interpretations of the endogenous response of monetary policy. On the one hand, Brunnermeier et al. (2019) argue that the Fed responds to shocks to household debt only indirectly and to the extent that these shocks are inflationary. On the other hand, Bachmann and Rüth (2020) estimate a Taylor rule with loan-to-value ratios and show that, historically, the

Fed systematically responded to housing market conditions.

In sum, the macro-financial VAR models do not reject as a whole the existence of a negative relationship between household debt expansions and subsequent economic contractions. Rather, multivariate models suggest that not considering the endogenous, direct or indirect, response of monetary policy may result in an omitted variable problem.

1.4 Some unresolved issues

Different strands of literature suggest that there is a negative correlation between household debt and economic activity. However, single-equation regressions and multivariate models point to different, though not necessarily contrasting, interpretations of this correlation. In addition to this fundamental difference, there are other unresolved issues in the literature. I now review some of these issues which I touched upon in the previous sections. To fix ideas, I shall show some impulse responses estimated from a simple VAR model of the US economy inspired by the just reviewed literature.

1.4.1 Stock *vs.* flow of household debt

There is some ambiguity in the literature on whether it is debt growth (flow) or the level of household debt (stock) that poses risks for the economy (see Table 1.1). Although the two measures are correlated (positive flows contribute to raise the level of debt) it is useful to distinguish between stock and flow effect in order to identify the mechanisms that generate the negative correlation between household debt and future economic activity. Moreover, whether the risk factor is debt growth or high debt is important for the design of policies aiming at improving macroeconomic and financial stability.

High levels of household debt are critical for those mechanisms that focus on worsening balance sheets to explain the correlation between debt and economic activity.[13] High levels of debt may be problematic for macroeconomic stability when there are large declines in house prices. This can cause a dramatic drop in loan-to-asset ratios as home values (the main real asset in the balance sheet of households) diminish relative to the nominal value of debt. As a result, the burden of debt rises and the asset-liability imbalance worsens the sustainability of balance sheets. Similarly, a macroprudential policy that tights lending standards through higher loan-to-value or loan-to-income ratios may be detrimental for households with high levels of debt. In fact, for these households, credit constraints may suddenly become binding. Even the expectation that credit constrains may bind in the future is able to reduce consumption through precautionary saving. Moreover, lenders generally decide how much to lend to single borrowers according to loan-to-value or loan-to-income ratios. For households with high levels of debt it will be easy to reach the maximum ratios soon and this will impair further borrowing.

[13] These interpretations date back at least to Fisher (1933), Minsky (1986), Mishkin et al. (1977), Mishkin (1978), Kindleberger (1978).

Another reason for which the level of debt may be problematic concerns the response of households to unemployment and income shocks. If households are hit by unemployment, their income falls and they will be forced to cut back on consumption if they decide to continue servicing the debt obligations and avoid defaulting.[14] Similarly, a rise in interest rates may increase the debt service and force households to reduce consumption with detrimental effects on aggregate demand.

The panel data studies in Section 1.2.1 use flow concepts as the change in debt-to-GDP ratios or new borrowing-to-GDP. Similarly, in Mian and Sufi (2010), the main explanatory variable is the change in debt-to-income from 2002 to 2006. Although the level of debt increases because of continuously positive flows, it is not clear what is the autonomous contribution of debt growth to macroeconomic (in)stability. Some studies find that in a horse race between debt levels and debt growth in predicting future contractions in GDP, debt growth wins in terms of statistical significance (Bridges et al., 2017). A possible reason for this finding is that since large build-up of debt raises the stock of household debt, fast debt growth may contribute to debt overhang problems. Andersen et al. (2016) provides another explanation for why the growth of debt may reduce subsequent consumption. They argue that the contraction in spending follows periods during which households overspend relative to their disposable income. Because overspending is financed through new borrowing and households return to *normal* level of spending in the future, overspending would explain both the expansion in borrowing and the subsequent reduction in spending.

It is important to stress that a level of debt that is excessively high from the perspective of a single household does not need to be dangerously high from the perspective of the society. In particular, to be dangerous for macroeconomic stability, it is important to understand the distribution of debt and how borrowers, at each point of the distribution, would react to shocks hitting their ability of servicing debt without reducing spending. In other words, it is important to know the distribution of debt across households and the marginal propensity to consume of indebted households out of income and wealth. Hence, evidence from aggregate macroeconomic data may not be enough.

1.4.2 Household financial fragility *vs.* reaction of monetary policy: what does explain the downturn?

What does explain the downturn in economic activity following household debt expansions? Answering to this question is of primary importance not only to shed light on various episodes of business cycles, but also to understand which is the most appropriate set of policies to address macroeconomic problems potentially triggered by growing household debt. This survey

[14] As stressed by Svensson (2019), households may decide to default on their debts and keep consumption levels virtually unchanged. If defaults are widespread, financial institutions may incur into losses and restrain the supply of credit or, worse, they may become insolvent. In this case, household debt is a risk factor for financial stability rather than for macroeconomic stability.

identified two potential sources for this correlation. On the one hand, single-equation regression models suggest that financial fragility arising in the household sector may be responsible for future contractions in GDP and consumption. On the other hand, macro-financial VAR models attribute the decline in economic activity following household debt shocks to the endogenous response of monetary policy.

In this section, I show that the two narratives can be represented using a simple VAR model of the US economy.[15] More specifically, I present impulse responses from a VAR model that nests the above hypothesis on the factors driving the correlation between household debt expansions and downturns in economy activity. This allows me to show how the dynamic relationship between household debt and economic activity changes when the endogenous response of interest rates is included in the model. The reduced-form VAR model is:

$$\mathbf{y}_t = \mathbf{c} + \sum_{j=1}^{p} \mathbf{B}_j \mathbf{y}_{t-j} + \mathbf{u}_t \tag{1.4}$$

The model is estimated using US quarterly data from 1960Q1 to 2007Q4. The lag length p is set to 4 based on the Akaike information criteria and the structural shocks are identified using a Cholesky decomposition.

I estimate a two versions of a traditional monetary VAR model augmented with household debt. In the first version, the vector of endogenous variables is $\mathbf{y}_t = [y_t, \pi_t, d_t^{HH}, i_t]'$ where y_t is log real GDP, π_t is inflation, d_t^{HH} is household debt-to-GDP and i_t is the effective federal funds rate. For what concerns the debt-to-GDP ratio, I normalized the stock of household debt, D, by nominal GDP in the previous quarter, Y (Mian et al., 2017). Hence, $d_t^{HH} = {}^{D_t}/_{Y_{t-1}}$.[16] The ordering of variables in the VAR implies that monetary policy responds to contemporaneous disturbances in the household credit sector. For this reason, I call this model the *model with active monetary policy*. The model with active monetary policy resembles the VAR model in Bachmann and Rüth (2020) in which monetary policy systematically responds to changes in lending standards in the housing market. However, monetary policy in the US does not necessarily react to contemporaneous shocks to household debt. Hence, I estimates also a model in which the effective federal funds rate is ordered just after inflation and just before household debt-to-GDP, namely $\mathbf{y}_t = [y_t, \pi_t, i_t, d_t^{HH}]'$. I refer to this model as the *model with passive monetary policy* meaning that the effective federal funds rate responds to household debt shocks with delay.

[15] A similar exercise for the role of monetary policy in shaping the response of residential investment to mortgage loan-to-value ratios shocks is presented in Bachmann and Rüth (2020). See Figure 1 at page 504 of their paper.

[16] Real GDP (y_t), is Real Gross Domestic Product, billions of dollars, seasonally adjusted annual rate (FRED code: RGDP). Inflation (π_t) is the percent change from one year ago in the Personal Consumption Expenditure price index, excluding food and energy, seasonally adjusted (FRED code: BPCCRO1Q156NBEA). Household debt (D_t^{HH}) is the sum of home mortgages (the level of one-to-four family residential mortgages on the liability side of the household sector, seasonally adjusted, FRED code: HHMSDODNS) and consumer credit (the level of consumer credit on the liability side of the household sector, seasonally adjusted, FRED code: HCCSDODNS). Nonfinancial firm debt (d_t^F) is the level of debt securities and loans on the liability side of the nonfinancial corporate business sector (FRED code: BCNSDODNS). The stock of debt is normalized by nominal GDP (FRED code: GDP) in the previous quarter.

The (black) solid lines in Figure 1.3 plot the median response of log real GDP (top-left panel), inflation (top-right panel), household debt-to-GDP (bottom-left panel) and the effective federal funds rate (bottom-right panel) to a household debt shock from the model with active monetary policy. Similarly, (red) dots trace the same impulse responses from the model with passive monetary policy.

The shock immediately raises the household debt-to-GDP ratio which continues to grow for roughly three years. After the peak, the household debt cycle gradually fades away. The shock to household debt temporarily boosts GDP which peaks roughly after one year from the impulse. However, the rise in GDP is not significant. Thereafter, the response of GDP turns slightly negative though not significant. The top-right panel suggests that household debt shocks are inflationary, at least in the short-run, as predicted by Brunnermeier et al. (2019). So far, the dynamic relationship between household debt, GDP and prices is very similar the impulse responses reported in Mian et al. (2017) from a panel-VAR estimated on annual data (see Figure 1, p. 1765, of their paper). However, the bottom-right panel shows that the household debt expansion raises the effective federal funds rate by almost 0.2 percent at the peak (bottom-right panel). This suggests that monetary policy reacts to household debt shocks and perhaps exactly because these shocks are inflationary. These results are consistent with Brunnermeier et al. (2019) which argue that "excessive growth in household credit can forecast negative long-term real output growth [...] However, our model implies that the decline in output growth following this [household credit] shock can be entirely accounted for by the rise in interest rates it elicits." They also add that "The response of the system to the credit shocks, combined with a sequence of monetary policy shock values that keep the interest rate constant, eliminates the decline in output. [...] Our interpretation is that the credit expansions generated by the credit shocks are followed with a delay by slow growth due to monetary tightening, not financial market distresses" (ibid. pp. 22-23).

1.4.3 The consequences of household and non-financial firm debt: are they different?

The literature on the macroeconomic effects of household debt suggests that, contrary to household debt, non-financial firm debt expansions have weak (and even immediately negative) effects on future GDP growth (Mian et al., 2017; Müller and Verner, 2020). Similarly, Jordà et al. (2016) show that post-crises recoveries are longer when preceded by large mortgage debt expansions which debt is predominantly a liability of households rather than of firms. In contrast, there is no evidence that non-mortgage credit booms delay the recovery.

I use the same VAR model from the previous section to show that household debt and non-financial debt expansions may have different macroeconomic effects. In particular, I obtain impulse responses by estimating the same VAR model in equation 1.4 but with $\mathbf{y}_t = [y_t, \pi_t, i_t, d_t^F, d_t^{HH}]'$ where d_t^F is non-financial firm debt normalized by GDP in the previous

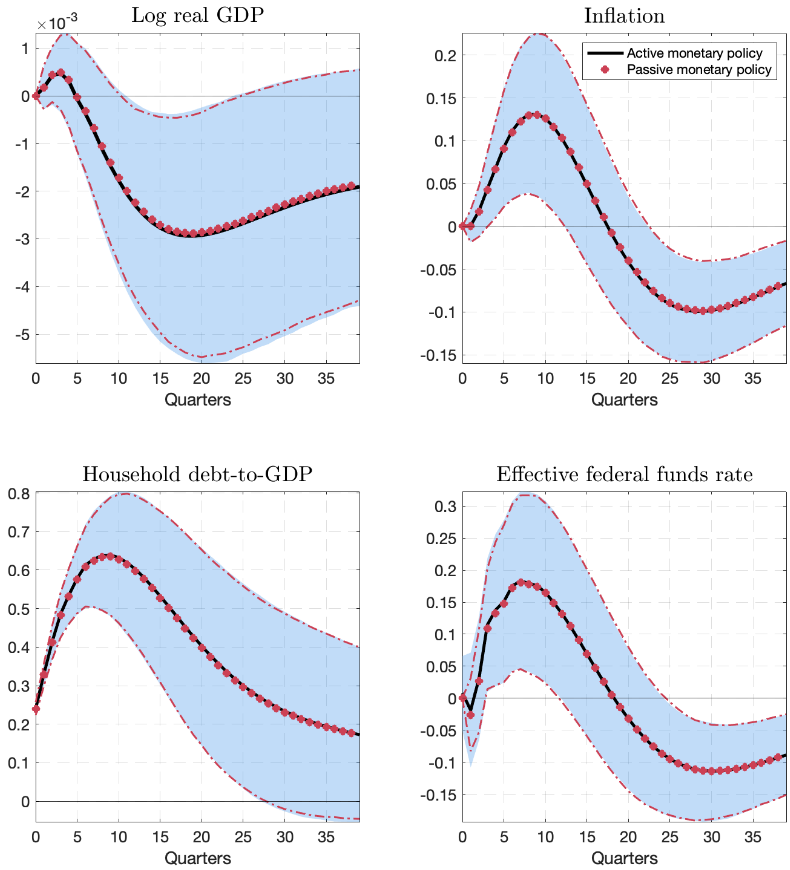


FIGURE 1.3: THE EFFECTS OF HOUSEHOLD DEBT EXPANSIONS

Notes: this figure shows medium impulse responses of log real GDP (y_t), inflation (π_t), household debt-to-GDP (d_t^{HH}) and the effective federal funds rate (i_t) to a shock to household debt-to-GDP. For the model with active monetary policy $\boldsymbol{y}_t = [y_t, \pi_t, d_t^{HH}, i_t]'$ while $\boldsymbol{y}_t = [y_t, \pi_t, i_t, d_t^{HH}]'$ for the model with passive monetary policy. The model is estimated using OLS. The shaded areas are 68% confidence bands for the model with active monetary policy. The dot-dashed lines are 68% confidence bands for the model with passive monetary policy. Confidence bands are obtained using a sampling with replacement bootstrap algorithm (5,000 replications).

quarter. This model is inspired by the panel-VAR model in Mian et al. (2017) though I augment it with an inflation and monetary policy equation since debt shocks may be capturing monetary policy shocks. Figure 1.4 compares the effects of household debt shocks (red line with markers) and non-financial firm debt shocks (black solid line) on real GDP, inflation, debt-to-GDP ratios and the effective federal funds rate. Non-financial firm debt shocks immediately increase the non-financial firm debt-to-GDP ratio for roughly one year (middle-left panel). However, the non-financial firm debt cycle is short-lived and it runs out in approximately five years. On the contrary, household debt cycles are large and persistent (middle-right panel). As it has been showed in other studies (Mian et al., 2017, Figure 1, p. 1765), shocks to household and non-financial firm debt have different effects on real GDP (top-left panel). For the US, household debt shocks leads to a short-run not significant increase in GDP followed by a long lasting contraction. Instead, the effects of non-financial firm debt shocks on GDP are positive but not significant. Household debt shocks are more inflationary when compared to non-financial firm debt shocks (top-right panel) and they induce an increase in the effective federal funds rate (bottom-right panel).[17]

Why are the effects of non-financial firm debt expansions different from those of household debt expansions? Some authors attribute this difference to the fact that non-financial firm debt has a shorter maturity relative to household debt (Drehmann et al., 2018). Jordà et al. (2020) argue that the weak correlation between non-financial firm debt expansions and persistent contractions in economic activity may be due to the fact that firm debt can be easily restructured relative to household debt. The muted or slightly negative correlation between non-financial firm debt shocks and GDP growth in the short-run is puzzling if one assumes that firms borrow to finance investment spending. Surprisingly, there is few literature on this topic.

1.5 Concluding remarks

The distinctiveness of the Great Recession in the US was the extraordinary rise in household debt that preceded the largest contraction in economic activity since the Great Depression. A recent literature in empirical macroeconomics argues that, historically, household debt expansions have been associated with boom-and-bust cycles in economic activity. This finding is not limited to the US macroeconomic history but it pertains to several business cycles around the world. Much of this research inherits some insights from Fisher (1933), Minsky (1986) and Kindleberger (1978).

In this chapter, I surveyed this recent literature. I showed that the literature on the macroe-

[17]It is interesting to note that the real effects of household and non-financial firm debt shock changes when the system omits the effective federal funds rate. In fact, in a VAR model without the monetary policy equation, household debt shocks lead to significant boom-and-bust cycles in GDP while non-financial firm debt shocks are immediately recessionary. This suggests that in VAR model with debt but without interest rates (e.g. Mian et al., 2017) debt shocks may be capturing monetary policy shocks. I am grateful to Gert Peersman for pointing out this difference.

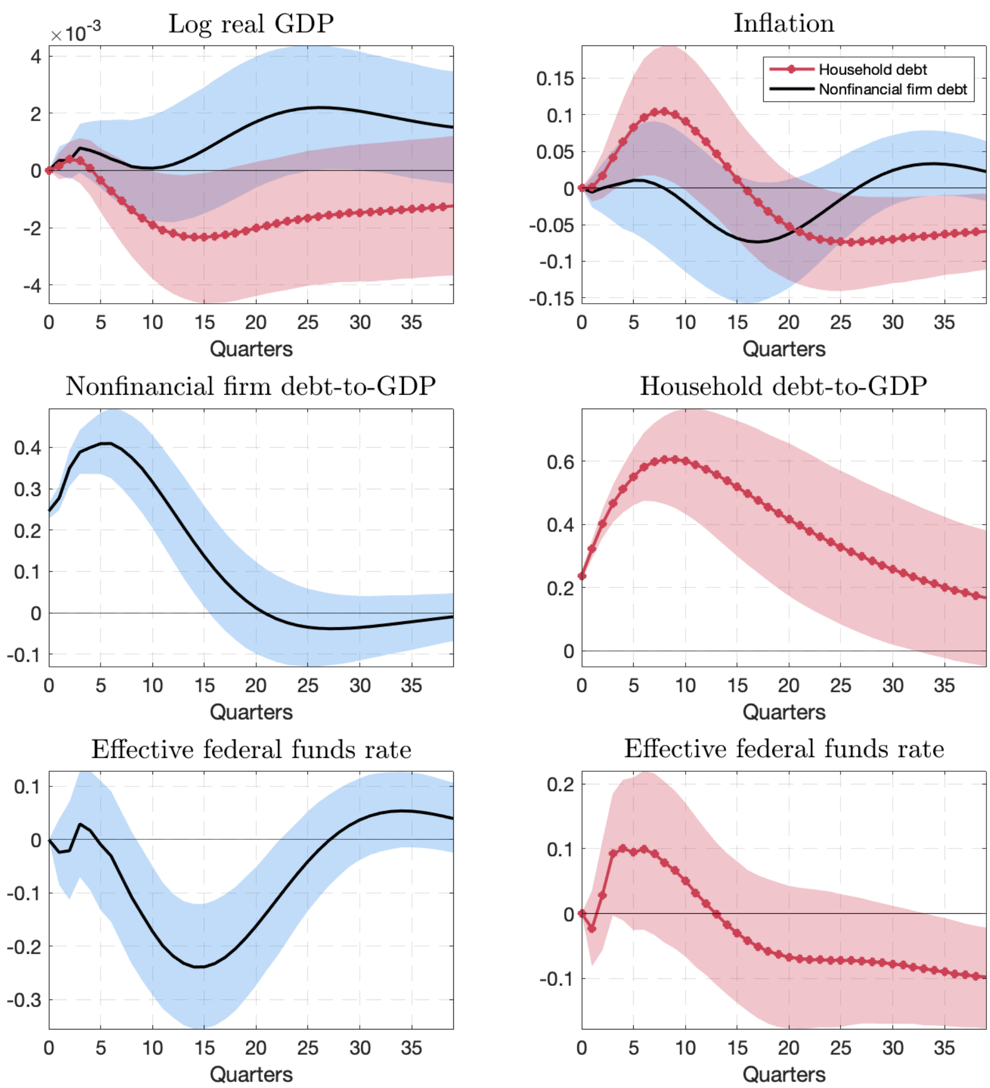


FIGURE 1.4: SECTORAL DEBT EXPANSIONS

Notes: this figure shows medium impulse responses of log real GDP (y_t), inflation (π_t), the effective federal funds rate (i_i), nonfinancial debt-to-GDP (d_t^F) and household debt-to-GDP (d_t^{HH}) to a shock to household and nonfinancial firm debt-to-GDP. The variables in the VAR are ordered as follows: $\boldsymbol{y}_t = \left[y_t, \pi_t, i_t, d_t^F, d_t^{HH}\right]'$. The model is estimated using OLS. The black solid lines are median responses to nonfinancial firm debt-to-GDP shocks. The shaded blue areas are 68% confidence bands for the responses to nonfinancial firm debt shocks. The red lines with markers are median responses to household debt-to-GDP shocks. The shaded red areas are 68% confidence bands for the responses to nonfinancial firm debt shocks. Confidence bands are obtained using a sampling with replacement bootstrap algorithm (5,000 replications).

conomic effects of household debt can be organized into three main strands. The first branch of literature estimates cross-country panel data models and it is mostly focused on advanced economies. The second strand of literature explores the extent to which the large increase in household debt in the early 2000s was responsible for the drop in consumption during the Great Recession in the US. Papers in the third strand of literature estimate macro-financial VAR models of the interaction between credit, macroeconomic aggregates and monetary policy.

Although all strands of literature concur that household debt expansions are followed by contractions in economic activity, different models highlight different channels. In particular, the literature identifies two potential mechanisms that may generate the negative correlation between household debt and real activity. On the one hand, panel and cross-sectional models favor an explanation that hinges on household financial fragility. On the other hand, macro-financial VAR models challenge this view and favor an explanation according to which the negative correlation is caused by the endogenous increase in interest rates elicited by (inflationary) household debt expansions.

In the last part of the chapter, I addressed some key unresolved issues. In particular, I focused on three issues. First, household and non-financial firm debt expansions have substantially different macroeconomic effects. Second, there is some ambiguity on whether contractions in economic activity are influenced by fast growth or by the ex-ante level of household debt. Third, macro-financial VAR models and single-equation regressions favor different hypotheses on the mechanism driving the correlation between household debt and economic activity. However, the former strand of literature derives this result from US macroeconomic data while the latter focuses on large cross-country datasets. In the reality, it is likely that both mechanisms - financial fragility and rising interest rates - jointly determine the observed correlation between household debt expansions and contractions in economic activity though their quantitative importance may differ. Making clear these ambiguities is important for improving our knowledge on which mechanisms drive the macroeconomic effects of household debt and for the design of macroprudential policies aimed to tame the adverse consequences of credit cycles.

TABLE 1.2: NESTED SINGLE-EQUATION PANEL DATA MODEL (EQUATION 1.1)

Dependent variable:	Real GDP growth (Δy_{it+h})			
	Mian et al. (2017)	Drehmann et al. (2018)	Jordà et al. (2016)	Müller and Verner (2020)
Credit block				
3-year change in nonfinancial firm debt-to-GDP	✓			
3-year change in government debt-to-GDP	✓			
Debt service-to-GDP[1]		✓		
Non-mortgage credit accumulated in the expansion[2]			✓	
3-year change in tradable credit-to-GDP				✓
3-year change in non-tradable credit-to-GDP				✓
Financial block				
Lending spread on mortgages[3]		✓		
Change in interest rate on household debt[4]		✓		
Change in loan loss provision		✓		
Change in corporate spreads[5]		✓		
Term spread		✓		
3-month government bonds yields			✓	
5-year government bonds yields			✓	
Housing				
Growth rate of real residential property prices		✓		
Real household net worth		✓		
Real activity block				
(lagged) 3-year change in log real GDP	✓			
Growth rate of unemployment		✓		
Change in CPI inflation rate		✓		
Growth rate of labor productivity		✓		
(lagged) growth rate of real GDP per capita			✓	
CPI inflation rate			✓	
Growth rate of real investment share per capita			✓	
Openness				
(lagged) 3-year change in foreign debt-to-GDP	✓			
Current account-to-GDP		✓	✓	
Change in the real effective exchange rate		✓		

[1] Debt service is the sum of interest payments and amortizations..
[2] Annual change in non-mortgage credit accumulated during the expansion as share of GDP and in percentage point per year, and in deviation from country-specific historical mean.
[3] Lending spread on mortgages is the difference between the prime lending rate and the 3-month money market rate.
[4] The interest rate on household debt is obtained as ratio between total interest paid by households from the National Accounts and the stock of debt.
[5] Corporate credit spreads are obtained as difference between a general corporate bond index and the weighted average og the 5- and 10-year government bond yields (Krishnamurthy and Muir, 2017).

TABLE 1.3: NESTED SINGLE-EQUATION MODEL OF THE GREAT RECESSION (EQUATION 1.2)

Dependent variable:	Household expenditure growth (ΔC_i)		
	Mian and Sufi (2010)	Mian et al. (2013)	Dynan (2012)
Credit block			
Debt-to-income ratio, 2001Q4	✓		
Default rate, 2006Q4	✓		
Default rate, 2001Q4	✓		
Fraction borrowers with credit score $<$ 660, 2001Q4	✓		
Credit card utilization, 2006Q4	✓		
($\Delta_{2006-09}$ Home value)$\times$(Housing leverage ratio 2006)		✓	
Debt service-to-income ratio, 2007			✓
Real activity block			
Unemployment rate, 2006Q4	✓		
Unemployment rate, 2001Q4	✓		
Fraction black, 2000	✓		
Fraction with high school education or less, 2000	✓		
Fraction black, 2000	✓		
Ln(median household income), 2000	✓		
Employment share in construction, 2006Q4	✓		
Employment share in real estate, 2006Q4	✓		
Employment share in finance, 2006Q4	✓		
Employment share in retail, 2006Q4	✓		
Employment share in exports, 2006Q4	✓		
Income per household, 2006	✓		
($\Delta_{2006-09}$ Home value)$\times$(Income per household, 2006)		✓	
$\Delta_{2007-09}$ Income			✓
Income			✓
$\Delta_{2007-09}$ state unemployment rate			✓
State unemployment rate			✓
Age of household head			✓
Education level of household head			✓
Housing			
Fraction homeowners, 2000	✓		
Ln(median home value), 2000	✓		
$\Delta_{2006-09}$ Home value		✓	
Net worth, 2006		✓	
($\Delta_{2006-09}$ Home value)$\times$(Net worth, 2006)		✓	
$\Delta_{2007-09}$ Wealth			✓

TABLE 1.4: NESTED VAR MODEL (EQUATION 1.3)

Dependent variable:	VAR			
	Brunnermeier et al. (2019)	Guerini et al. (2018)	Peersman and Wagner (2015)	Bachmann and Rüth (2020)
Credit block				
Real commercial bank C&I loans	✓			
Real federal debt: total public debt		✓		
Real nonfinancial corporate business debt securities		✓		
(volume of) Retained mortgages and consumer loans			✓	
(volume of) securitized mortgages and consumer loans			✓	
Financial block				
M1 money supply	✓			
Term spread (10-year - 3-month Treasury yield)	✓			
Corporate bond spread (Gilchrist and Zakrajšek, 2012)	✓			
TED spread (3-month Eurodollars - 3-month Treasuries)	✓			
Mortgage rates				✓
Housing block				
Real residential investment				✓
Residential investment relative price inflation				✓
Real Activity				
Industrial production	✓			
PCE price index	✓			
Commodity price index	✓			
Real GDP		✓		✓
Real personal consumption expenditures		✓	✓	
GDP deflator		✓		
Inflation rate				✓
Non-residential investment relative price inflation				✓
Real non-residential investment				✓
Policy				
Federal funds rate	✓		✓	✓
3-month treasury bill: secondary market rate		✓		

Appendix A

A.1 The role of time fixed effects

The nested panel-data model in equation 1.1 in Chapter 1 does not include time fixed effects. As I argued in Section 1.2.1, the inclusion of time- fixed effects dramatically reduces the significance of boom-and-bust cycles in GDP induced by household debt expansions. To prove this point, in this appendix, I replicate Figure II, page 1770, in Mian et al. (2017) buy using their same specifications and dataset. Their series are annual, from the 1960s to 2012, and cover a rather heterogeneous set of 30 advanced and emerging countries.

In Panel A and Panel B in Figure A.1, I report estimates of $\beta^h_{HH,1}$ for $h = 1, \ldots, 10$ from the following regression:

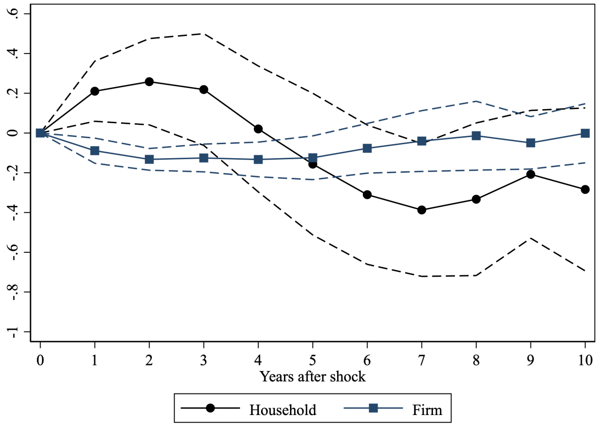
$$y_{it+h-1} = \alpha^h_i + \theta^h_t + X_{it-1}\Gamma^h + \sum_{j=1}^{5} \beta^h_{HH,j} d^{HH}_{it-j} + \sum_{j=1}^{5} \beta^h_{F,j} d^F_{it-j} + \sum_{j=1}^{5} \delta^h_j y_{it-j} + \varepsilon^h_{it+h-1}$$

Panel A in Figure A.1 shows that responses of log real GDP (y_{it+h-1}) to a unit change in the household debt-to-GDP ratio (d^{HH}_{it-1}) and in the non-financial firm debt-to-GDP ratio (d^F_{it-1}) when θ^h_t is zero, namely when there are not time fixed effects. These are the impulse responses that Mian et al. (2017) show in panel A of Figure II of their paper. When time fixed effects are excluded, household debt expansions are correlated with significant boom-and-bust cycles in economic activity. In contrast, the effects of non-financial firm debt expansions are small compared to those of household debt expansions. Moreover, non-financial firm debt booms lead to short-run through small negative effects on GDP. Panel B in Figure A.1 reports the same impulse responses obtained from a specification in which time fixed effects are included, namely when θ^h_t is not restricted to be zero. When time fixed effects are included, the correlation between non-financial firm debt expansions and the future level of log real GDP turns essentially zero and the immediate small negative effect on GDP is eliminated. For the case of household debt, the inclusion of time fixed effects make the boom-and-bust cycles dramatically smaller in size and not statistically significant for most of the forecasting horizon. Most importantly, with time fixed effects, GDP returns to the initial level after ten years from the debt expansion.

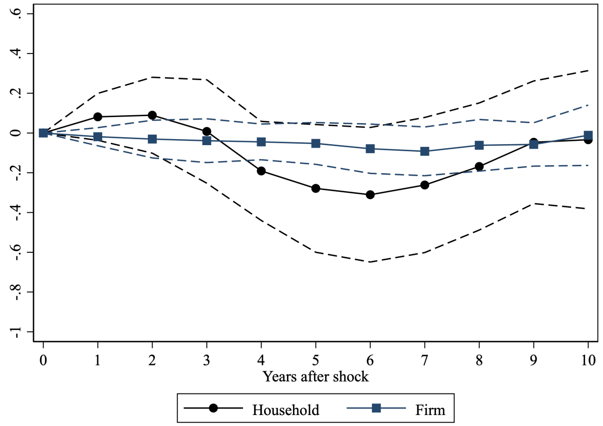
In Panel C and Panel D in Figure A.1, I report estimates of $\beta^h_{HH,1}$ for $h = 1, \ldots, 10$ from the following regression:

$$\Delta_h y_{it+h-1} = \alpha^h_i + \theta^h_t + X_{it-1}\Gamma^h + \sum_{j=1}^{5} \beta^h_{HH,j} \Delta d^{HH}_{it-j} + \sum_{j=1}^{5} \beta^h_{F,j} \Delta d^F_{it-j} + \sum_{j=1}^{5} \delta^h_j \Delta y_{it-j} + u^h_{it+h-1}$$

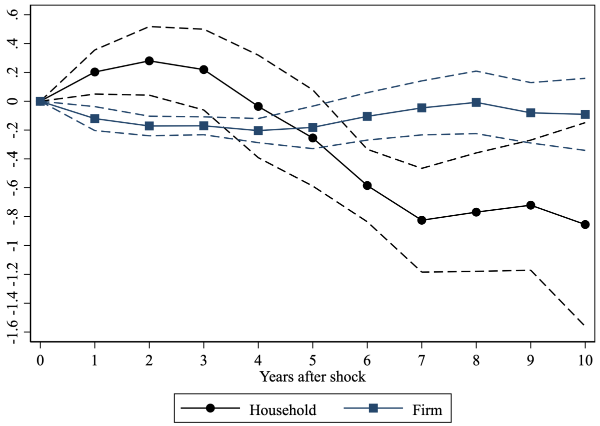
Panel C shows that responses of the h-year change in log real GDP ($\Delta_h y_{it+h-1}$) to a shock to the one-year change in household debt-to-GDP ratio (Δd^{HH}_{it-1}) and in the non-financial firm debt-to-GDP ratio (Δd^F_{it-1}) when θ^h_t is zero, namely when there are not time fixed effects. These are the impulse responses that Mian et al. (2017) show in panel B of Figure II of their paper. Panel D in Figure A.1 shows the same responses when θ^h_t is not restricted to be zero. As with the specification in levels, adding time fixed effects dramatically reduces the significance of the correlation between household debt and business cycles.



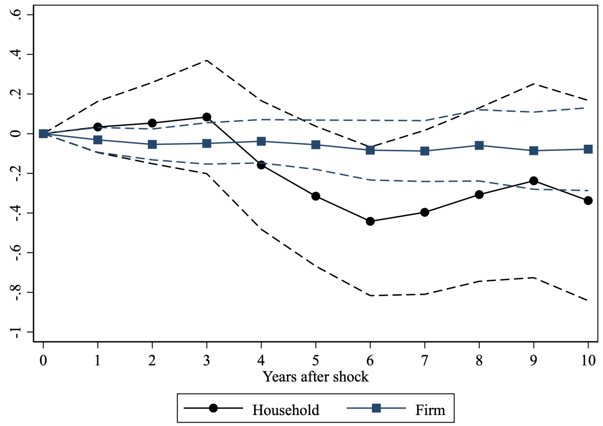
(A) *Level specification, w/o time effects*



(B) *Level specification, w/ time effects*



(C) *Difference specification, w/o time effects*



(D) *Difference specification, w/ time effects*

FIGURE A.1: THE EFFECTS OF HOUSEHOLD DEBT EXPANSIONS: THE ROLE OF TIME EFFECTS

Notes: this figure replicates Figure II, page 1770, in Mian et al. (2017) by comparing specifications with (panels B and D) and without (panel A and C) time fixed effects.

Chapter 2

THE FED, HOUSING AND HOUSEHOLD DEBT OVER TIME*

ABSTRACT

Did the transmission mechanism of monetary policy through housing and household debt change over time? I explore this question using a ten-variable time-varying parameter VAR model with stochastic volatility estimated on US data from 1960 to 2018. The model captures the joint dynamics of aggregate economy, housing sector, policy and household debt. Monetary policy shocks are identified with timing restrictions. I find evidence that the transmission mechanism of monetary policy through housing and household debt changed over time. New housing starts and residential investment have become slightly more sensitive to monetary policy shocks despite reacting slower in most recent periods. In contrast, the sensitivity of household debt to monetary policy shocks diminished since the late 1960s, except in the early 2000s when it has increased. House prices stand as the most important variable for the transmission of monetary policy through housing in the most recent decades. In the last part of the chapter, I frame the aggregate evidence in light of the institutional changes that have been affecting the US housing finance system since the 1970s.

Keywords: time-varying parameter VAR, monetary policy, housing, household debt
JEL codes: E44, E52, E58, G51, N1

2.1 Introduction

This chapter explores the relationship between monetary policy, the housing sector and household debt in the US since the early 1960s. Many of the channels through which monetary policy affects the economy involve housing and housing finance, and the transmission of monetary policy depends on the structure of the housing finance system. Between the 1970s and 1980s, the US housing finance system was affected by major institutional changes, partly in response to evolving macroeconomic conditions. Ultimately, these institutional changes transformed

*I am grateful to Marco P. Tucci, Gert Peersman, Sarah Zubairy, Wouter Van der Veken, Frédéric Opitz, Martin Iseringhausen, Dimitris Korobilis, Antonio M. Conti, Andrea Borsato and Mehmet Ulug for helpful comments and suggestions. I am grateful to Dimitris Korobilis and Gary Koop for sharing their codes with the research community. An earlier version of this chapter was published as The Fed, housing and household debt over time, Working Paper n. 850, Quaderni del Dipartimento di Economia Politica e Statistica, University of Siena.

housing finance into a system more integrated into capital markets.[1] As a result, as it has been argued by many scholars (Bernanke, 2007), the role of housing finance in the transmission of monetary policy may have changed.

Housing, housing finance and mortgage debt are of great importance for the dynamics of the overall economy in the US (Adelino et al., 2018; Leamer, 2007; Mian and Sufi, 2009, 2010) as well as in other advanced economies (Jordà et al., 2016; Mian et al., 2017). Likewise, the institutional features of the housing finance system influence the effectiveness of monetary policy. For example, the prevailing type of mortgages, the possibility of borrowing against rising home values and the role of the government in mortgage markets may accentuate or weaken the importance of housing finance in the transmission of monetary policy.[2]

In principle, a monetary policy tightening that increases short-term rates may depress housing demand because higher rates increase the cost of borrowing to purchase a house.[3] At the same time, higher short-term rates may affect interest rates charged on a wide array of consumer credit products, e.g. auto loans and credit cards. In addition to the impact on prospective borrowers, monetary policy may affect existing indebted homeowners. A rise in interest rates may increase the interest payments of homeowners with adjustable-rate mortgages while leaving the debt service unaltered for borrowers with fixed-rate mortgages. As a result, higher rates reduce discretionary income of homeowners with adjustable-rate mortgages and, consequently, consumption spending (*cash-flow* or *income channel of monetary policy*). Besides, because higher short-term rates are associated with falling asset prices, tight monetary policy may lead to a decline in house prices and a contraction in the value of housing wealth (*balance sheet channel of monetary policy*). This will reduce the value of the collateral that borrowers can pledge when applying for a mortgage and raise the external finance premium (Bernanke and Gertler, 1995).

In the US only a very small share of mortgages is of the adjustable-rate type although this share was high in the 1980s. Amromin et al. (2020) estimate that more than 90% of new home mortgages in 2018 were 30-year fixed-rate mortgages. In general, the fixed-rate mortgage in the US makes easy for homeowners to refinance their mortgage to benefit from lower interest rates when monetary policy is accommodative (*refinancing channel of monetary policy*). Mortgage refinancing can also provide homeowners a way to tap in home equity and finance the purchase

[1]Throughout the chapter, I refer to the housing finance system a system of three intertwined markets (McCarthy and Peach, 2002). In the primary market, homeowners borrow from lenders and pledge their homes as collateral. In the secondary market, lenders sell the mortgages originated in the primary market to government agencies and private specialized investors. In the market of mortgage-backed securities (MBSs), government agencies and private specialized investors issue MBSs using mortgage pools as collateral.

[2]Conventional monetary policy through raising and lowering short-term interest rates may affect aggregate demand via a variety of channels that involve the housing sector and mortgages. See Mishkin (2007) for an extended survey on the channels of monetary policy involving the housing sector and Amromin et al. (2020) on the most recent findings on the refinancing channel of monetary policy.

[3]Gilchrist et al. (2015) estimate a sizable effect of monetary policy changes on mortgage rates in the US. A conventional monetary policy that lowers the 2-year nominal Treasury yield by 10 basis points leads to a reduction in the 30-year fixed-rate mortgage yield of about 6 basis points.

of consumer durables, or pay off existing debts, through home equity loans. However, there are times, like recessions, when the efforts to stimulate mortgage refinancing via lower rates may be ineffective. Recessions are generally characterized by rising delinquency rates, tighter credit standards, and falling house prices which may compromise the ability of homeowners to refinance.

In this chapter, I use a 10-variable time-varying parameter vector autoregression (TVP-VAR, hereafter) to study the changing effects of monetary policy shocks on housing and household debt since 1960 in the US. Because the volatility of many variables included in the model changed substantially over time, I allow for heteroskedastic innovations. As a result, the model considers two sources of time variation, namely changing size of shocks and changing propagation mechanism of these shocks. The model departs from the previous literature on the time-varying effects of monetary policy on housing and household debt in two aspects. First, I allow for parameters and volatility to continuously evolve rather than imposing sample splits or discrete regime changes. This modeling choice is critical because the institutional changes that may have caused the monetary policy transmission mechanism to evolve did not occur as clearly identifiable breaks. Second, I build on estimation methods recently proposed by Koop and Korobilis (2013, 2014) in order to increase the information set generally spanned by models with time-varying parameters. These authors introduce approximation methods to overcome the drawback that traditional TVP-VAR models à la Primiceri (2005) can only consider few variables. Hence, building on Koop and Korobilis (2013, 2014), I provide a wider picture of how the effects of monetary policy shocks evolved relative to small-scale models.

The model provides some interesting insights into how the relationship between monetary policy, the housing sector and household debt changed over time. First, new housing starts and residential investment have become slightly more sensitive to monetary policy shocks despite reacting slower in most recent periods. In general, the effects of contractionary monetary policy shocks on household debt diminished except in some periods during which they have increased. Tight monetary policy led to large contractions in home mortgages and consumer credit during the credit crunches of the late 1960s. On the contrary, the reaction of all components of household debt to monetary policy shocks weakened during the Great Moderation. However, home mortgages were very reactive to monetary policy during the early 2000s and just before the Great Financial Crisis but by less than what was in the late 1960s. The most striking result regards the increase in the responsiveness of house prices to monetary policy shocks. In the last part of the chapter, I observe that these results are consistent with some interpretations that suggest that the transmission of monetary policy shocks may have changed because of the institutional changes that affected the US housing finance system between the 1970s and 1980s, e.g. the repeal of interest rate ceilings and the integration of housing finance into capital markets.

ROAD MAP. The chapter is organized as follows. Section 2.2 surveys the related literature.

In Section 2.3, I introduce the model, detail the estimation methods and present the identification strategy. Section 2.4 presents and discusses the time-varying statistics generated by the model. In Section 2.5, I interpret the time-varying relationship between monetary policy, housing and household debt in light of different institutional regimes of the US housing finance system. Section 2.6 concludes.

2.2 Related literature

This chapter is related to different strands of literature on the role of household debt in the monetary transmission mechanism and on the time-varying effects of monetary policy shocks.

The institutional features of the housing finance system affect the transmission of monetary policy through the housing sector (Campbell, 2012; Mishkin, 2007; Slacalek et al., 2020). These features differ substantially across countries and, to some extent, are determined within regulatory frameworks which are independent of the conduct of monetary policy. Calza et al. (2013) find that the response of house prices and residential investment to contractionary monetary policy shocks is larger in countries with low down-payment rates, widespread home equity withdrawals, high mortgage debt-to-GDP ratios and with predominantly adjustable-rate mortgages. Analogously, Musso et al. (2011) show that the reduction in residential investment, house prices and mortgage debt in response to rising interest rates is larger in the US relative to the euro area, two economies with very different housing finance systems.

This chapter is related to the literature that investigates to what extent household debt affects the effectiveness of monetary policy. The literature using aggregate time series for advanced economies finds conflicting results.[4] For the US, Alpanda and Zubairy (2019) and Breitenlechner and Scharler (2020) find that monetary policy has weaker effects on output when the household debt-to-GDP ratio is high relative to its trend level. Furthermore, there is a growing empirical literature that explores the transmission of monetary policy through mortgage debt using household-level data (Cloyne et al., 2020; Cumming and Hubert, 2020; Di Maggio et al., 2017; Flodén et al., 2019; Jappelli and Scognamiglio, 2018). These studies show that the response of household spending to monetary policy shocks is almost entirely driven by households holding adjustable-rate mortgages and that the distribution of debt rather than its aggregate level affects the transmission of monetary policy. Moreover, cross-country comparisons suggest that the role of mortgage debt in the transmission of monetary policy varies across countries.[5]

[4] The international evidence is mixed. In panels of advanced economies, a monetary policy tightening has larger effects in countries where non-financial sector debt (Hofmann and Peersman, 2017a) and mortgage debt (Calza et al., 2013) are high relative to GDP. In contrast, Alpanda et al. (2019) find that monetary policy is less effective in stimulating output in periods of high household debt-to-GDP ratios.

[5] For Sweden, Flodén et al. (2019) find that in response to a policy-induced rise in interest rates, highly indebted households reduce spending by more than households with little debt. The response of indebted households to monetary policy shocks is largely driven by households holding adjustable-rate mortgages according to a cash-flow channel of monetary policy. For the US, Di Maggio et al. (2017) find that, in response to a sudden drop in mortgage interest payments between 2005 and 2007, households with adjustable-rate mortgages increase car purchases and, to a lesser extent, deleverage on previous debts. Instead, for Italy, Jappelli and Scognamiglio (2018) find only a weak

From a methodological perspective, this chapter is related to the literature on time-varying parameter models used to explore the changing transmission of monetary policy shocks in the US. Time variation in the transmission of monetary policy implies that the parameters describing the relation between the federal funds rate (or any other policy instrument) and some real variable of interest have changed. Researchers working with VAR models use different approaches for evaluating potential changes in these parameters, namely constant-parameter models estimated over different samples, regime-switching models, and models with parameters and variances that continuously evolve. The model studied in this chapter belongs to the last class of models which have been initially popularized in macroeconomics by Cogley and Sargent (2005) and Primiceri (2005).

The literature on the time-varying effects of monetary policy in the US has reached mixed conclusions. Boivin et al. (2010) survey this vast literature. For what concerns the time-varying effects of monetary policy on housing and household debt, results are mixed too. McCarthy and Peach (2002) argue that the transmission of monetary policy through the housing sector has changed as the housing finance system transited toward a fully market-based system between the 1970s and 1980s. Under the new system, monetary policy shocks lead to slower though larger contractions in residential investment, persistent increases in mortgage rates, and long-lasting drops in house prices, relative to pre-1980s periods. Hofmann and Peersman (2017b) find analogous results for residential investment and house prices while they show that the response of mortgage debt has increased since the mid-1980s. In contrast, Den Haan and Sterk (2010) do not find any sizable change in the response of mortgage debt. However, they show that, since the mid-1980s, monetary contractions lead non-banks to increase the holding of mortgages. While the previous findings arise in the context of constant-parameter VAR models estimated before and after the mid-1980s, Finck et al. (2018) show that in a small TVP-VAR the response of mortgage debt to monetary policy shocks has diminished over time.

2.3 A medium-scale model of the US economy

The regulatory changes in the housing finance system did not occur sharply but as a continuously evolving process between the 1970s and 1980s. This suggests that it is reasonable to assume that the propagation mechanism of monetary policy shocks through the housing sector and household debt evolved gradually over time. Therefore, I model the interaction between aggregate economy, the housing sector, monetary policy and household debt with a TVP-VAR model of the US economy. This section introduces the empirical model, the estimation strategy, and the identification assumptions.

and not statistically significant increase in spending by households with adjustable-rate mortgages in response to lower interest rates. For the UK and the US, Cloyne et al. (2020) find that the positive response of households with mortgages accounts for the bulk of the response of aggregate consumption to an expansionary monetary policy shock. Using UK loan-level data, Cumming and Hubert (2020) find that the effects of monetary policy are amplified by the distribution of loan-to-income ratios among households rather than by the sector-level ratio.

2.3.1 The empirical model

The TVP-VAR model with stochastic volatility is described by the following system of n equations:

$$\underset{n\times 1}{\mathbf{y}_t} = \underset{n\times 1}{\mathbf{c}_t} + \underset{n\times n}{\mathbf{B}_{1,t}}\mathbf{y}_{t-1} + \cdots + \underset{n\times n}{\mathbf{B}_{p,t}}\mathbf{y}_{t-p} + \underset{n\times 1}{\mathbf{u}_t} \quad \text{with} \quad \mathbf{u}_t \sim \mathcal{N}\left(\underset{n\times 1}{\mathbf{0}}, \underset{n\times n}{\mathbf{\Omega}_t}\right) \tag{2.1}$$

where $\mathbf{y}_t$ is a $(n \times 1)$ vector of endogenous variables, $\mathbf{c}_t$ is a $(n \times 1)$ vector of time-varying intercepts, $\mathbf{B}_{j,t}$ are $(n \times n)$ matrices of time-varying parameters with $j = 1, \ldots, p$, $\mathbf{u}_t$ is a $(n \times 1)$ vector of innovations with zero mean and time-varying variance-covariance matrix $\mathbf{\Omega}_t$. Time is indexed by $t = 1, \ldots, T$, each time period is a quarter, and the maximum lag length p is set to 4 as it is standard in VAR models using US macroeconomic time series.

The model in equation 2.1 involves unobserved components and it can be expressed as a state-space model. A state-space model is composed of two *objects*: a measurement equation and a state equation (Kim and Nelson, 1999). The measurement equation specifies the evolution of the endogenous observed variables and their relationship with the unobserved parameters. The state equation describes a law of motion for the unobserved parameters and it is generally specified as a first order difference equation.

THE STATE-SPACE FORM. The state-space form is obtained by stacking the right-hand-side parameters in equation 2.1 into a $(k \times 1)$ vector $\boldsymbol{\beta}_t$ where $k = n(np+1)$ is the number of parameters in all $\mathbf{B}_{j,t}$ matrices. Formally, the vector $\boldsymbol{\beta}_t$ is obtained as:

$$\underset{k\times 1}{\boldsymbol{\beta}_t} = \text{vec}(\mathbf{B}_t) \quad \text{with} \quad \underset{(np+1)\times n}{\mathbf{B}_t} = \begin{bmatrix} \mathbf{c}_t' \\ \mathbf{B}_{1,t}' \\ \vdots \\ \mathbf{B}_{p,t}' \end{bmatrix}$$

The right-hand-side variables in equation 2.1 are organized into a $(n \times k)$ matrix $\mathbf{X}_t'$:

$$\underset{n\times k}{\mathbf{X}_t'} = \left(\mathbf{I}_n \otimes \underset{1\times(np+1)}{\left[1, \mathbf{y}_{t-1}', \mathbf{y}_{t-2}', \ldots, \mathbf{y}_{t-p}'\right]} \right)$$

The state-space representation of the TVP-VAR model is shown in equations 2.2 (measurement equation) and 2.3 (state equation):

$$\underset{n\times 1}{\mathbf{y}_t} = \underset{n\times k}{\mathbf{X}_t'} \underset{k\times 1}{\boldsymbol{\beta}_t} + \underset{n\times 1}{\mathbf{u}_t} \quad \text{with} \quad \mathbf{u}_t \sim \mathcal{N}\left(\underset{n\times 1}{\mathbf{0}}, \underset{n\times n}{\mathbf{\Omega}_t}\right) \tag{2.2}$$

$$\underset{k\times 1}{\boldsymbol{\beta}_t} = \underset{k\times 1}{\boldsymbol{\beta}_{t-1}} + \underset{k\times 1}{\boldsymbol{\eta}_t} \quad \text{with} \quad \boldsymbol{\eta}_t \sim \mathcal{N}\left(\underset{k\times 1}{\mathbf{0}}, \underset{k\times k}{\mathbf{Q}_t}\right) \tag{2.3}$$

The specification of the state equation amounts to choosing a law of motion for the parameters in the vector $\boldsymbol{\beta}_t$. Since Cogley and Sargent (2005), a popular specification for $\boldsymbol{\beta}_t$ is the drift-less random walk with innovations $\boldsymbol{\eta}_t$. The innovations have zero mean and time-varying variance-covariance matrix $\mathbf{Q}_t$, as in Koop and Korobilis (2013). The elements of $\mathbf{Q}_t$ govern the rate of drift in the parameters. The random walk specification is desirable because it is consistent with assuming that parameters evolve in a gradual but unpredictable fashion. However, this assumption may have less desirable implications for the stability of the system which I discuss later.

2.3.2 Data

The vector of endogenous variables $\mathbf{y}_t$ contains 10 quarterly time series from 1959Q1 to 2018Q4 (see Table 2.1). The length of the sample is chosen in order to capture different phases of the US macroeconomic history as well as distinct institutional configurations of the housing finance system. Quantities and prices enter the VAR in first differences of their natural logarithm apart from the personal consumption expenditure price index which enters in second differences of natural logarithm. The effective federal funds rate enters the VAR in levels, namely in percent, as in Paul (2020).[6] Real variables are obtained by deflating nominal variables using the GDP implicit price deflator.

The times series are organized in blocks and appear in the vector $\mathbf{y}_t$ as they are ordered in Table 2.1. The first block is the aggregate economy and it consists of real GDP (RGDP), a commodity price index (PCOM), the personal consumption expenditure or PCE price index (P). As it is standard in VARs, a commodity price index is included in order to alleviate the price puzzle, namely the positive response of the price level to a monetary tightening (see Christiano et al., 1996; Sims, 1992). The housing sector block includes a real house price index (HP) from Shiller (2015), new housing starts (HOUST) and real residential investment (RES).

The monetary policy block consists of the effective federal funds rate (R) which is assumed to be the key monetary policy indicator.[7] The effective federal funds rate is the weighted average of the rates at which depository institutions lend reserve balances among each other through unsecured overnight loans. The Fed uses open market operations to close the gap between the effective rate and the target policy rate. The effective federal funds rate is originally available at monthly frequency. I use the average rate during the last month of each quarter instead of averaging the monthly observations across each quarter. This choice should ensure

[6] As in Koop and Korobilis (2013, 2014), all series apart from the effective federal funds rate are transformed to be *approximately stationary*. Tables B.1 and B.2 in Appendix B.1.2 provide more information on the transformations and results from a battery of unit root tests. Appendix B.1.1 provides a detailed description of the source of data and construction of variables. From the literature, it is unclear whether VAR models should be estimated in log levels or in differences. On the one hand, a specification that leaves variables in log levels preserves possible cointegrating relationships in the data. On the other hand, differencing variables with unit roots improves forecasting accuracy in presence of instabilities (see Carriero et al., 2015, and references therein). Indeed, Carriero et al. (2015) show that VAR specifications in log levels and in growth rates yields analogous forecast performances. Moreover, for the type of Minnesota prior that I use for the model in this chapter, they suggest working with a VAR in differences.

[7] To take into account for the QE period, I replace the effective federal funds rate series with the 3-Month Treasury Bill on the secondary market from March 2009 (2009Q1) to November 2014 (2014Q4). This time window covers the QE1, QE2, and QE3. Hence, I assume that during QE, the Treasury Bill rate is a better indicator for the stance of monetary policy. Krishnamurthy and Vissing-Jorgensen (2011) show that QE announcements of asset purchases were effective in immediately lower yields on Treasury bonds.

TABLE 2.1: DATASET

N[1]	Series ID	Definition	Unit	Source	T[2]
1	RGDP	Real GDP	BoC 2012$	BEA	5
2	PCOM	Commodity price index	2012 = 100	BEA	5
3	P	PCE price index	2012 = 100	BEA	6
4	HP	Real house price index	2000 = 100	Shiller (2015)	5
5	HOUST	New housing starts	1000 Units	CB-NRW	5
6	RES	Real residential investment	2012 = 100	BEA	5
7	R	Effective federal funds rate	Percent	FRB H.15	1
8	HM	Real home mortgages	Bil. of 2012$	FRB Z.1	5
9	CC	Real consumer credit	Bil. of 2012$	FRB Z.1	5
10	HHL	Real other loans to households	Bil. of 2012$	FRB Z.1	5

[1] All series but the effective federal funds rate are seasonally adjusted. If seasonally adjusted series are not available, I perform seasonal adjustments using the X-13 ARIMA-SEATS quarterly seasonal adjustment method by the U.S. Census Bureau.

[2] T stands for Transformation code (see Stock and Watson, 2009). T = 1 means no transformation (levels), T = 5 means first difference of logarithm, T = 6 means second difference of logarithm. See Table B.2 for further information.

that the monetary policy instrument R in quarter t incorporates the response of disturbances to the aggregate economy and the housing sector, and reduce the probability that these variables respond to monetary policy shocks within quarter t.[8]

The household debt block consists of the main financial liabilities of the household sector, namely real home mortgages (HM), real consumer credit (CC), and real other loans to households (HHL). Home mortgages are long-term loans collateralized by one-to-four family residential properties and they account for between 60% and 80% of total household debt in the model. Consumer credit consists of unsecured short- and medium-term loans such as credit card receivables, auto loans, student loans and other loans incurred for the purchase of durable goods. Consumer credit accounts for between 18% and 30% of total household debt. Other loans to households is a residual category that includes depository institutions loans which do not fall in the previous groups. Other loans account for less than 10% of total household debt.

2.3.3 Estimation

TVP-VARs are generally estimated using Bayesian methods which involve the computation of the posterior distribution of the model. Since the posterior distribution is a complex object, researchers use simulation methods like Monte Carlo Markov Chains (MCMC) to characterize its shape and conduct inference. However, MCMC methods have the drawback that only a

[8] In other words, since R is observed during the last month of quarter t, all variables ordered before R respond to monetary policy shocks starting from next month after the shock occurs, namely, in quarter $t+1$, and not during the same month of the shock. A similar argument on why using the effective federal funds rate during the last most of each quarter is preferable to using the average rate during the quarter is contained in Den Haan and Sterk (2010).

few series can be included in the model. A full exploration of the posterior distribution using simulation methods is computationally expensive and impractical in large models. Indeed, both Cogley and Sargent (2005) and Primiceri (2005) estimate 3-variable models. For these reasons, I estimate the 10-variable model in equations 2.2 and 2.3 using the approach recently proposed by Koop and Korobilis (2013, 2014).[9]

In a series of papers, Koop and Korobilis (2013, 2014) introduce an alternative estimation strategy for large TVP-VAR models through the use of forgetting factors and variance discounting methods. These approximations yield estimates of time-varying parameters and volatilities directly from the recursions of the Kalman filter. Koop and Korobilis (2013) use this approach to forecast with a 25-variable TVP-VAR model with stochastic volatility while Koop and Korobilis (2014) update the previous algorithm to estimate a TVP-VAR model augmented with factors (TVP-FAVAR). The advantage of using forgetting factors and discounting methods is that they dispense with the simulation algorithms used to characterize the joint posterior distribution of the model, e.g. MCMC methods. However, the use of variance discounting methods yields point estimates of the volatilities and, therefore, makes this approach not fully Bayesian (Kapetanios et al., 2019).[10]

Brief overview of the estimation algorithm

I estimate the TVP-VAR model by re-adapting the estimation algorithm introduced in Koop and Korobilis (2014). Here, I provide a brief overview that emphasizes the differences with more traditional simulation algorithms. Later, I will discuss the values assigned to each hyperparameter. Section B.2.1 in Appendix provides a detailed step-by-step explanation of the estimation algorithm.

The first step in the estimation is the choice and calibration of the prior distributions for the system in equations 2.2 and 2.3. The priors for the time-varying parameters $\boldsymbol{\beta}_t$ and for the TVP-VAR variance-covariance matrix $\boldsymbol{\Omega}_t$ are:

$$\boldsymbol{\beta}_0 \sim \mathcal{N}\left(\underset{k\times 1}{\bar{\boldsymbol{\beta}}_0}, \underset{k\times k}{\mathbf{V}_0}\right) \quad \text{and} \quad \underset{n\times n}{\boldsymbol{\Omega}_0}$$

[9] A popular simulation algorithm in the TVP-VARs literature is the Gibbs sampler. The basic mechanics of the Gibbs sampler is the following: after having partitioned the set of parameters into blocks, the sampler recursively draws blocks of parameters from less complex conditional distributions. For a fairly large number of draws (generally tens of thousands) from the conditional distributions, these draws will converge to the joint posterior distributions. See Chan and Strachan (2020) for a survey on the estimation methods used in macroeconometrics.

[10] The model in equations 2.2 and 2.3 could have been broken down in small sub-models and estimated using MCMC methods on each sub-model. In this case, the estimation would have been fully Bayesian but with the drawback of losing the information potentially embedded in a larger model. Indeed, a large literature on forecasting with large VARs provides firm evidence on the gains from using medium- and large-scale models relative to small-scale models (see for example Bańbura et al., 2010). Moreover, a model that jointly encompasses information on multiple sectors rather than on separate sectors in different models would provide a better characterization of the transmission of monetary policy (see Hofmann and Peersman, 2017b, on this point). In addition to Koop and Korobilis (2013, 2014), there are other approaches proposed to solve the dimensionality problem associated with TVP-VARs. To the best of my knowledge, Kapetanios et al. (2019) and Chan et al. (2020) develop different approaches to address the same problem.

The initial vector of unobserved parameters $\boldsymbol{\beta}_0$ is a normally distributed random variable with mean $\bar{\boldsymbol{\beta}}_0$ and variance $\mathbf{V}_0$. The moments of the prior distribution of $\boldsymbol{\beta}_0$ are set according to a variation of the Minnesota prior (Doan et al., 1984). The Minnesota prior imposes a-priori restrictions on the parameters in $\boldsymbol{\beta}_t$ and these restrictions are intended to alleviate overfitting problems inherent in models with many parameters. More specifically, the Minnesota approach incorporates the prior belief that many macroeconomic variables follow a random walk or an AR(1) process.

In the original Minnesota prior, the covariance matrix $\mathbf{V}_0$ is assumed to be diagonal and this assumption implies the belief that time-varying parameters are independent of each other. The entries of the principal diagonal in $\mathbf{V}_0$ are set in a more structured manner that involves setting several shrinkage hyperparameters. The hyperparameters implement the prior information that parameters tend to zero as the lags increase, and that, for each variable, its own lags have higher predictive power relative to lags of other variables. In setting $\mathbf{V}_0$, I follow the simplified version of the Minnesota prior used in Koop and Korobilis (2014) which involves an unique shrinkage hyperparameter. Let $\mathbf{V}_{i,0}$ be the i-th diagonal element of $\mathbf{V}_0$, the prior covariance matrix $\mathbf{V}_0$ has the following entries on the main diagonal:

$$\mathbf{V}_{i,0} = \begin{cases} \frac{\gamma}{j^2}, & \text{for coefficients on lag } j \text{ for } j = 1, \ldots, p \\ \underline{\text{a}}, & \text{for the intercepts} \end{cases}$$

where p is the lag length, γ is the shrinkage hyperparameter and $\underline{\text{a}}$ is the hyperparameter that governs the initial variance of the intercept. In a Bayesian setting, high values of γ and $\underline{\text{a}}$ reflect a-priori high uncertainty about the location of the time-varying parameters in $\boldsymbol{\beta}_t$. Therefore, for a given γ, this prior assigns a higher variance to parameters associated to less distant lags while it shrinks the variance of parameters associated to more distant lags. With regards to $\underline{\text{a}}$, a non-informative prior is generally chosen. For what concerns the variance-covariance matrix of the TVP-VAR, I follow Koop and Korobilis (2014) and set the prior $\boldsymbol{\Omega}_0$ to be non-informative.

Once the prior distributions are calibrated, the estimation algorithm can be thought of as made of two main blocks. The first block is a forward pass algorithm based on both the Kalman filter and the Exponentially Weighted Moving Average filter (EWMA, hereafter) that estimates the time-varying parameters and the variance-covariance matrix of the TVP-VAR. The second block consists of a backward fixed-interval smoother (Rauch et al., 1965) to obtain optimal estimates of the parameters. Additionally, a backward smoother is also used to obtain more precise estimates of the TVP-VAR variance-covariance matrix. As I previously mentioned, Koop and Korobilis (2013, 2014) introduce two innovations in the estimation of time-varying parameters and stochastic volatility that greatly reduce the computational burden associated with the estimation of TVP-VAR models.

The first innovation is a simplification of the equations of the Kalman filter used to estimate the time-varying parameters in $\boldsymbol{\beta}_t$. In estimating TVP-VAR models, one of the most computational demanding steps is the prediction step of the Kalman filter which involves the following equations:[11]

$$\hat{\boldsymbol{\beta}}_{t|t-1} = \hat{\boldsymbol{\beta}}_{t-1|t-1}$$
$$\mathbf{P}_{t|t-1} = \mathbf{P}_{t-1|t-1} + \mathbf{Q}_t$$

where $\hat{\boldsymbol{\beta}}_{t|t-1}$ is a prediction for the time-varying parameters at time t given observations up to and including time $t-1$, while $\mathbf{P}_{t|t-1}$ is the predicted estimate of the variance-covariance matrix of $\hat{\boldsymbol{\beta}}_{t|t-1}$, namely a measure of accuracy of the prediction. $\hat{\boldsymbol{\beta}}_{t|t-1}$ and $\mathbf{P}_{t|t-1}$ define the moments of the predictive density $p(\boldsymbol{\beta}_t|\mathbf{y}^{1:t-1}) = \mathcal{N}\left(\hat{\boldsymbol{\beta}}_{t|t-1}, \mathbf{P}_{t|t-1}\right)$.[12] In traditional TVP-VAR models, the matrix $\mathbf{Q}_t$ is simulated or estimated. Because $\mathbf{Q}_t$ is generally a very large $(k \times k)$ matrix, its simulation or estimation is computationally demanding. Instead, Koop and Korobilis (2013, 2014) propose to replace the equation for computing $\mathbf{P}_{t|t-1}$ with the following equation:

$$\mathbf{P}_{t|t-1} = \lambda^{-1}\mathbf{P}_{t-1|t-1}, \quad 0 < \lambda \leq 1$$

where λ is the forgetting factor. This specification for $\mathbf{P}_{t|t-1}$ greatly reduces the computational complexity since there is no need to estimate or simulate the matrix $\mathbf{Q}_t$. In the original formulation of $\mathbf{P}_{t|t-1}$, the matrix $\mathbf{Q}_t$ is responsible for the amount of time variation in the parameters. In contrast, in the new specification, the rate of drift in $\boldsymbol{\beta}_t$ is governed by the forgetting factor λ. However, it can be easily shown that $\mathbf{Q}_t = \left(\lambda^{-1} - 1\right)\mathbf{P}_{t-1|t-1}$.

The second innovation concerns the estimation of the time-varying variance-covariance matrix of the TVP-VAR model ($\boldsymbol{\Omega}_t$). In traditional TVP-VAR models, this matrix is simulated using algorithms for multivariate stochastic volatility. Koop and Korobilis (2013, 2014) suggest to directly estimate this matrix using the following EWMA estimator:

$$\hat{\boldsymbol{\Omega}}_{t|t} = \kappa\hat{\boldsymbol{\Omega}}_{t-1|t-1} + (1-\kappa)\hat{\mathbf{u}}_{t|t}\hat{\mathbf{u}}'_{t|t}$$

where the vector $\hat{\mathbf{u}}_{t|t} = \mathbf{y}_t - \mathbf{X}'_t\hat{\boldsymbol{\beta}}_{t|t}$ contains the post-fit residuals (or prediction errors) in the measurement equation. These are the estimated residuals of the reduced form TVP-VAR model obtained using the filtered estimates of the time-varying parameters ($\hat{\boldsymbol{\beta}}_{t|t}$). The parameter κ is a decay factor that discounts previous estimates of $\boldsymbol{\Omega}_t$ and governs the time variation in volatility.

2.3.4 Implementation of the estimation algorithm

The random walk assumption

The time-varying parameters in $\boldsymbol{\beta}_t$ are modeled as drift-less random walks (see equation 2.3). As previously mentioned, the choice of a random walk specification comes at the cost of a potentially unstable system. For example, if some elements in $\boldsymbol{\beta}^{1:T}$ reach a region with ex-

[11] For a detailed treatment of the Kalman filter steps in state space models see Kim and Nelson (1999) and Frühwirth-Schnatter (2006). The Appendix of this chapter provides all Kalman filter equations used to estimate the model.

[12] For a generic vector $\mathbf{y}$, the notation $\mathbf{y}^{1:t}$ denote the history of the vector $\mathbf{y}$ up to and including time t.

plosive fluctuations, then the impulse responses will display illogical and erratic dynamics. Additionally, it may be unrealistic to assume that the relations between the observed data vary indefinitely over time. Otherwise, permanent shifts in the macroeconomic relationships would be more frequent than what is generally observed. It may be therefore desirable to constrain the potentially unbounded growth of parameters. Since Cogley and Sargent (2001, 2005) this is obtained by imposing a stability condition on the model at each point in time.[13]

I limit the path of the time-varying parameters from reaching the explosive region by imposing a stability condition on the model.[14] However, the constraint of the stability condition is never binding because the smoothed estimates are always in the stability region. This may be due to multiple factors. First of all, the forgetting factor λ that governs the time variation in parameters is set to a value slightly smaller than 1. Hence, the parameters vary rather slowly and T would need to be very large to push the random walk toward the instability region (Primiceri, 2005). Additionally, the prior distributions are chosen to impose some restrictions on the space spanned by the time-varying parameters, for example by shrinking the variance of each parameter and assuming that the parameters are (a-priori) not correlated. A further stabilizing factor is the smoother which massively reduces the time variation in the estimates produced by the Kalman filter (Sims, 2001).[15]

Hyperparameters and the prior amount of time variation

In TVP-VAR models estimated with MCMC methods, researchers generally elicit the prior variance-covariance matrix and other hyperparameters by using a training sample. For example, Primiceri (2005) uses the first 10 years of the sample to estimate a fixed-coefficient VAR with OLS and uses these estimates to calibrate the priors. According to Koop and Korobilis (2014), the training sample approach is preferable over using uninformative subjective priors when the researcher is working with MCMC methods. Simulation methods would encounter several numerical instability problems if uninformative priors are used. Hence, the priors need to be very informative to *discipline* the model. This is not the case if the model is estimated using approximations methods. Moreover, truncating the sample to calibrate the initial con-

[13] In Cogley and Sargent (2001, 2005), the stability of the VAR is checked at each point in time by investigating the eigenvalues of the companion matrix. A draw of $\boldsymbol{\beta}^{1:T}$ is accepted if the stability condition is satisfied at each point in time, otherwise, the entire vector $\boldsymbol{\beta}^{1:T}$ is discarded. For example, Cogley and Sargent (2001, 2005) draw a vector of time-varying parameters from a normal density penalized by an indicator function that works as a *reflecting barrier*. For a discussion of different stability conditions for TVP-VAR models see Koop and Potter (2011).

[14] The stability condition that I use is analogous to many others used in TVP-VAR models estimated using MCMC techniques (see for example Cogley and Sargent, 2005). At each point in time, I write the VAR(p) as a VAR(1) and use the smoothed estimates $\boldsymbol{\beta}_{t|T}$ to obtain the companion matrix. If the stability condition is satisfied (i.e. if all eigenvalues of the companion matrix are less than one in absolute value), the estimation algorithm proceeds to the next iteration in $t+1$. Otherwise, I restrict the smoothed estimates of $\boldsymbol{\beta}_t$ at time t to be the same as in the previous period times an arbitrary scalar equal to 0.999. The variance of the smoothed estimates is simply set to be the same as in the previous period. This stability condition ensures that the parameters are always in the stability region while allowing for some degree of time variation, though minimal.

[15] Beyond purely statistical considerations, imposing a stability condition on the space spanned by the parameters reflects the belief that the US economy, as represented by the VAR in equations 2.2 and 2.3, has not been characterized by extremely explosive dynamics.

ditions would imply a loss of potentially precious historical information on the time-varying effects of monetary policy. For these reasons, I follow the uninformative approach of Koop and Korobilis (2014).

TIME-VARYING PARAMETERS. The Minnesota prior involves choosing the prior mean and variance of $\boldsymbol{\beta}_t$. If the VAR consists of growth rates or approximately stationary series, Koop and Korobilis (2014) suggest to set all elements in the vector $\bar{\boldsymbol{\beta}}_0$ to zero (i.e. $\mathbb{E}(\boldsymbol{\beta}) = \bar{\boldsymbol{\beta}}_0 = 0$). Hence, I set all but one element of $\bar{\boldsymbol{\beta}}_0$ to zero because most of the variables have been transformed to be approximately stationary. The non-zero element is the element in $\bar{\boldsymbol{\beta}}_0$ corresponding to the first autoregressive parameter in the effective federal funds rate equation, which enters the VAR in levels. This element is set equal to 1 to implement the belief that the effective federal funds rate features some persistence.[16] Choosing the prior variance $\mathbf{V}_0$ requires setting the prior variance of the intercept ($\underline{a}$) and the shrinkage hyperparameter (γ). The latter is particularly important since it governs the variance of the autoregressive parameters and, in turn, the overall tightness of the prior (Giannone et al., 2015). I follow Koop and Korobilis (2014) and choose non-informative values for $\underline{a}$ and γ, namely $\underline{a} = 10^2$ and $\gamma = 0.1$. These values heuristically minimize the probability that $\boldsymbol{\beta}_t$ is pushed toward the instability region while being rather uninformative. Additionally, they are in line with the literature.[17]

TIME-VARYING VARIANCE-COVARIANCE MATRIX. The EWMA estimator of the variance - covariance matrix of the TVP-VAR model ($\boldsymbol{\Omega}_t$) requires setting an initial condition, $\boldsymbol{\Omega}_0$. To the best of my knowledge, there is no established method to calibrate $\boldsymbol{\Omega}_0$ in the context of TVP-VARs that do not rely on MCMC methods. For example, Koop and Korobilis (2013) estimate $\boldsymbol{\Omega}_0$ using a training sample on an expanding window of observations but their model is only used for forecasting. Instead, Koop and Korobilis (2014) calibrate $\boldsymbol{\Omega}_0$ to be an identity matrix. In setting $\boldsymbol{\Omega}_0$, I follow the uninformative approach by Koop and Korobilis (2014) and set $\boldsymbol{\Omega}_0 = k_\Omega \mathbf{I}_n$ where the hyperparameter k_Ω is a scalar. In the baseline model this hyperparameter is set equal to the shrinkage hyperparameter of the Minnesota prior, namely $k_\Omega = 0.1$. In a series of robustness checks, I show that the results from the baseline model are qualitatively unchanged when k_Ω is slightly changed.

FORGETTING FACTOR. The forgetting factor λ disciplines the rate of drift in $\boldsymbol{\beta}_t$ since it enters into the Kalman filter equation that predicts the variance-covariance matrix of the estimated parameters, $\mathbf{P}_{t|t-1} = \lambda^{-1}\mathbf{P}_{t-1|t-1}$. It is straightforward to see that by increasing (lowering)

[16] I find that results are not sensitive to the choice of this particular hyperparameter. For a VAR where variables enter in log levels, the prior implies setting most of the elements of the vector $\bar{\boldsymbol{\beta}}_0$ to zero except for the elements associated to the own first lag of each dependent variable. Instead, these elements are generally set to 1 or values slightly smaller than 1 according to the prior belief. For a VAR specification in log levels, Carriero et al. (2015) shows that the Minnesota prior should be augmented with the sum of coefficients and initial dummy observation prior to improve forecasting accuracy relative to a specification in first differences or growth rates.

[17] Koop and Korobilis (2013) set $\underline{a} = 10^2$ while they use a grid of values for γ that goes from 10^{-5} to 0.1 and, at each t, select the value that yield the *best* forecasting performance. Koop and Korobilis (2014) set $\underline{a} = 4$ and $\gamma = 0.1$. Moreover, consistently with the shrinkage interpretation of γ, I find that reducing γ enforces the stability of the VAR at each point in time.

the forgetting factor, the variance-covariance matrix of the predicted parameters ($\mathbf{P}_{t|t-1}$) will change little (substantially) relative to the its value in the previous iteration. The extreme case is when $\lambda = 1$. In this case, the innovations in the state equation will have zero variance and the parameters of the VAR will be constant over time.[18] Following Koop and Korobilis (2013, 2014), I set $\lambda = 0.99$. Hence, $\boldsymbol{\beta}_t$ moves very gradually and slowly over time. This treatment of time variation corresponds to the *business-as-usual* prior in Cogley and Sargent (2005). They conservatively calibrate the prior on $\mathbf{Q}_t$ in such a way that time variation is little.[19]

DECAY FACTOR. The decay factor κ governs the time evolution of the estimated covariance matrix of the TVP-VAR model. Values of κ close to 1 make the estimate of variance-covariance matrix less responsive to the information carried by the most recent observations that are encapsulated in the VAR residuals. I set $\kappa = 0.96$ as in Koop and Korobilis (2013, 2014).

Smoothed *vs.* filtered estimates

All *statistics* on time variation reported in this chapter are based on smoothed estimates. These estimates are obtained using a smoother that runs backward and refines the filtered estimates. According to Sims (2001), the difference between the smoothed estimates and the filtered estimates are due to a learning component. To see this point, it is useful to recall what the filter and the smoother estimate. Suppose β_t is one of the parameters in the vector $\boldsymbol{\beta}_t$ (subscripts are suppressed for the sake of simplicity). Then, the filtered estimate $\beta_{t|t}$ is an estimate of β_t given the information up to and including time t. Instead, the smoothed estimate $\beta_{t|T}$ is an estimate of β_t conditional on the information up to and including time T. Therefore, the smoothed estimate reflects the ex-post knowledge about what was happening at time t, namely learning. Sims (2001) advocates for the use of smoothed estimates and argues that early TVP-VAR models concluded that parameters were greatly time-varying because they based inference on filtered estimates of the parameters.

2.3.5 Identification of monetary policy shock

The model in equation 2.1 leaves all shocks unidentified. Therefore, it is necessary to formulate a set of identifying assumptions that allow recovering the structural shocks. The identification of monetary policy shocks is achieved through the recursiveness assumption of Christiano et al.

[18]To see the extreme case, I write the variance-covariance matrix of the innovations in the state equation, namely the variance of $\boldsymbol{\eta}_t$. This matrix reads as $\mathbf{Q}_t = \left(\lambda^{-1} - 1\right) \mathbf{P}_{t-1|t-1}$. If $\lambda = 1$, then $\mathbf{Q}_t$ will be zero. The other extreme case is when λ gets very close to zero. In this case, the variance of the innovations in the state equation will tend to infinite and the time variation in the parameters will be unrealistically large. An estimate of $\mathbf{Q}_t$ can be found by equating the traditional Kalman filter expression for $\mathbf{P}_{t|t-1}$ ($\mathbf{P}_{t|t-1} = \mathbf{P}_{t-1|t-1} + \mathbf{Q}_t$) to the formula that uses the forgetting factor approximation ($\mathbf{P}_{t|t-1} = \lambda^{-1}\mathbf{P}_{t-1|t-1}$), and then solving for $\mathbf{Q}_t$.

[19]An additional interpretation of the forgetting factor λ is that is can be used to decide how much past information is used for estimation at time t. For a given λ, the forgetting factor approach implies that j quarters old data has weight λ^j (Jazwinski, 1970; Raftery et al., 2010). In the case of $\lambda = 0.99$, for estimation at time t, data two years ago obtain roughly 92% weight as last quarters data and the 25 years are effectively used for estimation.

(1996, 1999). This assumption entails partitioning the vector of endogenous variables as:

$$\mathbf{y}_t = [\mathbf{y}_{1t}, \mathrm{R}_t, \mathbf{y}_{2t}]'$$

with all variables in $\mathbf{y}_t$ ordered as they are listed in Table 2.1. The vector $\mathbf{y}_{1t}$ consists of the variables in the aggregate economy and in the housing sector. These variables are real GDP, commodity price index, PCE price index, real house price index, new housing starts and real residential investment. Hence, $\mathbf{y}_{1t} = [\mathrm{RGDP}_t, \mathrm{PCOM}_t, \mathrm{P}_t, \mathrm{HP}_t, \mathrm{HOUST}_t, \mathrm{RES}_t]'$. The vector $\mathbf{y}_{2t}$ includes the household debt variables, namely real home mortgages, real consumer credit and real other loans to households. Hence, $\mathbf{y}_{2t} = [\mathrm{HM}_t, \mathrm{CC}_t, \mathrm{HHL}_t]'$. The partition of $\mathbf{y}_t$ implies that the variables in $\mathbf{y}_{2t}$ react quickly and simultaneously to a monetary policy shock, while the variables in $\mathbf{y}_{1t}$ respond with some delay.

The recursiveness assumption is essentially a timing restriction useful to estimate the effects of monetary policy shocks: the Fed responds to disturbances arising in the aggregate economy and the housing sector within the same quarter but the aggregate economy and the housing sector respond to policy shocks only starting from the following quarter. Moreover, this assumption implies that the Fed intervenes in response to disturbances to household debt with a delay of one quarter. The effective federal funds rate equation (R_t) can be interpreted as a monetary policy reaction function. This interpretation together with the identification assumption implies that the entire endogenous variation in the effective federal funds rate can be captured by controlling for the contemporaneous variables in the aggregate economy and the housing sector as well as for four lags of the variables in all blocks (Nakamura and Steinsson, 2018).

Having said that, the relationship between the reduced-form innovations and the structural shocks is described by the following linear transformation:

$$\underset{n\times 1}{\mathbf{u}_t} = \underset{n\times n}{\mathbf{A}_t}\underset{n\times 1}{\boldsymbol{\varepsilon}_t} \tag{2.4}$$

where $\mathbf{A}_t$ is a non-singular impact matrix and $\boldsymbol{\varepsilon}_t$ is a vector of structural shocks. The structural shocks in $\boldsymbol{\varepsilon}_t$ are assumed to be orthogonal to each other, hence $\mathrm{Var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Sigma}_t = \mathrm{diag}\left(\sigma^2_{\varepsilon_{1t}}, \sigma^2_{\varepsilon_{2t}}, \ldots, \sigma^2_{\varepsilon_{nt}}\right)$. The identification assumption is implemented via a triangular factorization of the variance-covariance matrix of the reduced-form model, namely $\boldsymbol{\Omega}_t = \mathbf{A}_t\boldsymbol{\Sigma}_t\mathbf{A}_t'$. This factorization implies that $\mathbf{A}_t$ is lower triangular with ones on the principal diagonal, and that $\boldsymbol{\Sigma}_t$ is diagonal. Consistently with the recursiveness assumption, the seventh column of $\mathbf{A}_t$ has zeros on its first six elements, one on its seventh element, while the three remaining elements are unrestricted. Consequently, a contractionary monetary policy shock is a 1% increase in the effective federal funds rate. According to Christiano et al. (1999), the recursiveness assumption is enough to identify the monetary policy shock. Although the factorization identifies up to nine shocks in addition to the monetary policy shock, I do not give any economic interpretation to these other shocks. Therefore, the identified model can be thought of as a semi-structural model with the policy shock ordered near the bottom of the recursive order

(Kilian and Lütkepohl, 2017, p. 228).[20]

The recursiveness assumption is standard in many VAR models in the literature which this chapter is related to, regardless of the hypotheses on time variation (Calza et al., 2013; Den Haan and Sterk, 2010; Finck et al., 2018; Hofmann and Peersman, 2017b; McCarthy and Peach, 2002; Musso et al., 2011; Primiceri, 2005). However, Nakamura and Steinsson (2018) fiercely argue against the use of the recursiveness assumption for the identification of monetary policy shocks (and against VAR models, in general) because it implies restrictions that are far from being minimal and innocuous. For example, the form of the structural impact matrix $\mathbf{A}_t$ implies a specific timing for shocks and responses which can be excessively restrictive in a quarterly model. Also, there are times at which the Fed makes policy decisions in relation to exceptional events which are not included in the model. In these cases, the variations in the effective federal funds rate driven by the endogenous response of the Fed to exceptional events will be mistakenly interpreted as an exogenous policy shock. Another, perhaps more serious, problem is that the Fed is likely to take policy decisions conditional on a larger set of information relative to the information set that can be included in a VAR model. In the literature on VARs, this problem of information deficiency of the researcher relative to the policy maker is known as the *non-invertibility problem* and it causes part of the endogenous response of policy to be erroneously classified as exogenous shock.[21]

There is little to do if one wants to address the critique of Nakamura and Steinsson (2018) in the context of TVP-VAR models. For example, non-invertibility is an inescapable problem for models that generally include few variables. However, I take several precautions to alleviate these drawbacks. First of all, I use estimation techniques that allow me to include up to 10 variables. Hence, my model should suffer less from non-invertibility relative to classical TVP-VAR models which generally include between 3 and 6 variables. The dimensional constraint

[20] The structural model is:

$$\underset{n\times n}{\mathbf{A}_{0,t}}\underset{n\times 1}{\mathbf{y}_t} = \underset{n\times 1}{\mathbf{a}_t} + \underset{n\times n}{\mathbf{A}_{1,t}}\mathbf{y}_{t-1} + \cdots + \underset{n\times n}{\mathbf{A}_{p,t}}\mathbf{y}_{t-p} + \underset{n\times 1}{\boldsymbol{\varepsilon}_t} \quad \text{with} \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}\left(\underset{n\times 1}{\mathbf{0}}, \underset{n\times n}{\boldsymbol{\Sigma}_t}\right) \tag{2.5}$$

with $\mathbf{u}_t = \mathbf{A}_t\boldsymbol{\varepsilon}_t$ and $\mathbf{A}_t = (\mathbf{A}_{0,t})^{-1}$. For the identification, I start by calculating $\mathbf{H}_t$ which is the Cholesky factor of $\boldsymbol{\Omega}_t$, i.e. $\boldsymbol{\Omega}_t = \mathbf{H}_t\mathbf{H}_t'$. Since $\boldsymbol{\Omega}_t$ is a positive definite symmetric matrix, it follows that it can be triangularly factorized as $\boldsymbol{\Omega}_t = \mathbf{A}_t\boldsymbol{\Sigma}_t\mathbf{A}_t'$ with $\mathbf{A}_t$ lower triangular with ones on the principal diagonal and $\boldsymbol{\Sigma}_t$ diagonal. Hence, the following holds:

$$\boldsymbol{\Omega}_t = \mathbf{A}_t\boldsymbol{\Sigma}_t\mathbf{A}_t' = \mathbf{A}_t\boldsymbol{\Sigma}_t^{1/2}\left(\boldsymbol{\Sigma}_t^{1/2}\right)'\mathbf{A}_t' = \mathbf{A}_t\boldsymbol{\Sigma}_t^{1/2}\left(\mathbf{A}_t\boldsymbol{\Sigma}_t^{1/2}\right)' = \mathbf{H}_t\mathbf{H}_t'$$

with $\mathbf{H}_t \equiv \mathbf{A}_t\boldsymbol{\Sigma}_t^{1/2}$ and $\mathbf{A}_t \equiv (\mathbf{A}_{0,t})^{-1}$. The matrix $\mathbf{H}_t$ is lower triangular and contains the square roots of the elements of $\boldsymbol{\Sigma}_t$ on the principal diagonal. Then, given the Cholesky factor $\mathbf{H}_t$, $\mathbf{A}_t$ and $\boldsymbol{\Sigma}_t$ are obtained. For the triangular factorization of a positive definite symmetric matrix see Hamilton (1994, pp. 87-92).

[21] There at least other two drawbacks connected to the type of model that I use. First of all, the identification of monetary policy hinges on the assumption that the Fed operates through short-term interest rates. In some periods the monetary policy rule may have changed relative to the one conjectured in the model. Potential episodes are Volcker's monetarist experiment and the post-2008 unconventional monetary policies. In addition, the responses of all variables are independent of the sign of the monetary policy shock. However, many studies find evidence that contractions in monetary policy have sizable negative effects on economic activity while the effects of a monetary easing are rather small if not null. This is the so-called *push-on-a-string* metaphor (Angrist et al., 2018; Barnichon and Matthes, 2014).

in these models prevents monetary policy to respond to more than few variables on output and prices. Instead, I allow monetary policy to systematically respond to disturbances in the housing sector, in addition to output and prices. The inclusion of the housing sector in the monetary policy reaction function is motivated by the importance that housing plays for the US business cycle (Leamer, 2007).[22] The assumed timing for the shocks and responses does not allow for contemporaneous feedbacks from the policy shock to the variables in the aggregate economy and the housing sector. To alleviate problems derived from this extremely restrictive assumption, the effective federal funds rate is the average policy rate during the last month of the quarter. Hence, it is reasonable to assume that monetary policy shocks occurring during the last month of the quarter move real variables and prices only starting from the next quarter.

Despite these precautions, reverse causality and omitted variables bias can not be completely ruled out, and therefore the monetary policy shocks generated by the model can still contain some sizable endogenous response of the Fed. Alternatively, I could have used the Romer and Romer (2004) identified monetary policy shocks in place of the effective federal funds rate. However, using this shock series would have implied censoring the early and the most recent part of the sample.

2.4 Results

In this section I present and discuss the results. I begin by showing the time-varying standard deviation of monetary policy shocks in Section 2.4.1. Then, Section 2.4.2 introduces a general discussion of the impulse responses generated by the model. In Section 2.4.3, I discuss in detail the time-varying impulse responses of the housing sector and household debt and how the importance of monetary policy shocks changed over time. In Section 2.4.4, I show that baseline results are robust to alternative specification choices.

2.4.1 The standard deviation of monetary policy shocks has changed substantially

Figure 2.1 displays the time-varying standard deviation of the monetary policy shocks together with the effective federal funds rate. The exceptionally high volatility of monetary policy shocks between the end of the 1970s and mid-1980s immediately stands out. The figure reveals a pattern for the time-varying standard deviation of monetary policy shocks that is consistent with results in Primiceri (2005) and Sims and Zha (2006b).

The volatility of monetary policy shocks began to rise in the first half of the 1970s. In 1973, the Fed tightened monetary policy in response to accelerating inflation but eased it in the following year when unemployment rose and the US economy entered recession. The timing

[22] The Fed seems to pay some attention to the conditions of the housing sector and this justifies why real house price index, new housing starts and real residential investment are ordered before the effective federal funds rate in the VAR. The Beige Book on the current economic conditions reports a full section dedicated to the economic conditions in the residential real estate sector (see here) while forecasts of residential investment and housing starts are included in the Greenbook which informs the FOMC on expected economic conditions (see here).

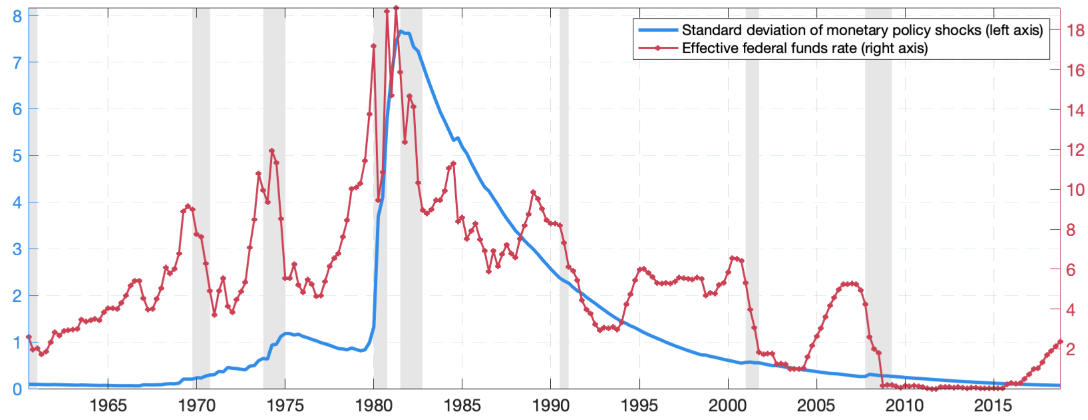


FIGURE 2.1: STANDARD DEVIATION OF MONETARY POLICY SHOCKS

Notes: this figure shows the standard deviation of shocks to the effective federal funds rate equation (R_t). The blue solid line (left axis) is the square root of the seventh element on the main diagonal of the identified variance-covariance matrix, $\mathbf{\Sigma}_t$, namely $\sigma_{\varepsilon_{MP,t}}$ (the effective federal funds rate is ordered as the seventh variable in the vector $\boldsymbol{y}_t$). The red line with markers (right axis) plots the effective federal funds rate in percent. Shaded areas are NBER recessions.

of the spikes in the standard deviation of monetary policy shocks coincides with the Volcker chairmanship at the Fed. These spikes in the standard deviation of monetary policy shocks are consistent with the monthly VAR model in Brunnermeier et al. (2019) which identifies four dates during the Volcker chairmanship (March 1980, May 1980, February 1981 and, May 1981) when the residuals from a monetary policy equation are extremely large. Starting from 1979, the Fed shifted its target from the federal funds rate to monetary aggregates and deliberately let interest rates go up to lower inflation, at any cost. This caused a harsh tightening of financial conditions with the effective federal funds rate reaching almost 20% at the end of 1980. As financial conditions worsened, firms faced liquidity problems, the unemployment rate rose, and the economy entered two recessions between 1980 and the end of 1982. Thereafter, the standard deviation of monetary policy shocks dropped. These events marked the transition from the Great Inflation to the Great Moderation.

2.4.2 The effects of monetary policy shocks: the general picture

Figure 2.2 and Figure 2.3 plot the time-varying effects of monetary policy shocks originating at each point in time between 1960 and 2018. The responses are accumulated, hence they represent the log level effects of monetary policy contractionary shocks over 32 quarters. Since the effective federal funds rate enters the model in levels, its response to monetary policy shocks has not been accumulated.

The response of log real GDP is roughly in line with the literature (upper left panel in Figure 2.2). A monetary tightening leads to a persistent albeit sluggish contraction in real GDP (RGDP). Real GDP initially rises but the increase is small and temporary. The decrease in real GDP is larger and quicker in the initial part of the sample relative to the most recent periods.

For what concerns the reaction of prices, results are more mixed. The commodity price index (PCOM) rises in response to a monetary policy contraction for most of the sample and this is at odds with results generally reported in the literature (upper right panel in Figure 2.2). However, the response displays a hump-shaped pattern and, between the early 1980s and the first half of the 2000s, the rise in commodity prices is only temporary. After an initial flat or barely positive increase, the PCE price index (P) persistently declines in response to contractions in monetary policy (middle left panel in Figure 2.2). In most recent periods, the effects of monetary policy shocks on the PCE price index turn completely null or slightly positive. This result is consistent with Barakchian and Crowe (2013) which find that between 1988 and 2008 monetary policy contractions raised prices. Overall, the dynamic effects of monetary policy shocks on real GDP and the PCE price index have become weaker since the early 1980s and this is consistent with results in Boivin et al. (2010).

Continuing with the housing sector in Figure 2.2, a contractionary monetary policy shock produces an immediate and long-lasting drop in the real house price index (HP), new housing starts (HOUST), and real residential investment (RES) (middle right, bottom left and bottom right panels in Figure 2.2). The response of real house prices increased over time and this is consistent with results in McCarthy and Peach (2002) and Hofmann and Peersman (2017b). Overall, the responses of new housing starts and residential investment as well as their evolution over time are very similar.

The monetary policy shock raises the effective federal funds rate (R) on impact (upper left panel in Figure 2.3). The resulting rise in interest rates is rather persistent and the persistence increased over time. Moving to household debt, a contractionary monetary policy shock induces an initial positive albeit small or flat response of real home mortgages (HM), real consumer credit (CC), and real other loans to households (HHL) (upper right, bottom left, and bottom right panels in Figure 2.3). However, the response is negative at higher horizons and for most of the sample. The scale and time evolution of the responses largely depends on the type of debt. For what concerns home mortgages, monetary policy contractions lead to persistent medium-run reductions in home mortgages although the intensity of the response has changed substantially over time. The effect of monetary policy shocks on real consumer credit has grown weak and changed sign in the late part of the sample. The response of real other loans to households follows a similar but more erratic pattern relative to that of consumer credit.[23]

2.4.3 Monetary policy, housing and household debt

To gain a better view of the time-varying effects of monetary policy shocks, I plot the reaction of the variables in the housing sector (Figure 2.4) and household debt (Figure 2.5) 4 and

[23]These irregularities may reflect the heterogeneous nature of debt instruments included in other loans to households.

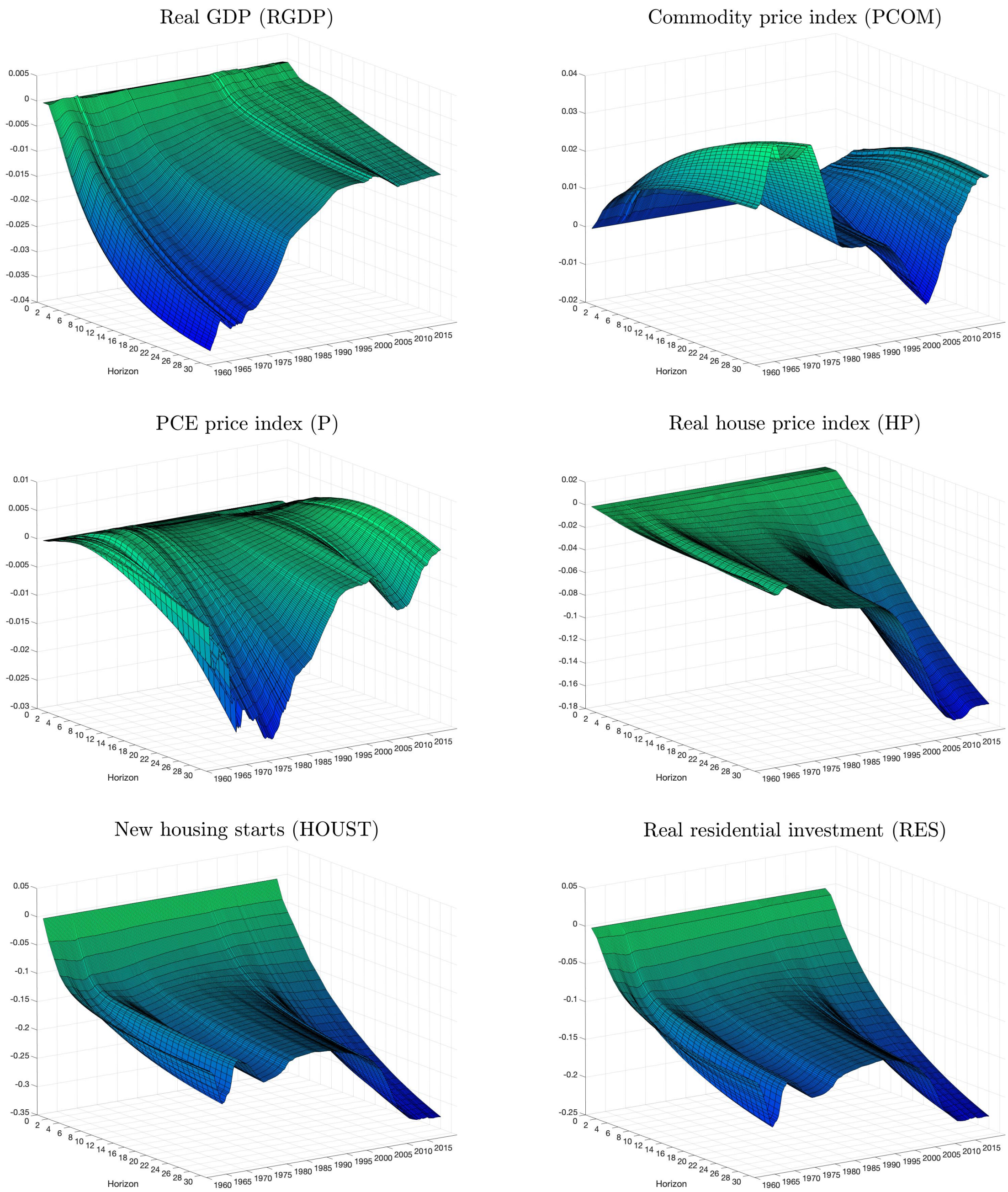


FIGURE 2.2: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS: AGGREGATE ECONOMY AND HOUSING SECTOR

Notes: this figure shows the cumulative average impulse responses to a contractionary monetary policy shock that increases the effective federal funds rate by 1% on impact.

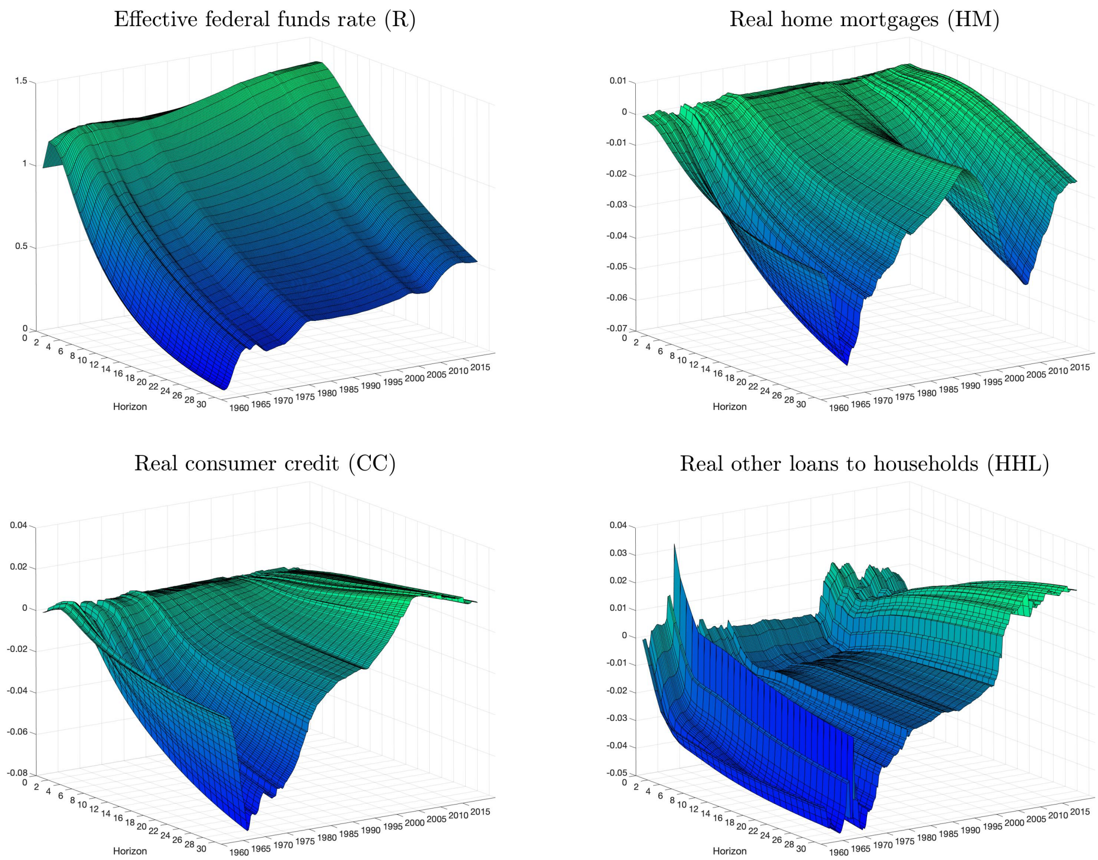


FIGURE 2.3: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS: POLICY BLOCK AND HOUSEHOLD DEBT

Notes: this figure shows the cumulative average impulse responses to a contractionary monetary policy shock that increases the effective federal funds rate by 1% on impact.

12 quarters after the shock.[24] Hereafter, I will refer to the response after 4 and 12 quarters as short-run response and medium-run response, respectively. For household debt, Figure 2.5 plots also the impact response. In all figures, the black solid line shows the short- and medium-run responses and shaded areas are 68 and 90 percent confidence bands. In Figure 2.5, the red line with markers is the impact response and the dashed red lines delimit the 68 percent confidence band. The confidence bands are constructed using the residual-based block bootstrap by Brüggemann et al. (2016) and are based on 10,000 bootstrap replications.[25]

The Fed and the housing sector

The top panel in Figure 2.4 depicts the short- and medium-run reactions of the real house price index. The short-run reaction of (log real) house prices to a monetary policy tightening has passed from -0.30 percent in 1960 to -0.45 percent in 2018. The increase in the responsiveness of house prices to monetary policy shocks is even more pronounced in the medium-run. The medium-run response in 2018 is about six times larger than it was in 1960, from about -1 to -5.8 percent.[26]

The middle and bottom panels in Figure 2.4 show that the effect of monetary policy shocks on new housing starts and real residential investment have changed less sharply relative to the effects on house prices. The short-run responses became slightly smaller over time. Moving to the medium-run, the reactions of new housing starts and real residential investment were rather stable during the Great Moderation while they slightly increased at the onset of the housing bubble of the early 2000s.

The Fed and household debt

Figure 2.5 plots the short- and medium-run reactions of real home mortgages (top panel), real consumer credit (middle panel) and real other loans to households (bottom panel). Overall, the time-varying responses of the different components of household debt display very similar patterns and they suggest that the sensitivity of household debt to monetary policy has decreased over time. Interestingly, monetary policy shocks in the 1960s led to large fluctuations in all categories of household debt, especially for home mortgages and consumer credit.

The short-run reaction of real home mortgages is not statistically significant for most of the sample apart from the second half of the 1960s when the response is negative. A monetary pol-

[24] Figures 2.4 and 2.5 are obtained by *slicing* the 3D impulse response functions in Figure 2.2 and Figure 2.3 at horizons 4 and 12. do not discuss in detail the responses of real GDP and of prices because the focus of the chapter is on the effects of monetary policy shocks on both the housing sector and household debt. I report the responses 4 and 12 quarters after the shock of the variables in the aggregate economy and in the policy block in Figure B.15 in Appendix B.4. Figures B.16, B.17, and B.18 show the responses of all variables 1, 4, 12, and 24 quarters after the monetary policy shock occurs.

[25] See Kilian and Lütkepohl (2017, p. 355) for a comparison of the residual-based block bootstrap by Brüggemann et al. (2016) with other bootstrap methods and Paul (2020) and Känzig (2021) for recent applications.

[26] Figure B.17 in Appendix B.4 shows that the disruptive effects of monetary policy contractions on house prices 24 quarters after the shock have grown even more dramatically since the 1990s.

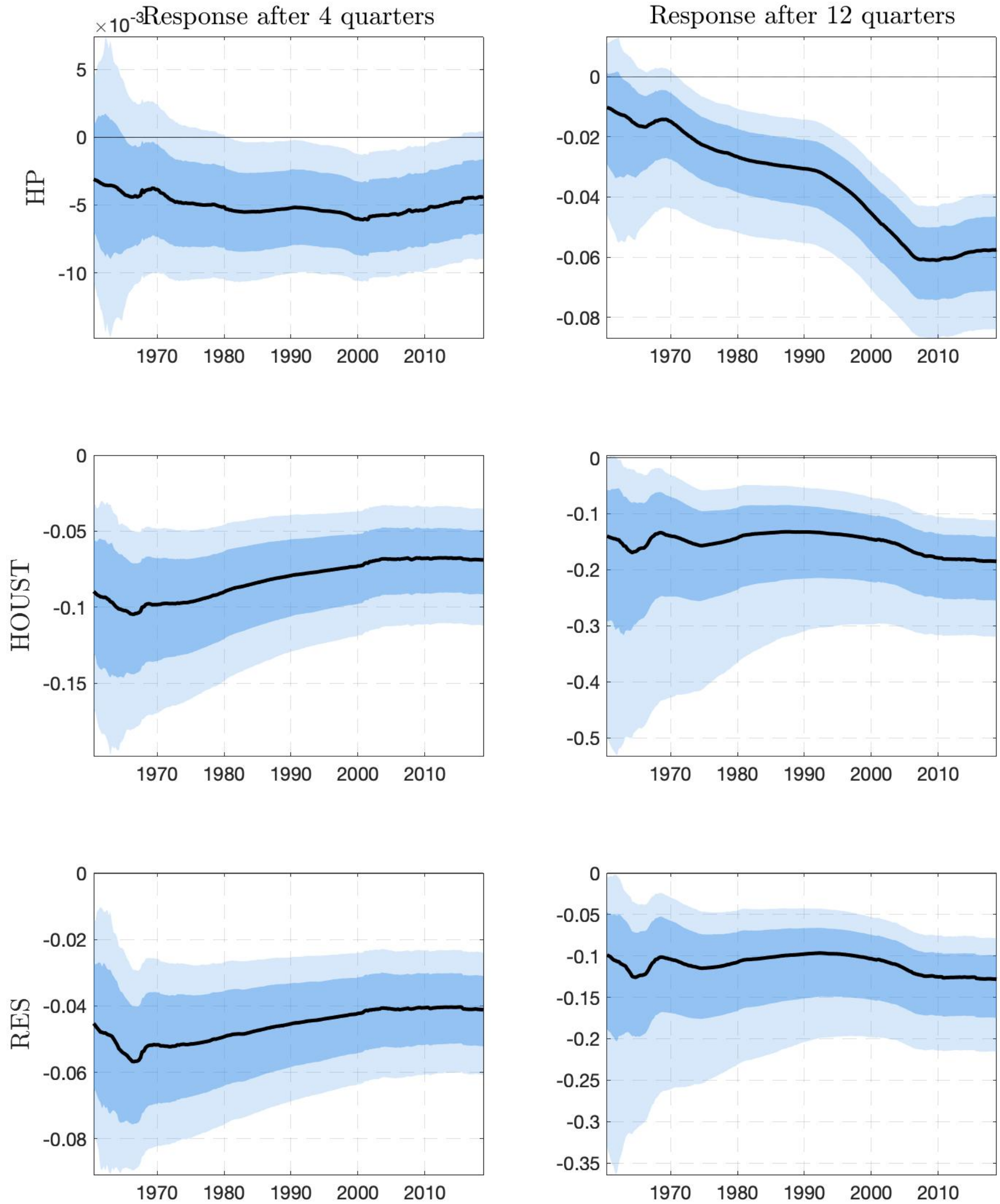


FIGURE 2.4: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSING

Notes: this figure shows the cumulative average impulse responses to a contractionary monetary policy shock that increases the effective federal funds rate by 1 % on impact.. The short-run is 4 quarters after the shock while the medium-run is 12 quarters after the shock. The black solid line is the average response while shaded areas are 68 and 90 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016). Figure B.17 reports the same impulse responses but at 1, 4, 12, and 24 quarters after the shock.

icy tightening in 1966 induced a reduction in log real home mortgages by about -0.67 percent. Similarly, the medium-run response was higher in the 1960s relative to the most recent periods. For example, the medium-run response in 1966 is more than three times as large as in 2004, from -3.1 to -0.92 percent.[27] However, there is a slight increase in the medium-run response of home mortgages starting from the early 2000s. The time variation in the short- and medium-run responses of real consumer credit and real other loans to households are comparable to those of real home mortgages. However, the short- and medium-run effects of monetary policy shocks on other loans to households are never statistically significant.

The reduced magnitude of the reaction of household debt to monetary policy shocks clashes with results in Hofmann and Peersman (2017b) and Den Haan and Sterk (2010). These authors find that, when comparing impulse responses produced by constant-parameter VAR models estimated before and after the mid-1980s, the response of mortgages increased. On the contrary, the reduced responsiveness of real home mortgages over time is consistent with results from a small TVP-VAR model in Finck et al. (2018).

Time-varying peak responses

A further way in which it is possible to explore the time-varying effects of monetary policy is by plotting the peak responses at each point in time. Figure 2.6 summarizes the time-varying peak responses of both the housing sector and household debt.[28] For each variable in each panel, the blue solid line depicts the peak response in absolute value (left axis), while the red line with markers displays the natural logarithm of the variable of interest (right axis). Additionally, the yellow dots mark some selected turning points in the peak response.

Overall, the figure confirms the pattern of time variation revealed above. The peak response of the real house price index to monetary policy shocks dramatically increased over time, mostly so between the 1990s and the Great Financial Crisis.[29] The peak responses of new housing starts and real residential investment have increased too but by less than the response of house prices. On the contrary, the peak responses of real home mortgages, real consumer credit, and real other loans to households diminished over time except for the early 2000s when they increased.

The analysis of the peak responses highlights some important changes in the transmission of monetary policy through housing and household debt. First of all, the peak response of most

[27] Figure B.18 in Appendix B.4 shows a very similar pattern for the response of real home mortgages 24 quarters after the shock occurs.

[28] Hofmann and Peersman (2017b) and Finck et al. (2018) report similar statistics together with information regarding the timing of when the peak response occurs. Figure B.19 in the Appendix B.4 shows the time-varying peak responses for the variables in the aggregate economy and policy block.

[29] The upper-left panel of Figure 2.6 suggests, at least visually, a positive correlation between the responsiveness of the real house price index and house prices inflation. This is in direct contrast with Paul (2020) who argues that, after 1992, "house prices are less responsive to monetary policy shocks when house prices are high, and more responsive when prices are low" (ibid., p. 700). Although Paul (2020) provides a more sophisticated identification of monetary policy shocks, the correlation between the time-varying response of house prices and house prices is a result of a small TVP-VAR with constant volatility.

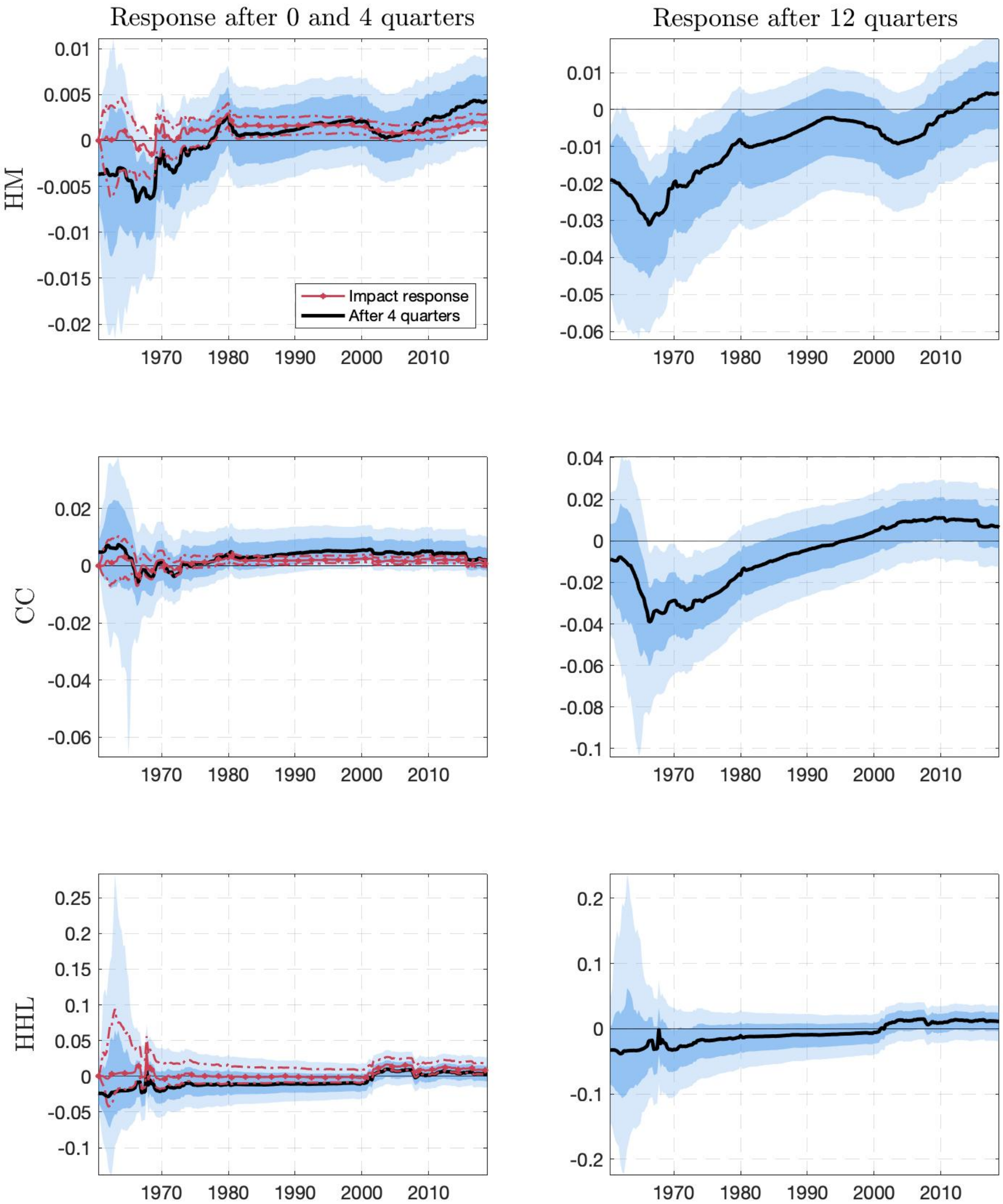


FIGURE 2.5: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSEHOLD DEBT

Notes: this figure shows the cumulative average impulse responses to a contractionary monetary policy shock that increases the effective federal funds rate by 1 % on impact.. The short-run is 4 quarters after the shock while the medium-run is 12 quarters after the shock. The black solid line is the average response while shaded areas are 68 and 90 percent confidence bands. The red line with markers is the average impact response while the dashed red lines are 68 confidence bands for the impact response. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016). Figure B.18 reports the same impulse responses but at 1, 4, 12, and 24 quarters after the shock.

variables considered culminates between the mid-1960s and mid-1970s. During this period, monetary policy shocks had large negative effects on household debt. During this period, monetary policy shocks had large negative effects on household debt. Second, the sensitiveness of construction activity (new housing starts and residential investment) and household debt was lower during the Great Moderation relative to the 1960s, 1970s, and the early 2000s. Third, the early 2000s marked a turning point in the sensitiveness of many variables in the model. Figure 2.6 suggests that construction activity, consumer credit, and other loans to households were more reactive to monetary policy shocks since 2000. For what concerns home mortgages, the turning point occurred earlier, around the mid-1990s. Lastly, house prices stand as the most important variable for the transmission of monetary policy in the most recent decades.

The importance of monetary policy shocks has decreased over time

How important are monetary policy shocks? Did the importance of monetary policy shocks change over time? To address this question I study the forecast error variance decomposition produced by the model. Figure 2.7 plots the time-varying contribution of monetary policy shocks to the forecast error variance of each variable in both the housing sector and household debt. As before, I distinguish between short- (4 quarters, blue solid line) and medium-run (12 quarters, red line with markers) horizons.

Figure 2.7 suggests that monetary policy shocks contribute little to the volatility of house prices, new housing starts, residential investment, and household debt. The conclusion that monetary policy shocks contribute little to fluctuations in many macroeconomic variables is consistent with results in Ramey (2016), Sims and Zha (2006a) and Bernanke et al. (2005).[30] For what concerns time variation, the contribution of monetary policy shocks to the volatility of most of the variables in the model fell dramatically over time, especially after the 1970s. Instead, the contribution to the volatility of the real house price index has somewhat increased since the 1990s, especially for the medium-run horizon. This confirms that house prices became an important factor in the transmission of monetary policy through housing. The decline in the contribution of monetary policy shocks is consistent with the survey in Ramey (2016) and suggests that monetary policy in the most recent decades has been conducted in a more systematic less erratic way relative to the 1960s and 1970s.

As I previously mentioned, the model produces nine shocks in addition to the monetary policy shock. Although I do not attach any behavioral interpretation neither to the equations nor to the shocks, I find that these shocks represent a larger source of fluctuations for macroeconomic variables in comparison to monetary policy shocks.[31] Moreover, the same shocks ac-

[30] Figure B.20 in Appendix B.4 points to a little importance of monetary policy shocks for the variables in the aggregate economy block too. On the contrary, monetary policy shocks were a very important source of fluctuations in the effective federal funds rate in the 1960s and 1970s. These findings are confirmed also by the forecast error variance decomposition of all variables after 1, 4, 12, and 24 quarters, as shown in Figure B.21.

[31] Appendix B.4 reports the contributions of shocks to the real house price index equation (Figure B.22), real residential investment equation (Figure B.23) and real home mortgages equation (Figure B.24) to the forecast error

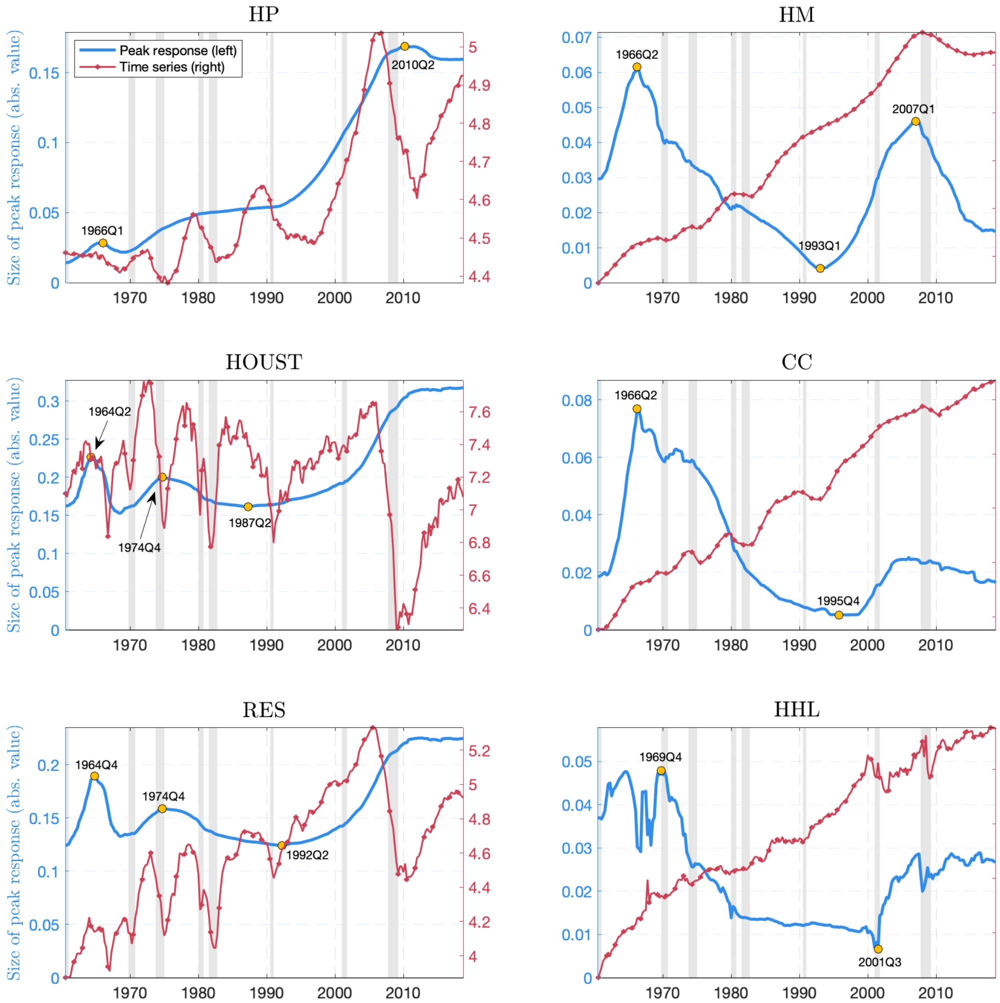


FIGURE 2.6: TIME-VARYING PEAK RESPONSES OF HOUSING AND HOUSEHOLD DEBT

Notes: the figure shows the time-varying peak average responses of the housing sector (left column) and of household debt (right column). The blue solid line is the size of the peak response in absolute value and it is measured on the left axis. The red line with markets is the natural logarithm of the variable of interest and it is measured on the right axis. The yellow dots are selected turning points in the time-varying peak responses. Shaded areas are NBER recessions.

count for a sizable share of the forecast error variance of the effective federal funds rate. These results suggest that most of the variation in monetary policy instruments reflects the systematic response of the Fed to the state of the economy rather than policy shocks, as argued in Sims (1998) and Sims and Zha (2006a).

2.4.4 Sensitivity analysis

In this section, I replicate Figure 2.4 and Figure 2.5 using alternative priors and specifications.[32] The results of the robustness checks are shown in Appendix B.3.

Priors for the initial states. The shrinkage hyperparameter γ of the Minnesota prior governs the prior uncertainty about the time-varying parameters. High (low) values of γ imply more (less) uncertainty about the parameters. Figure B.3 and Figure B.4 in Appendix B.3 show how the effects of monetary policy shocks on housing and household debt change when imposing a tighter ($\gamma = 0.05$) and looser ($\gamma = 0.2$) prior relative to the baseline model ($\gamma = 0.1$). In both cases, the results are qualitatively unchanged. In contrast, the hyperparameter for the initial condition of the variance-covariance matrix of the TVP-VAR (k_Ω) plays a more important role. Figure B.5 and Figure B.6 show the effect of changing k_Ω on the responses of the housing sector and household debt to monetary policy shocks. In these figures, I test different values for k_Ω and include the special case of $k_\Omega = 1$ as in Koop and Korobilis (2014). Overall, the results are qualitatively in line with the baseline model. However, the impulse responses of house prices and other loans to households are rather sensitive to the choice of k_Ω.

Prior belief about the amount of time variation. In Figure B.7 and Figure B.8, I explore the effects of changing the prior belief about the amount of time variation in the parameters on the responses of housing and household debt to monetary policy shocks. This is achieved by changing the value of the forgetting factor λ, which in the baseline model is 0.99. In a different context, Primiceri (2005) find that results may be sensitive to the prior belief about the amount of time variation in the parameters. However, I find that the difference in the results is minimal. Although higher values of λ relative to the baseline model make the impulse

variance of all variables in the model.

[32]I conducted other robustness tests which, however, are not included in this version of the chapter. First, most of the results hold when I estimate a 10-variable constant-parameter VAR model on sub-samples (1959Q1-1979Q3 and 1984Q1-2018Q4). However, in contrast to the baseline model and in accordance with models estimated using sample splits, I find that the response of home mortgages has increased after mid-1980s. Second, all results are robust when I use the shadow federal funds rate of Wu and Xia (2016) for the zero lower bound period. Third, most of the results hold when I estimate the TVP-VAR model using the Romer and Romer (2004) narrative monetary policy shock until 2007 (using the extended series by Miranda-Agrippino and Ricco (2018)) and when I exclude the zero lower bound period. For the VAR with the narrative monetary policy shock, I order the shock as first variable in the system. However, I find that the response of home mortgages has increased between the late 1960s and 2007 in both cases. Fourth, I estimate a version of the model in which I replace the household debt variables with total household debt, total nonfinancial noncorporate debt and total nonfinancial corporate debt (in this order after the effective federal funds rate). I find that the response of household debt to monetary policy shocks has become smaller over time, while monetary policy shocks lead to a positive response of corporate and noncorporate debt after the 1980s. All results on the housing sector variables are robust. I am grateful to Sarah Zubairy and Gert Peersman for suggesting these further robustness checks and extensions.

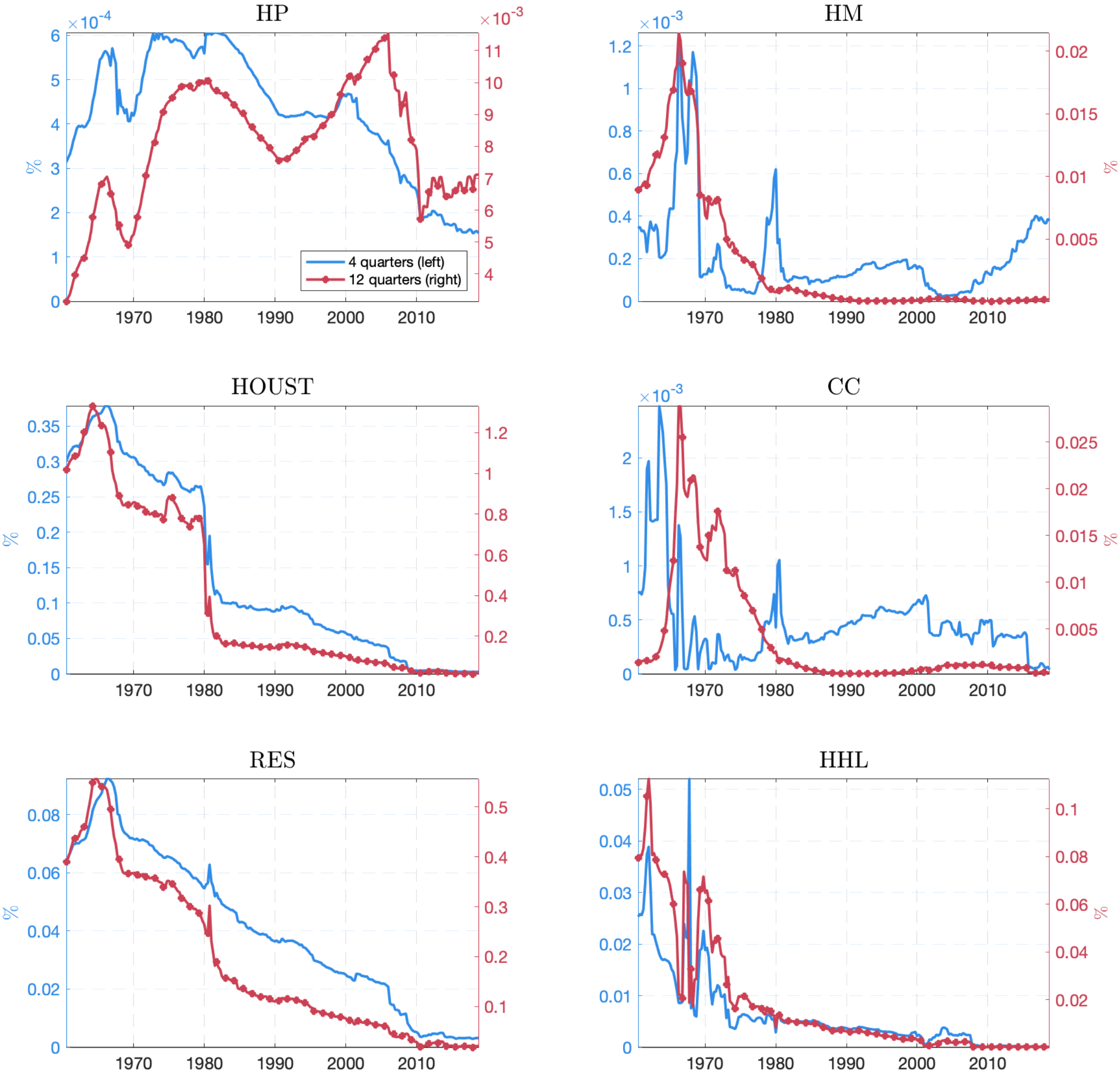


FIGURE 2.7: TIME-VARYING CONTRIBUTION OF MONETARY POLICY SHOCKS

Notes: the figure shows the time-varying average contribution of monetary policy shocks to the housing sector (left column) and of household debt (right column). The blue solid line is the contribution of monetary policy shocks after 4 quarters (or short-run contribution) and it is measured on the left axis. While the red line with markers is the contribution after 12 quarters (or medium-run contribution) and it is measured on the right axis.

response functions flatter over time, there is still substantial time variation. Similar results are obtained when changing the decay factor κ that discounts the amount of past information used in the estimation of the variance-covariance matrix of the TVP-VAR model (see Figure B.9 for the housing sector and Figure B.10 for household debt).

ALTERNATIVE SPECIFICATION. In Figure B.11 and Figure B.12, I explore whether the results are sensitive to choice of lags. While the baseline model considers 4 lags, these figure presents results for a model estimated using 2 lags. For what concerns the effects of monetary policy on household debt, the results are unaffected when considering few lags. However, the increased sensitivity over time of house prices to monetary policy shocks is smaller relative to the results from the baseline model.

ALTERNATIVE ORDERING. In the baseline model, I assume that monetary policy immediately reacts to current disturbances in the aggregate economy and in the housing sector but responds to disturbances to household debt only with a lag. As a results, home mortgages, consumer credit and other loans to households are the only variables that are allowed to quickly move after the monetary policy shock occurs. In Figure B.13 and B.14, I show that the results are qualitatively unchanged if I allow monetary policy to react contemporaneously to disturbances arising in all sectors. In this case, the vector of endogenous variables is partitioned with the effective federal funds rate order last, namely $\mathbf{y}_t = [\mathbf{y}_{1t}, \mathbf{y}_{2t}, R_t]'$ instead of $\mathbf{y}_t = [\mathbf{y}_{1t}, R_t, \mathbf{y}_{2t}]'$.

2.5 The role of institutional changes in the housing finance system

The results from the previous section suggest that the transmission of monetary policy through housing and household debt may have changed. House prices have become dramatically more reactive to monetary policy shocks. New housing starts and residential investment have become slightly more sensitive to monetary policy shocks though most of the rise in the response is concentrated between the late 1990s and 2010. In contrast, the sensitivity of household debt diminished over time although it was very high just before the Great Financial Crisis. In this section, I consider the institutional changes in the US housing finance system between the 1970s and 1980s as potentially responsible for the monetary policy transmission mechanism to change.[33]

As argued by McCarthy and Peach (2002), the US housing finance system has witnessed three major institutional changes between the 1970s and 1980s. Until the 1970s, the majority of home mortgages were originated by thrift institutions while by the mid-1990s most home mortgages were originated by less regulated lenders, e.g. finance companies. Since the early 1980s, financial innovations prompted mortgage originators to move from the originate-to-hold toward the originate-to-distribute banking model. This boosted the growth of securitization and, therefore, mortgage-backed securities. Figure 2.8 shows a clear trend in the distribution of

[33] Similar hypotheses have been previously formulated in Ryding (1990), McCarthy and Peach (2002), Bernanke (2007), Hofmann and Peersman (2017b) and Finck et al. (2018).

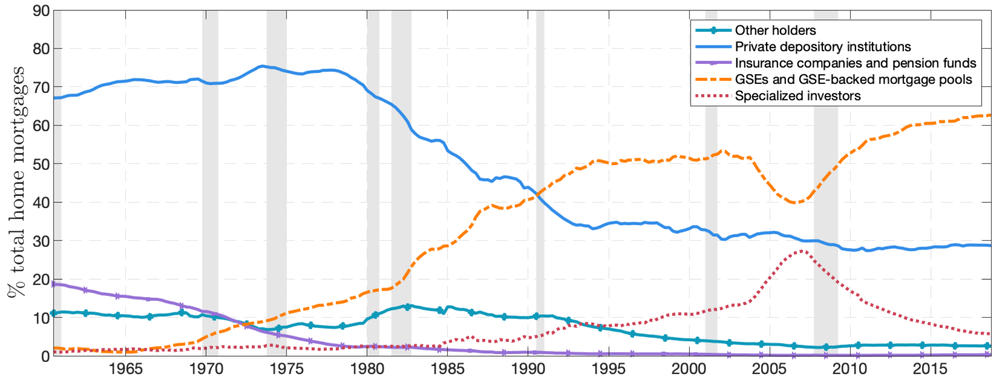


FIGURE 2.8: DISTRIBUTION OF OUTSTANDING HOME MORTGAGE DEBT BY HOLDER

Notes: this figure plots shares of outstanding home mortgage debt by holder according to the L.218: One-to-four-family residential mortgages table in the Financial Accounts of the United States (see here). Other holders are the household sector, nonfinancial corporate businesses, nonfinancial noncorporate businesses, the Federal government, and State and local government. Private depository institutions are US-chartered depository institutions, foreign banking offices in US, banks in US-affiliated areas, and credit unions. Insurance companies and pension funds are life insurance companies, private pension funds, and State and local government retirement funds. GSEs and GSEs-backed mortgage pools are government-sponsored enterprises (GSEs) and Agency- and GSE-backed mortgage pools. Specialized investor refers to asset-backed securities issuers, finance companies, and real estate investment trusts. See Appendix B.1.1 for more information on the data source.

home mortgages among the participants in the US financial system. Since the late 1970s, the share of home mortgages in the books of private depository institutions (thrift institutions and commercial banks) has declined from more than 70% to less than 30% of total home mortgages. At the same time, holdings of mortgages by GSEs and GSE-backed mortgage pools and private specialized investors (which include special purpose vehicles that buy mortgages from originators and issue mortgage-backed securities) have increased.

Although the implementation of the numerous regulatory changes in the housing finance system took time, many observers argue that around the mid-1980s most laws regulating the lending and financing activities of thrift institutions were repealed (Bernanke, 2007; McCarthy and Peach, 2002). To see how the regulatory changes in the housing finance system may have affected the transmission mechanism of monetary policy, Figure 2.9 compares the reaction of a set of variables to monetary policy shocks arising in periods that roughly correspond to different configurations of the housing finance system. These periods also reflect different macroeconomic environments in which monetary policy was conducted. I focus on the response of real house price index (HP), new housing starts (HOUST), real residential investment (RES), and real home mortgages (HM). The periods are Turbulent Times from 1960 to 1983, the Great Moderation from 1984 to 2006, and After the Great Financial Crisis from 2007 to 2018.[34]

[34]Although the dates are chosen somewhat arbitrarily, I selected them by consulting the account on monetary policy decisions in Romer and Romer (2004). Figure 2.9 reports the responses of the housing sector and home mortgages because they are likely to play the most important role in the transmission of monetary policy through housing and household debt. To simplify the comparison among impulse responses, Figure 2.9 omits the confidence bands. Figures B.25, B.26, B.27, and B.28 in Appendix B.4 plot the impulse responses for the real house price index, new housing starts, real residential investment and real home mortgages with the confidence bands.

2.5.1 Turbulent Times (1960-1983)

Before the 1980s, the institutional framework of the housing finance system was essentially the one conceived under the New Deal (Bernanke, 2007; Green and Wachter, 2005; McCarthy and Peach, 2002). The major financiers of home mortgages were thrift institutions whose main operations consisted in collecting short-term deposits and lending long-term fixed-rate residential mortgages. Interstate branching was prohibited and thrifts could only lend mortgages to and receive deposits from local communities. Regulation Q, which was under the jurisdiction of the Fed, imposed a cap on the maximum interest rate that thrifts could offer to depositors. Meanwhile, state usury laws capped the interest rate that lenders could charge on mortgages. Between the end of WWII and the early 1960s, the functioning of the mortgage market worked smoothly. Low inflation and low interest rates ensured the profitability of the thrift industry. Lenders paid depositors a yield slightly higher than the yield on Treasury bills (which never went beyond 4% before 1966) while charging between 5 to 6% on mortgages (Green and Wachter, 2005).

In the late 1960s, the smooth functioning of the thrift industry was hindered by a series of macroeconomic events. Ramping up inflation led the Fed to sharply increase interest rates with a consequential increase in all market interest rates. From 1966 to 1983, the combination of high inflation and high interest rates made Regulation Q often binding and caused numerous disintermediation episodes and credit crunches. The black solid line in Figure 2.9 shows how house prices, new housing starts, residential investment and home mortgages reacted to a tightening in monetary policy in this period, namely in 1967.[35] A tightening in monetary policy during Turbulent Times led to large reductions in real home mortgages as well as to quick falls in new housing starts and residential investment. In contrast, house prices fell very little.

In this period the monetary policy transmission mechanism through housing and household debt likely worked through Regulation Q and the maturity mismatch of thrift institutions (Bernanke, 2007; McCarthy and Peach, 2002). Because Regulation Q capped the interest rate that thrifts could pay to their depositors, deposits flew out thrifts in search of higher returns (e.g. Eurodollar deposits of Treasury bills) whenever nominal interest rates were pushed above the Regulation Q ceiling. Most importantly, rising interest rates above the ceiling threatened the profitability of thrift institutions that could not afford to pay going interest rates to depositors given the low and fixed yield earned on long-term mortgages on the asset side of their balance sheet. Hence, before the 1980s, tight monetary policy in response to rising inflation was likely to be disruptive for the balance sheets of thrift institutions. As a result, thrift institutions reacted by rationing the quantity of mortgage debt supplied. Moreover, the demand for homes and credit was likely to be discouraged by rising long-term interest rates pushed up by surging short-term rates. In fact, between the 1960s and mid-1980s, construction activity was

[35] See Minsky (1986) and Wojnilower (1980) on the role of the Fed and of regulation for the credit crunches in the 1960s and 1970s. See Mertens (2008) for the transmission of monetary policy shocks with interest rate ceilings.

very volatile and episodes of credit crunches and credit rationing were recurring.

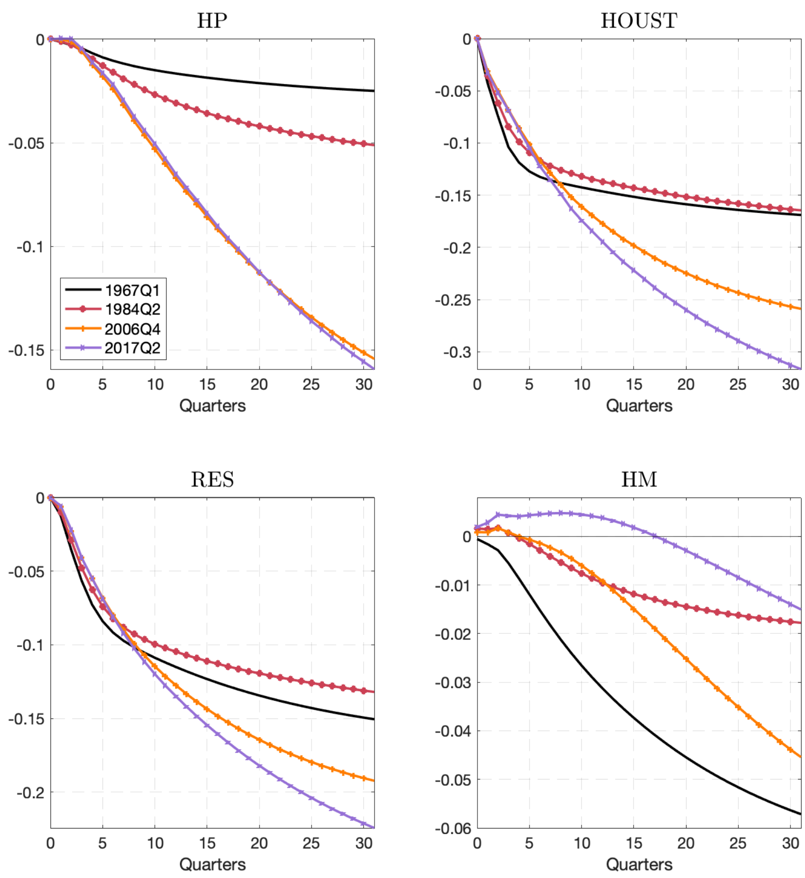


FIGURE 2.9: THE RESPONSE TO MONETARY POLICY SHOCKS IN SELECTED PERIODS

Notes: this figure shows the impulse responses of the real house price index (HP), new housing starts (HOUST), real residential investment (RES), and real home mortgages (HM) in some selected dates. The selected dates are 1967Q1 for the Turbulent Times, 1984Q2 and 2006Q4 for the Great Moderation, and 2017Q2 for After the Great Financial Crisis.

2.5.2 The Great Moderation (1984-2006)

The recurrent liquidity problems in the thrift industry as well as changing macroeconomic conditions eventually led to the first wave of institutional changes in the housing finance system (Bernanke, 2007; Green and Wachter, 2005). Already in 1970, Freddie Mac was created to securitize the mortgages originated by savings and loan institutions which suffered the balance sheet problems of the late 1960s. In the same year, the first mortgage-backed security was created to improve the liquidity conditions in the secondary market for mortgages. Between 1980 and 1986, the deposit ceilings imposed by Regulation Q were gradually removed with the 1980 Depository Institutions Deregulation and Monetary Control Act. At the same time, usury laws capping mortgage rates and interstate branching restrictions were repealed. Lenders started to offer adjustable-rate mortgages which relieved them from carrying the interest rate risk and protected them against rising inflation. The savings and loan crisis in the 1980s marked the end of the thrift industry and set the mortgage market toward full integration with capital markets. The massive use of securitization led the originate-to-distribute model to diffuse. To give an idea of the consequences of these changes, Bernanke (2007) reports that the share of securitized home mortgages on total home mortgages grew from 10% in 1980 to 56% in 2007.

In light of these regulatory changes in the housing finance system, what are the effects of a monetary policy shock during the Great Moderation? Figure 2.9 reports the effects of monetary policy shock at the beginning (1984Q2) and the end (2006Q4) of the Great Moderation. Between 1984 and 2006, the response of new housing starts and real investment has become slightly slower but the maximum decline is larger in 2006 relative to 1984, as in McCarthy and Peach (2002) and Hofmann and Peersman (2017b). Real home mortgages in 2006 decreased by more than in 1984, at least in the medium-run, but by less than in 1967. The most striking result is the growth in the response of house prices from the beginning to the end of the Great Moderation. This evidence corroborates the results in McCarthy and Peach (2002). They argue that monetary policy has still important albeit more lagged effects on housing and mortgage debt but shocks transmit via house prices and mortgage rates rather than through the quantity of mortgages. This change in the transmission of monetary policy may have been determined by the incorporation of mortgage markets within capital markets and by the repeal of interest rate ceilings.

2.5.3 After the Great Financial Crisis (2007-2018)

The Great Financial Crisis witnessed the implementation of unconventional monetary policies such as forward guidance, credit and quantitative easing. While the post-2007 housing finance system has remained rather intact after the crisis, the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act introduced several regulations to ensure better supervision and conduct in the financial sector, e.g. raising the standards for mortgages to be securitized and sold to GSEs. Figure 2.9 shows that a monetary policy shock in 2017 induces a reaction in house prices, new housing starts and residential investment nearly equal to the reaction to a shock occurring just before the crisis. However, the response of home mortgages is substantially different with mortgages temporarily increasing after a monetary policy tightening. This suggests that the transmission of monetary policy shocks through housing and household debt may have changed again after the Great Financial Crisis toward a less active role for home mortgages. However, this result has to be taken with precaution because the conduct and operations of monetary policy changed radically after the crisis.

2.6 Concluding remarks

The literature on monetary policy suggests that some of the most important channels through which monetary policy influences aggregate demand for stabilization purposes involve housing and household debt. In turn, the importance of housing and household debt in the monetary transmission mechanism depends on the institutional features of the housing finance system. For example, if housing purchases are financed predominantly with adjustable-rate mortgages, consumption spending and the solvency of homeowners holding these mortgages will be highly sensitive to interest rate shifts. This suggests that institutional changes in the housing finance system may cause the transmission mechanism of monetary policy through housing and household debt to change. The history of the US housing finance system records many of these changes, mostly concentrated between the 1970s and 1980s. Some of these institutional changes centered on the repeal of interest rate ceilings on lending, the cancellation of Regulation Q which capped interest rates payable on deposits, the entrance of less regulated funding institutions in the mortgage market, and the growth of the market for mortgage-backed securities.

In this chapter, I explored whether the transmission mechanism of monetary policy through housing and household debt has changed in the US during the last six decades. To address this question, I have estimated a medium-scale VAR model with parameters that continuously evolve and heteroskedastic innovations. I estimate the model using approximation methods originally introduced in the literature on forecasting with large models by Koop and Korobilis (2013, 2014). As a result, the model estimated in this chapter can embrace more sectors relative to a traditional TVP-VAR model à la Primiceri (2005). Also, this modeling and estimation strategy allowed me to improve upon the literature that uses sample slits and small TVP-VAR models to address similar questions.

The results suggest that the reforms that affected the US housing finance system between the 1970s and 1980s may have been responsible for the monetary transmission mechanism to change. The housing sector has become slightly more reactive to monetary policy shocks. Contractions in monetary policy lead to slower but slightly larger reductions in construction activity in most recent decades relative to the 1960s. In contrast, the reaction of home mortgages to monetary policy shocks was large during the late 1960s, when Regulation Q was binding and episodes of credit crunches and disintermediation were frequent. Perhaps the most important result concerns house prices which stands as the most important variable for the transmission of monetary policy through the housing sector in most recent decades. Interestingly, the model provides results that are overall in line with the literature that uses constant-parameter VAR models on sub-samples and small TVP-VAR models.

The exceptionally high responsiveness of mortgages and construction activity to monetary policy contractions in the 1960s and 1970s may suggest that the transmission of monetary policy worked through both Regulation Q and the maturity mismatch of thrift institutions (which were major lenders in the mortgage markets). Because of ceilings on lending rates and on interest rates that thrifts could offer to depositors, tight monetary policy in response to rising inflation was likely to be disruptive for the balance sheets of thrift institutions. Limits on the offered deposit rates at thrift institutions led to numerous disintermediation episodes whenever inflation was pushing interest rates beyond the ceiling. Indeed, with rising inflation, new saving products (e.g. certificate of deposits sold by commercial banks and Treasury bills) offered higher yields than what the thrift industry could afford to pay on deposits. In this period, nonprice credit rationing was crucial in determining large fluctuations in credit flowing to the housing sector whenever interest rates rose beyond the ceilings. The interpretation based on nonprice credit rationing mechanisms is even more plausible in light of the extremely low responsiveness of house prices to monetary policy shocks during the same period. However, with the advent of the Great Moderation, the relative importance of quantity rationing over price mechanisms likely decreased. Starting from the early 1980s, tighter monetary policy led to higher-and-higher contractions in house prices, while the sensitiveness of household debt in response to tightening policy shocks decreased. This suggests that after the late 1980s while Regulation Q was gradually lifted and the mortgage market was progressively integrated into capital markets, monetary policy shocks may have transmitted through the housing sector via house prices (and eventually mortgage rates) rather than through the quantity of mortgages supplied.

To conclude, this chapter contributes to the literature on the time-varying effects of monetary policy on housing and household debt using a more general model than constant-parameter models. The aggregate evidence suggests that the transmission mechanism of monetary policy through housing and household debt has shifted toward an increasing role for house prices. Although these results are interesting on their own, the model is limited in the interpretation. For example, the identification strategy prevents interpreting the reactions of household debt to monetary policy as resulting from changing demand or supply of credit. Second, the changing nature of the monetary policy transmission mechanism should be inspected using a more sophisticated and less ambiguous identification strategy than the one used in this chapter, e.g. narrative identification (Romer and Romer, 2004). Moreover, the aggregate nature of the model impedes identifying which regulatory changes have been responsible for the monetary transmission mechanism to change. Addressing these limitations is left for future research.

Appendix B

B.1 Data and transformations

B.1.1 Data sources

The baseline model includes the following variables:

1. **Real GDP** (RGDP): Real Gross Domestic Product.

   - Units: billions of chained 2012 dollars, originally seasonally adjusted annual rate.
   - Frequency: quarterly.
   - Source: US Bureau of Economic Analysis, Release: Gross Domestic Product.
   - BEA account code: A191RX (FRED code: GDPC1).

2. **Commodity price index** (PCOM): Producer Price Index by Commodity: All Commodities.

   - Units: 2012 = 100 (rescaled from 1982 = 100), seasonally adjusted with X-13 ARIMA-SEATS.
   - Frequency: originally monthly, transformed to quarterly (average across months).
   - Source: US Bureau of Labor Statistics, Release: Producer Price Index.
   - FRED code: PPIACO.

3. **PCE price index** (P): Personal Consumption Expenditures: Chain-type Price Index

   - Units: 2012 = 100, originally seasonally adjusted.
   - Frequency: originally monthly, transformed to quarterly (average across months).
   - Source: US Bureau of Economic Analysis, Release: Personal Income and Outlays.
   - BEA account code: DPCERG (FRED code: PCEPI).

4. **Real house price index** (HP): House prices data are from Shiller (2015) and they have been downloaded from here. Since they are provided at monthly frequency I transformed them to quarterly by taking the average across months. They have been deflated using the GDP implicit price deflator and seasonally adjusted with X-13 ARIMA-SEATS.
5. **New housing starts** (HOUST): Housing Starts: Total: New Privately Owned Housing Units Started.

   - Units: thousands of units, originally seasonally adjusted annual rate.
   - Frequency: originally monthly, transformed to quarterly (average across months).
   - Source: US Census Bureau, Release: New Residential Construction.
   - FRED code: HOUST.

6. **Real residential investment** (RES): Real gross private domestic investment: Fixed investment: Residential.

   - Units: 2012 = 100, originally seasonally adjusted.
   - Frequency: quarterly.
   - Source: US Bureau of Economic Analysis, Release: Gross Domestic Product.

- BEA account code: A011RA (FRED code: A011RA3Q086SBEA).

7. **Effective federal funds rate** (R): Effective Federal Funds Rate.

    - Units: percent, not seasonally adjusted.
    - Frequency: originally monthly, transformed to quarterly (end of the period value).
    - Source: Board of Governors of the Federal Reserve System, Release: H.15 Selected Interest Rates.
    - FRED code: FEDFUND.

8. **Real home mortgages** (HM): Households and Nonprofit Organizations; One-to-Four-Family Residential Mortgages; Liability, Level.

    - Units: billions of 2012 dollars (deflated using GDP implicit price deflator), seasonally adjusted with X-13 ARIMA-SEATS.
    - Frequency: quarterly (end of the period value).
    - Source: Board of Governors of the Federal Reserve System, Release: Z.1 Financial Accounts of the United States.
    - Z.1 code: FL153165105.Q (FRED code: HMLBSHNO).

9. **Real consumer credit** (CC): Households and Nonprofit Organizations; Consumer Credit; Liability, Level.

    - Units: billions of 2012 dollars (deflated using GDP implicit price deflator), seasonally adjusted with X-13 ARIMA-SEATS.
    - Frequency: quarterly (end of the period value).
    - Source: Board of Governors of the Federal Reserve System, Release: Z.1 Financial Accounts of the United States.
    - Z.1 code: FL153166000.Q (FRED code: CCLBSHNO).

10. **Real other loans to households** (HHL): Other loans to households consist of depository institution loans not elsewhere classified (as overdrafts on deposits, loans to individuals different than consumer credit and home mortgages, and loans to non-profit organizations), other loans and advances (as other loans made by the U.S. government for public purpose, policy loans secured by the value of life insurance policies, and loans from GSEs different from mortgages and consumer credit), and commercial mortgages, namely mortgages on non-residential properties owned by non-profit institutions. This category is a sum of:

    - Households and Nonprofit Organizations; Depository Institution Loans Not Elsewhere Classified; Liability, Level.
        - Units: billions of 2012 dollars (deflated using GDP implicit price deflator), seasonally adjusted with X-13 ARIMA-SEATS.
        - Frequency: quarterly (end of the period value).
        - Source: Board of Governors of the Federal Reserve System, Release: Z.1 Financial Accounts of the United States.
        - Z.1 code: FL153168005.Q (FRED code: BLNECLBSHNO).
    - Households and Nonprofit Organizations; Other Loans and Advances; Liability, Level.
        - Units: billions of 2012 dollars (deflated using GDP implicit price deflator), seasonally adjusted with X-13 ARIMA-SEATS.

  - Frequency: quarterly (end of the period value).
  - Source: Board of Governors of the Federal Reserve System, Release: Z.1 Financial Accounts of the United States.
  - Z.1 code: FL153169005.Q (FRED code: OLALBSHNO).
- Nonprofit Organizations; Commercial Mortgages; Liability, Level.
  - Units: billions of 2012 dollars (deflated using GDP implicit price deflator), seasonally adjusted with X-13 ARIMA-SEATS.
  - Frequency: quarterly (end of the period value).
  - Source: Board of Governors of the Federal Reserve System, Release: Z.1 Financial Accounts of the United States.
  - Z.1 code: FL163165505.Q (FRED code: CMLBSHNO).

Other variables used through the paper are:

1. **Gross Domestic Product: Implicit Price Deflator**
   - Units: 2012 = 100, originally seasonally adjusted.
   - Frequency: quarterly.
   - Source: US Bureau of Economic Analysis, Release: Gross Domestic Product.
   - BEA account code: A191RD (FRED code: GDPDEF).
2. **3-Month Treasury Bill: Secondary Market Rate**
   - Units: percent, not seasonally adjusted.
   - Frequency: originally monthly, transformed to quarterly (end of the period value).
   - Source: Board of Governors of the Federal Reserve System, Release: H.15.
   - FRED code: TB3MS.

Variables used to obtain Figure 2.8 are from the L.218 Table: One-to-four-family Residential Mortgages (Billions of dollars, amounts outstanding end of period, not seasonally adjusted) from the Z.1 Financial Accounts of the United States. The original table can be found here). The asset side of the table is organized as follows (I report original identifier codes):

- **Total assets** is FL893065105.
- **Other holders** is a sum of FL153065103, FL103065105, FL113065103, FL313065105 and FL213065103).
- **Private depository institutions** is a sum of FL763065105, FL753065103, FL743065103 and FL473065100.
- **Insurance companies and pension funds** is a sum of FL543065105, FL57306510 and FL223065143.
- **GSEs and GSE-backed mortgage pools** is a sum of FL403065105 and FL413065105.
- **Specialized investors** is a sum of FL673065105, FL613065105 AND FL643065105.

B.1.2 Stationarity tests and transformations

In order to test for stationarity, I run a battery of unit roots tests on the series expressed in natural logarithm from 1959Q1 to 2018Q4. The effective federal funds rate is in percent. I run the Augmented Dickey-Fuller test (ADF), the Phillips-Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and I allow for an intercept in the test. First and second differences have been implemented once tests statistics were rejecting the null hypothesis of a unit root (ADF and PP tests) or fails to reject the hypothesis of stationarity (KPSS test). These transformations make the logarithm series stationary or *approximately stationary* (Stock and Watson, 2009). Table B.1 reports how many differences are needed to make the series stationary, the significance level, and the chosen transformation. Stars indicate statistical significance: $\star$ $p < 0.10$, $\star\star$ $p < 0.05$, $\star\star\star$ $p < 0.01$. Table B.2 reports the transformations.

TABLE B.1: STATIONARITY TESTS

N	Series ID	ADF	PP	KPSS	T-code
1	RGDP	1^{***}	1^{***}	1^{***}	5
2	PCOM	1^{***}	1^{***}	1^{***}	5
3	PCE	1^{*},2^{***}	1^{***}	1^{**},2^{***}	6
4	HP	1^{***}	1^{***}	1^{***}	5
5	HOUST	0^{*},1^{***}	1^{***}	1^{***}	5
6	RES	1^{**},1^{***}	1^{***}	1^{***}	5
7	R	0^{*},1^{***}	1^{***}	1^{***}	1
8	HM	1^{**},2^{***}	1^{***}	1^{*},2^{***}	5
9	CC	1^{***}	1^{***}	1^{***}	5
10	HHL	1^{***}	1^{***}	1^{***}	5

TABLE B.2: DESCRIPTION

Acronym	Definition
BEA	Bureau of Economic Analysis
CB	U.S. Census Bureau
FRB	Board of Governors of the Federal Reserve System
FRB H.15	FRB: Selected Interest Rates (release)
FRB Z.1	FRB: Financial Accounts of the United States (release)
CB-NRW	U.S. Census Bureau: New Residential Construction (release)
BoC 2012$	Billions of Chained 2012 Dollars
1000 Units	Thousands of units
T	Treatment Code (T-code)
T-code	Transformation (Stock and Watson, 2009)
1	no transformation (levels), $x_t = y_t$
2	first difference, $x_t = y_t - y_{t-1}$
3	second difference, $x_t = y_t - y_{t-2}$
4	logarithm, $x_t = \ln y_t$
5	first difference of logarithm $x_t = \ln y_t - \ln y_{t-1}$
6	second difference of logarithm, $x_t = \ln y_t - \ln y_{t-2}$

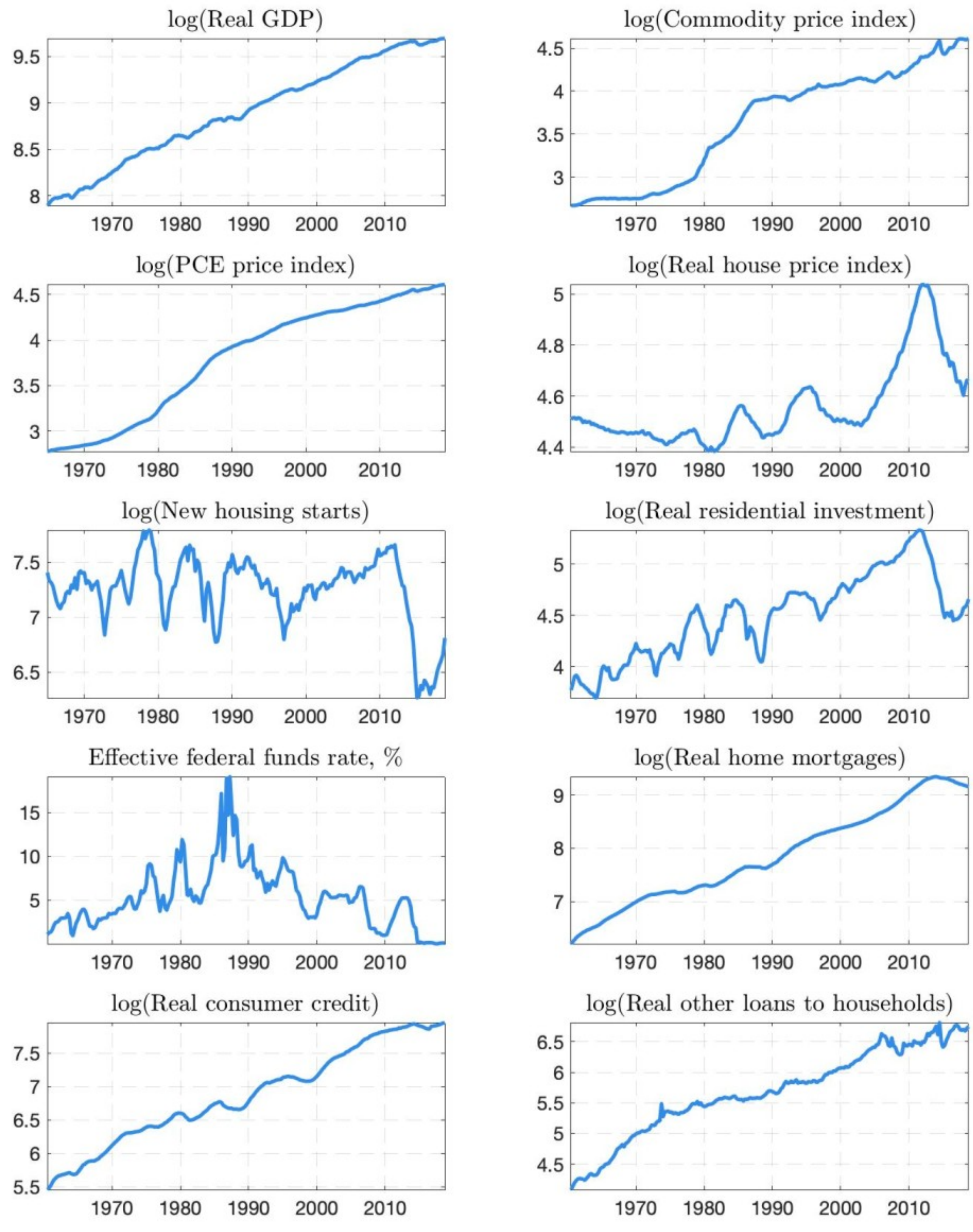


FIGURE B.1: ORIGINAL DATA SERIES

Notes: Data series in log levels.

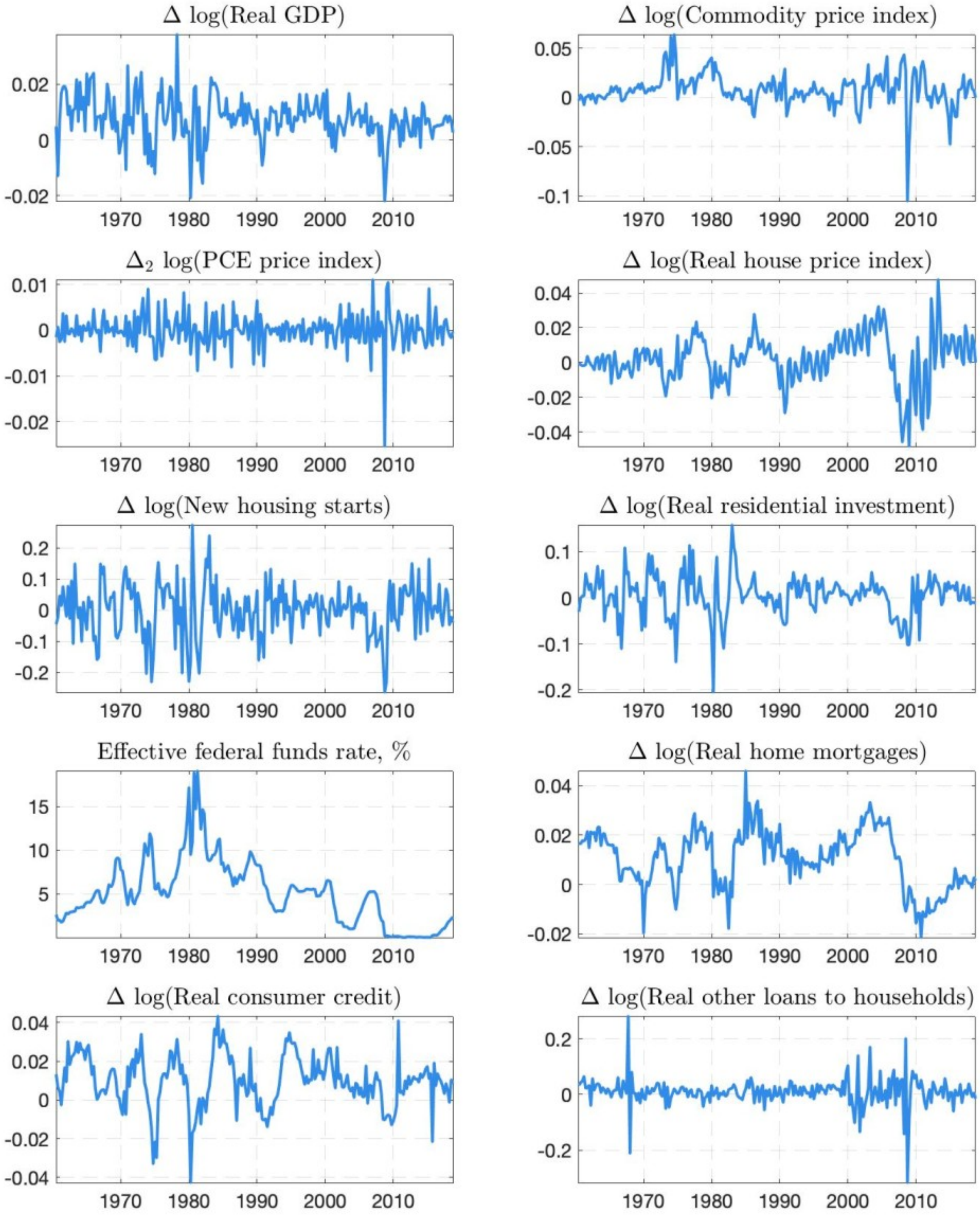


FIGURE B.2: TRANSFORMED DATA SERIES

Notes: Data in first differences of natural log (Δ), second difference of natural log (Δ_2), and level (%).

B.2 Estimation

B.2.1 The estimation algorithm step-by-step

Given the state-space model:

$$\underset{n\times 1}{\mathbf{y}_t} = \underset{n\times k}{\mathbf{X}_t'}\,\underset{k\times 1}{\boldsymbol{\beta}_t} + \underset{n\times 1}{\mathbf{u}_t} \quad \text{with} \quad \mathbf{u}_t \sim \mathcal{N}\left(\underset{n\times 1}{\mathbf{0}}, \underset{n\times n}{\boldsymbol{\Omega}_t}\right) \tag{B.1}$$

$$\underset{k\times 1}{\boldsymbol{\beta}_t} = \underset{k\times 1}{\boldsymbol{\beta}_{t-1}} + \underset{k\times 1}{\boldsymbol{\eta}_t} \quad \text{with} \quad \boldsymbol{\eta}_t \sim \mathcal{N}\left(\underset{k\times 1}{\mathbf{0}}, \underset{k\times k}{\mathbf{Q}_t}\right) \tag{B.2}$$

and the priors for the time-varying parameters $\boldsymbol{\beta}_t$ and for the TVP-VAR variance-covariance matrix $\boldsymbol{\Omega}_t$:

$$\boldsymbol{\beta}_0 \sim \mathcal{N}\left(\underset{k\times 1}{\bar{\boldsymbol{\beta}}_0}, \underset{k\times k}{\mathbf{V}_0}\right) \quad \text{and} \quad \underset{n\times n}{\boldsymbol{\Omega}_0},$$

the estimation algorithm can be thought of as made of two main blocks. The first block is a forward pass algorithm based on the Kalman filter and the exponentially weighted moving average filter (EWMA, hereafter) to estimate the time-varying parameters and the variance-covariance matrix of the TVP-VAR, respectively. The second block consists of a backward fixed-interval smoother (Rauch et al., 1965) to obtain optimal estimates of the parameters. Additionally, a backward smoother is also used to obtain more precise estimates of the TVP-VAR variance-covariance matrix. I introduce the following notation: for a generic vector $\mathbf{y}$, the notation $\mathbf{y}^{1:t}$ denote the history of the vector $\mathbf{y}$ up to and including time t. The estimation algorithm involves the following steps.

STEP 1. At time $t = 0$, the priors of the time-varying parameters $\boldsymbol{\beta}_0$ and of the TVP-VAR variance-covariance matrix $\boldsymbol{\Omega}_0$ are used as initial conditions for the Kalman filter and for the EWMA filter:

$$\hat{\boldsymbol{\beta}}_{0|0} = \bar{\boldsymbol{\beta}}_0, \quad \mathbf{P}_{0|0} = \mathbf{V}_0, \quad \hat{\boldsymbol{\Omega}}_{0|0} = \boldsymbol{\Omega}_0 \tag{B.3}$$

where, for a generic t, $\hat{\boldsymbol{\beta}}_{t|t}$ is the updated estimate of the time-varying parameters at time t given observations up to and including time t, $\mathbf{P}_{t|t}$ is the updated estimate of the variance-covariance matrix that measures the accuracy of $\hat{\boldsymbol{\beta}}_{t|t}$, and $\hat{\boldsymbol{\Omega}}_{t|t}$ is the post-fit estimate of the VAR variance-covariance matrix. While $\hat{\boldsymbol{\beta}}_{t|t}$ and $\mathbf{P}_{t|t}$ are *objects* of the Kalman filter, $\hat{\boldsymbol{\Omega}}_{t|t}$ is a result of the EWMA filter.

STEP 2. Given the initial conditions, the first block of the estimation algorithm implements the Kalman filter and the EWMA filter recursively from $t = 1 \ldots, T$ and according to the following steps:

(a) Predict the state vector $\boldsymbol{\beta}_t$ and its covariance matrix $\mathbf{P}_t$:

$$\hat{\boldsymbol{\beta}}_{t|t-1} = \hat{\boldsymbol{\beta}}_{t-1|t-1} \tag{B.4}$$

$$\mathbf{P}_{t|t-1} = \lambda^{-1}\mathbf{P}_{t-1|t-1}, \quad 0 < \lambda \leq 1 \tag{B.5}$$

where $\hat{\beta}_{t|t-1}$ and $\mathbf{P}_{t|t-1}$ define the moments of the predictive density

$$p(\beta_t|\mathbf{y}^{1:t-1}) = \mathcal{N}\left(\hat{\beta}_{t|t-1}, \mathbf{P}_{t|t-1}\right)$$

The main difference between this version of the Kalman filter and the original filter is the computation of $\mathbf{P}_{t|t-1}$. The usual expression is $\mathbf{P}_{t|t-1} = \mathbf{P}_{t-1|t-1} + \mathbf{Q}_t$ but Koop and Korobilis (2013, 2014) replace it by $\mathbf{P}_{t|t-1} = \lambda^{-1}\mathbf{P}_{t-1|t-1}$. Therefore, while in the original formulation of $\mathbf{P}_{t|t-1}$ the matrix $\mathbf{Q}_t$ is responsible for the amount of time variation in the parameters, now the rate of drift in β_t is governed by the forgetting factor λ. Using the forgetting factor, there is no need to compute $\mathbf{Q}_t$ and this greatly reduces the computational burden. However, it can be easily shown that $\mathbf{Q}_t = \left(\lambda^{-1} - 1\right)\mathbf{P}_{t-1|t-1}$.

(b) Estimate the pre-fit variance-covariance matrix of the TVP-VAR by applying the EWMA filter:

$$\hat{\mathbf{u}}_{t|t-1} = \mathbf{y}_t - \mathbf{X}_t'\hat{\beta}_{t|t-1} \tag{B.6}$$
$$\hat{\Omega}_{t|t-1} = \kappa\hat{\Omega}_{t-1|t-1} + (1-\kappa)\hat{\mathbf{u}}_{t|t-1}\hat{\mathbf{u}}_{t|t-1}' \tag{B.7}$$

where $\hat{\mathbf{u}}_{t|t-1}$ are the pre-fit residuals (or prediction errors) in the measurement equation, namely the estimated residuals of the reduced form TVP-VAR. The parameter κ is a decay factor that discounts previous estimates of Ω_t and governs the time variation in volatility.

(c) Update the estimates of the state vector and its covariance matrix conditional on information up to time t:

$$\mathbf{S}_t = \hat{\Omega}_{t|t-1} + \mathbf{X}_t\mathbf{P}_{t|t-1}\mathbf{X}_t' \tag{B.8}$$
$$\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{X}_t'\mathbf{S}_t^{-1} \tag{B.9}$$
$$\hat{\beta}_{t|t} = \hat{\beta}_{t|t-1} + \mathbf{K}_t\hat{\mathbf{u}}_t \tag{B.10}$$
$$\begin{aligned}\mathbf{P}_{t|t} &= \mathbf{P}_{t|t-1} - \mathbf{K}_t\mathbf{X}_t\mathbf{P}_{t|t-1} \\ &= \left(\mathbf{I}_n - \mathbf{K}_t\mathbf{X}_t\right)\mathbf{P}_{t|t-1} = \left(\mathbf{I}_n - \mathbf{K}_t\mathbf{X}_t\right)\lambda^{-1}\mathbf{P}_{t-1|t-1}\end{aligned} \tag{B.11}$$

The updated state estimate and covariance matrix define the moments of the filter density, namely $p(\beta_t|\mathbf{y}^{1:t}) = \mathcal{N}\left(\hat{\beta}_{t|t}, \mathbf{P}_{t|t}\right)$.

(d) Obtain the post-fit estimate of the residuals and of the TVP-VAR variance-covariance matrix $\hat{\Omega}_t$ conditional on the information entering at time t and using the equations from the EWMA filter:

$$\hat{\mathbf{u}}_{t|t} = \mathbf{y}_t - \mathbf{X}_t'\hat{\beta}_{t|t} \tag{B.12}$$
$$\hat{\Omega}_{t|t} = \kappa\hat{\Omega}_{t-1|t-1} + (1-\kappa)\hat{\mathbf{u}}_{t|t}\hat{\mathbf{u}}_{t|t}' \tag{B.13}$$

The full forward recursion of the Kalman filter and of the EWMA filter provides filtered estimates of the time-varying parameters, their variance-covariance and of the variance-covariance matrix of the TVP-VAR. More specifically, the filtering step provides the following collection of estimates: $\hat{\beta}_{t|t} = \left\{\hat{\beta}_{1|1}, \ldots, \hat{\beta}_{T|T}\right\}$, $\mathbf{P}_{t|t} = \left\{\mathbf{P}_{1|1}, \ldots, \mathbf{P}_{T|T}\right\}$, $\hat{\Omega}_{t|t} = \left\{\hat{\Omega}_{1|1}, \ldots, \hat{\Omega}_{T|T}\right\}$.

STEP 3. The filtered estimates can be improved in accuracy by running a backward smoother. While the forward filter provides optimal estimates of β_t conditional on information up to time t, the backward smoother improves these estimates conditional on the information from from 1 to T. When setting the initial conditions of the smoother, the smoothed estimates at time T are given by the last iterations of the forward filter, namely $\hat{\boldsymbol{\beta}}_{T|T}$, $\mathbf{P}_{T|T}$ and $\hat{\boldsymbol{\Omega}}_{T|T}$. Therefore, given the initial conditions, the backward smoother implements the following steps from $T-1$ to 1.

(a) Run the Rauch-Tung-Striebel (fixed-inteval) smoother recursively for $t = T-1, \ldots, 1$ by executing the following steps:

$$\mathbf{C}_t = \mathbf{P}_{t|t}(\mathbf{P}_{t+1|t})^{-1} \tag{B.14}$$

$$\hat{\boldsymbol{\beta}}_{t|T} = \hat{\boldsymbol{\beta}}_{t|t} + \mathbf{C}_t(\hat{\boldsymbol{\beta}}_{t+1|T} - \hat{\boldsymbol{\beta}}_{t+1|t}) \tag{B.15}$$

$$\mathbf{P}_{t|T} = \mathbf{P}_{t|t} + \mathbf{C}_t(\mathbf{P}_{t+1|T} - \mathbf{P}_{t+1|t})\mathbf{C}_t' \tag{B.16}$$

The smoother provides the moments of the posterior smoothing density $p(\boldsymbol{\beta}_t|\mathbf{y}^{1:T}) = \mathcal{N}\left(\hat{\boldsymbol{\beta}}_{t|T}, \mathbf{P}_{t|T}\right)$.

(b) Recursively update the variance-covariance matrix of the TVP-VAR:

$$\hat{\boldsymbol{\Omega}}_{t|T} = \kappa\hat{\boldsymbol{\Omega}}_{t|t} + (1-\kappa)\hat{\boldsymbol{\Omega}}_{t+1|T} \tag{B.17}$$

The backward smoother provides the following collection of estimates:
$\hat{\boldsymbol{\beta}}_{t|T} = \left\{\hat{\boldsymbol{\beta}}_{1|T}, \ldots, \hat{\boldsymbol{\beta}}_{T|T}\right\}$, $\mathbf{P}_{t|T} = \{\mathbf{P}_{1|T}, \ldots, \mathbf{P}_{T|T}\}$, $\hat{\boldsymbol{\Omega}}_{t|T} = \{\hat{\boldsymbol{\Omega}}_{1|T}, \ldots, \hat{\boldsymbol{\Omega}}_{T|T}\}$.

B.2.2 Structural impulse responses

Consider the reduced-form time-varying parameter TVP-VAR model with stochastic volatility:

$$\underset{n\times 1}{\mathbf{y}_t} = \underset{n\times n}{\mathbf{B}_{1,t}}\mathbf{y}_{t-1} + \cdots + \underset{n\times n}{\mathbf{B}_{p,t}}\mathbf{y}_{t-p} + \underset{n\times 1}{\mathbf{u}_t} \quad \text{with} \quad \mathbf{u}_t \sim \mathcal{N}\left(\mathbf{0}_n, \underset{n\times n}{\mathbf{\Omega}_t}\right) \tag{B.18}$$

and its structural version:

$$\underset{n\times n}{\mathbf{A}_{0,t}}\underset{n\times 1}{\mathbf{y}_t} = \underset{n\times n}{\mathbf{A}_{1,t}}\mathbf{y}_{t-1} + \cdots + \underset{n\times n}{\mathbf{A}_{p,t}}\mathbf{y}_{t-p} + \underset{n\times 1}{\boldsymbol{\varepsilon}_t} \quad \text{with} \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}\left(\mathbf{0}_n, \underset{n\times n}{\mathbf{\Sigma}_t}\right) \tag{B.19}$$

where the constant has been omitted for notation convenience. The relevant dimensions are the following: number of endogenous variables, $n = 10$, and maximum lag length, $p = 4$. The Kalman filter and smoother provide estimates of the reduced-form parameters matrices, $\mathbf{B}_{1,t}, \mathbf{B}_{2,t}, \ldots, \mathbf{B}_{p,t}$, as well as of the reduced-form errors, $\mathbf{u}_t$, for all periods $t = 1, \ldots, T$. The factorization of the reduced-form variance-covariance matrix:

$$\mathbf{\Omega}_t = \left(\mathbf{A}_{0,t}^{-1}\right)\mathbf{\Sigma}_t\left(\mathbf{A}_{0,t}^{-1}\right)' = \mathbf{A}_t\mathbf{\Sigma}_t\mathbf{A}_t' \quad \text{with} \quad \mathbf{A}_t = \mathbf{A}_{0,t}^{-1} \tag{B.20}$$

yields the variance-covariance matrix of the structural shocks as well as the matrix of contemporaneous parameters, for all periods $t = 1, \ldots, T$.

The structural impulse response functions are obtained by employing the following algorithm which runs recursively from 1 to T.

for $t = 1$ **to T**

- For notation convenience, I suppress the time subscripts for the matrices of parameters. Hence, $\mathbf{B}_{i,t} = \mathbf{B}_i$ with $i = 1, \ldots p$, and $\mathbf{A}_t = \mathbf{A}$.
- **Find the reduced-form (or Wold) impulse responses:**
  – Write the VAR(p) as a VAR(1), namely write the companion form:

$$\underbrace{\begin{bmatrix} \mathbf{y}_t \\ \mathbf{y}_{t-1} \\ \vdots \\ \mathbf{y}_{t-p+1} \end{bmatrix}}_{\substack{\mathbf{Y}_t \\ (np\times 1)}} = \underbrace{\begin{bmatrix} \mathbf{B}_1 & \mathbf{B}_2 & \ldots & \mathbf{B}_{p-1} & \mathbf{B}_p \\ \mathbf{I}_n & \mathbf{0}_n & \ldots & \mathbf{0}_n & \mathbf{0}_n \\ \mathbf{0}_n & \mathbf{I}_n & & \mathbf{0}_n & \mathbf{0}_n \\ \vdots & & \ddots & \vdots & \vdots \\ \mathbf{0}_n & \mathbf{0}_n & \ldots & \mathbf{I}_n & \mathbf{0}_n \end{bmatrix}}_{\substack{\mathbf{B} \\ (np\times np)}} \underbrace{\begin{bmatrix} \mathbf{y}_{t-1} \\ \mathbf{y}_{t-2} \\ \vdots \\ \mathbf{y}_{t-p} \end{bmatrix}}_{\substack{\mathbf{Y}_{t-1} \\ (np\times 1)}} + \underbrace{\begin{bmatrix} \mathbf{u}_t \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}}_{\substack{\mathbf{U}_t \\ (np\times 1)}} \tag{B.21}$$

  – If the stationarity condition is satisfied, namely if all eigenvalues of $\mathbf{B}$ are smaller than one in absolute value, then the VMA(∞) representation of the VAR(1) is:

$$\begin{aligned} \mathbf{Y}_t &= \mathbf{B}\mathbf{Y}_{t-1} + \mathbf{U}_t \\ &= \ldots \\ &= \mathbf{B}^j\mathbf{Y}_{t-j} + \mathbf{B}^{j-1}\mathbf{U}_{t-j+1} + \cdots + \mathbf{B}\mathbf{U}_{t-1} + \mathbf{U}_t \\ &= \sum_{j=0}^{\infty}\mathbf{B}^j\mathbf{U}_{t-j} \\ &= \mathbf{\Phi}_0\mathbf{U}_t + \mathbf{\Phi}_1\mathbf{U}_{t-1} + \mathbf{\Phi}_2\mathbf{U}_{t-2} + \ldots \end{aligned}$$

with $\mathbf{\Phi}_j = \mathbf{B}^j$. The matrix $\mathbf{\Phi}_j$ is a $(np \times np)$ matrix while the matrix of parameters of the Wold representation is its $(n \times n)$ upper left matrix. I call the upper left matrix $\mathbf{\Phi}_{W,h}$ which, for $h = 0, \ldots, H$, reads as:

$$\underset{(n\times n)}{\mathbf{\Phi}_{W,h}} = \frac{\partial \mathbf{y}_{t+h}}{\partial \mathbf{u}_t'} = \begin{bmatrix} \phi_{11,h} & \cdots & \phi_{n1,h} \\ \vdots & \ddots & \vdots \\ \phi_{n1,h} & \cdots & \phi_{nn,h} \end{bmatrix}$$

where $\phi_{ik,h} = \frac{\partial y_{i,t+h}}{\partial u_{k,t}}$ identifies the impact of the reduced-form shock in variable k at time t on variable y_i at time $t+h$. These are the impulse responses of the reduced form model. The Kalman filter and smoothed provides all the ingredients to find $\mathbf{\Phi}_{W,h}$.

- **Find the structural impulse responses:**
Because of the relation between the reduced and structural form, $\mathbf{u}_t = \mathbf{A}_t \boldsymbol{\varepsilon}_t$, the VMA($\infty$) can be written as a function of the structural shocks. The VMA(∞) representation for the $(n \times 1)$ vector $\mathbf{y}_t$ reads as:

$$\begin{aligned} \mathbf{y}_t &= \sum_{j=0}^{\infty} \mathbf{\Phi}_{W,j} \mathbf{u}_{t-j} \\ &= \mathbf{\Phi}_{W,0}\mathbf{u}_t + \mathbf{\Phi}_{W,1}\mathbf{u}_{t-1} + \mathbf{\Phi}_{W,2}\mathbf{u}_{t-2} + \ldots \\ &= \mathbf{\Phi}_{W,0}\mathbf{A}\boldsymbol{\varepsilon}_t + \mathbf{\Phi}_{W,1}\mathbf{A}\boldsymbol{\varepsilon}_{t-1} + \mathbf{\Phi}_{W,2}\mathbf{A}\boldsymbol{\varepsilon}_{t-2} + \ldots \\ &= \tilde{\mathbf{\Phi}}_0\boldsymbol{\varepsilon}_t + \tilde{\mathbf{\Phi}}_1\boldsymbol{\varepsilon}_{t-1} + \tilde{\mathbf{\Phi}}_2\boldsymbol{\varepsilon}_{t-2} + \ldots \\ &= \sum_{j=0}^{\infty} \tilde{\mathbf{\Phi}}_j \boldsymbol{\varepsilon}_{t-j} \end{aligned} \tag{B.22}$$

It follows that

$$\underset{(n\times n)}{\tilde{\mathbf{\Phi}}_h} = \frac{\partial \mathbf{y}_{t+h}}{\partial \boldsymbol{\varepsilon}_t'} = \begin{bmatrix} \tilde{\phi}_{11,h} & \cdots & \tilde{\phi}_{n1,h} \\ \vdots & \ddots & \vdots \\ \tilde{\phi}_{n1,h} & \cdots & \tilde{\phi}_{nn,h} \end{bmatrix}$$

where $\tilde{\phi}_{ik,h} = \frac{\partial y_{i,t+h}}{\partial \varepsilon_{k,t}}$ identifies the impact of the structural shock in variable k at time t on variable y_i at time $t+h$.

end

B.3 Sensitivity analysis

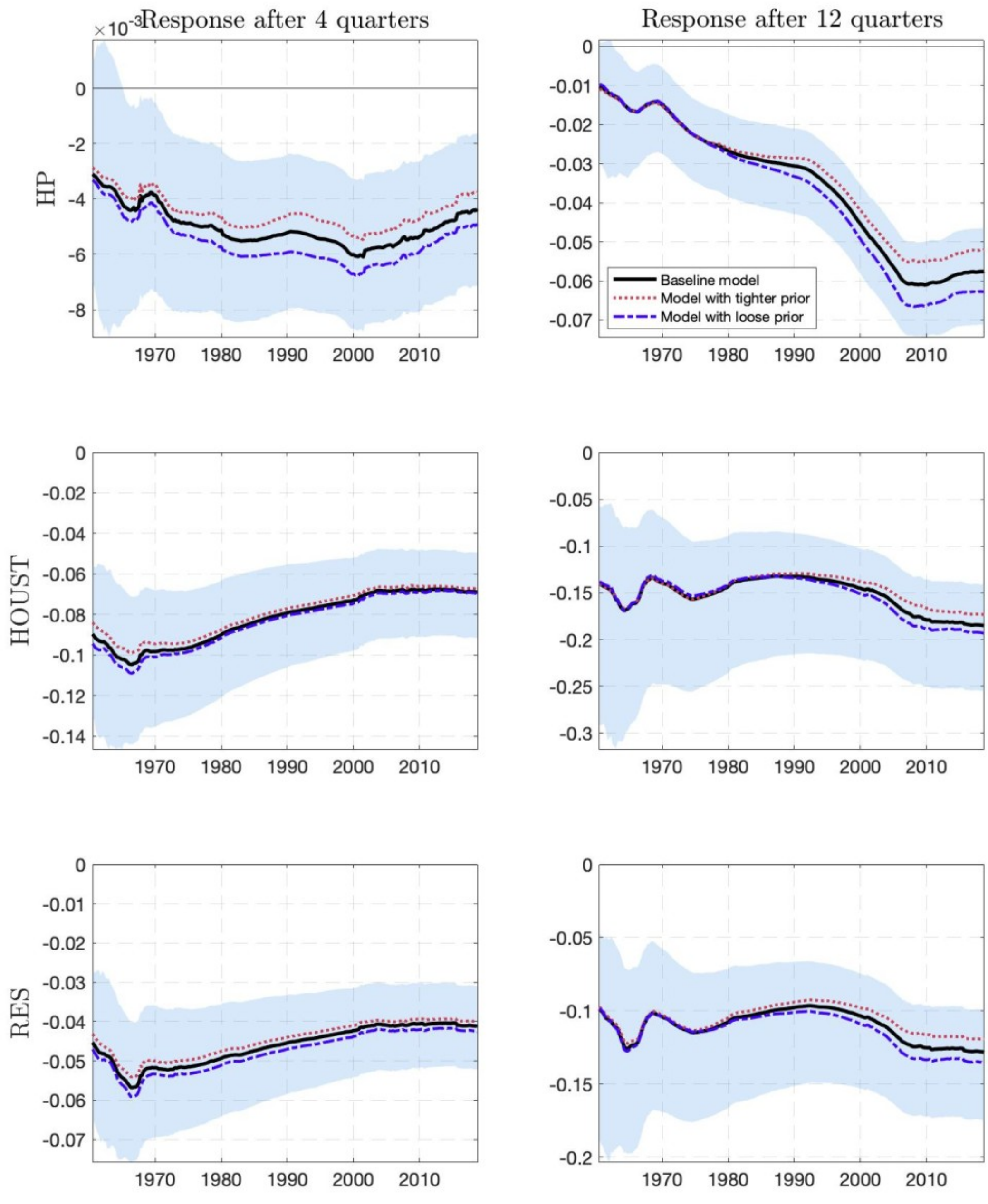


FIGURE B.3: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSING: SENSITIVITY TO γ

Notes: this figure shows the cumulative average responses of the housing sector for different values of the shrinkage hyperparameter of the Minnesota prior: $\gamma = 0.1$ *for the baseline model,* $\gamma = 0.05$ *for the model with tighter prior,* $\gamma = 0.2$ *for the model with loose prior. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).*

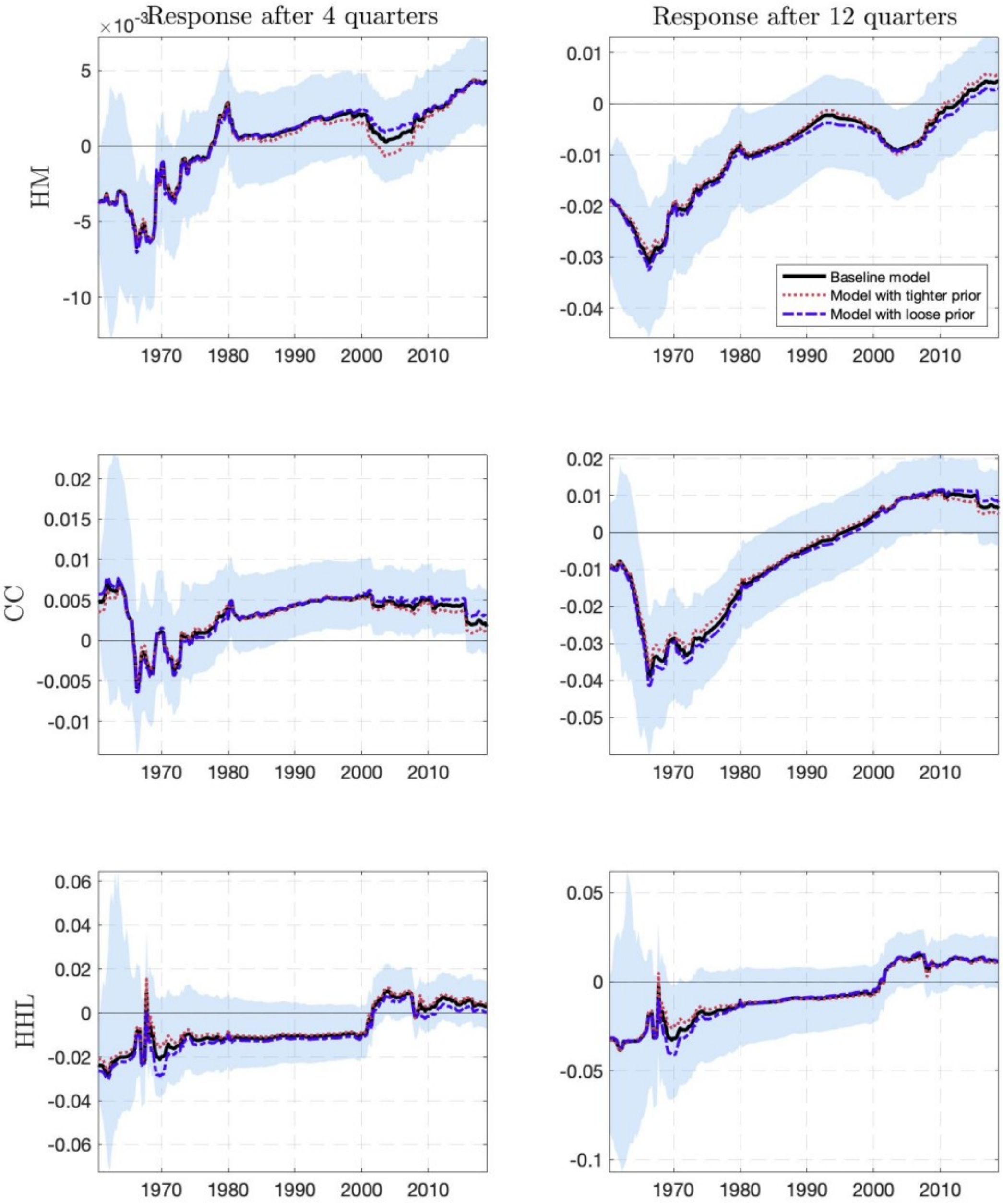


FIGURE B.4: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSEHOLD DEBT: SENSITIVITY TO γ

Notes: this figure shows the cumulative average responses of household debt for different values of the shrinkage hyperparameter of the Minnesota prior: $\gamma = 0.1$ for the baseline model, $\gamma = 0.05$ for the model with tighter prior, $\gamma = 0.2$ for the model with loose prior. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

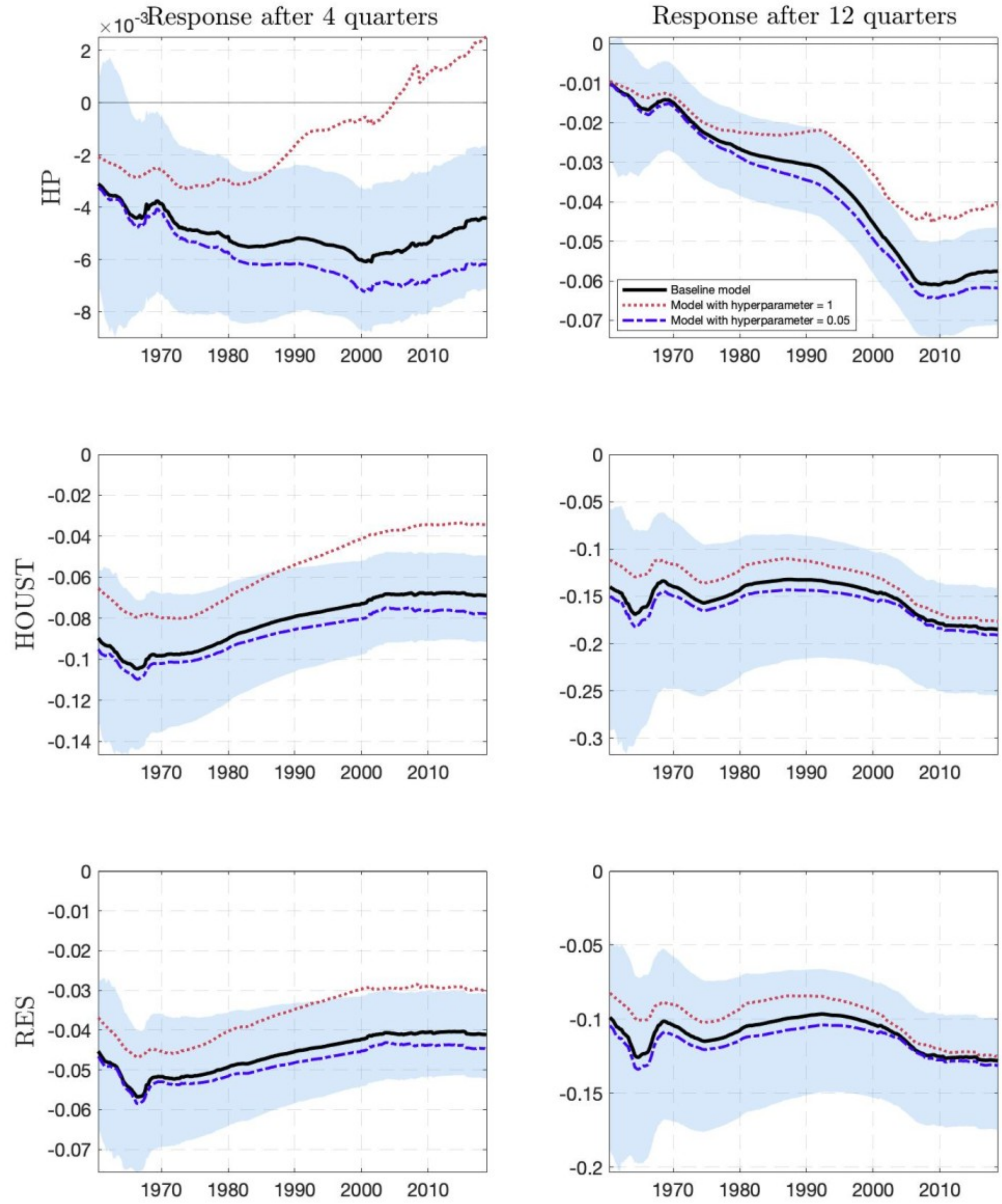


FIGURE B.5: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSING: SENSITIVITY TO k_Ω

Notes: this figure shows the cumulative average responses of the housing sector for different values of the hyperparameter of VAR variance-covariance matrix $k_\Omega = 0.1$ for the baseline model, $k_\Omega = 1$ and $k_\Omega = 0.05$. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

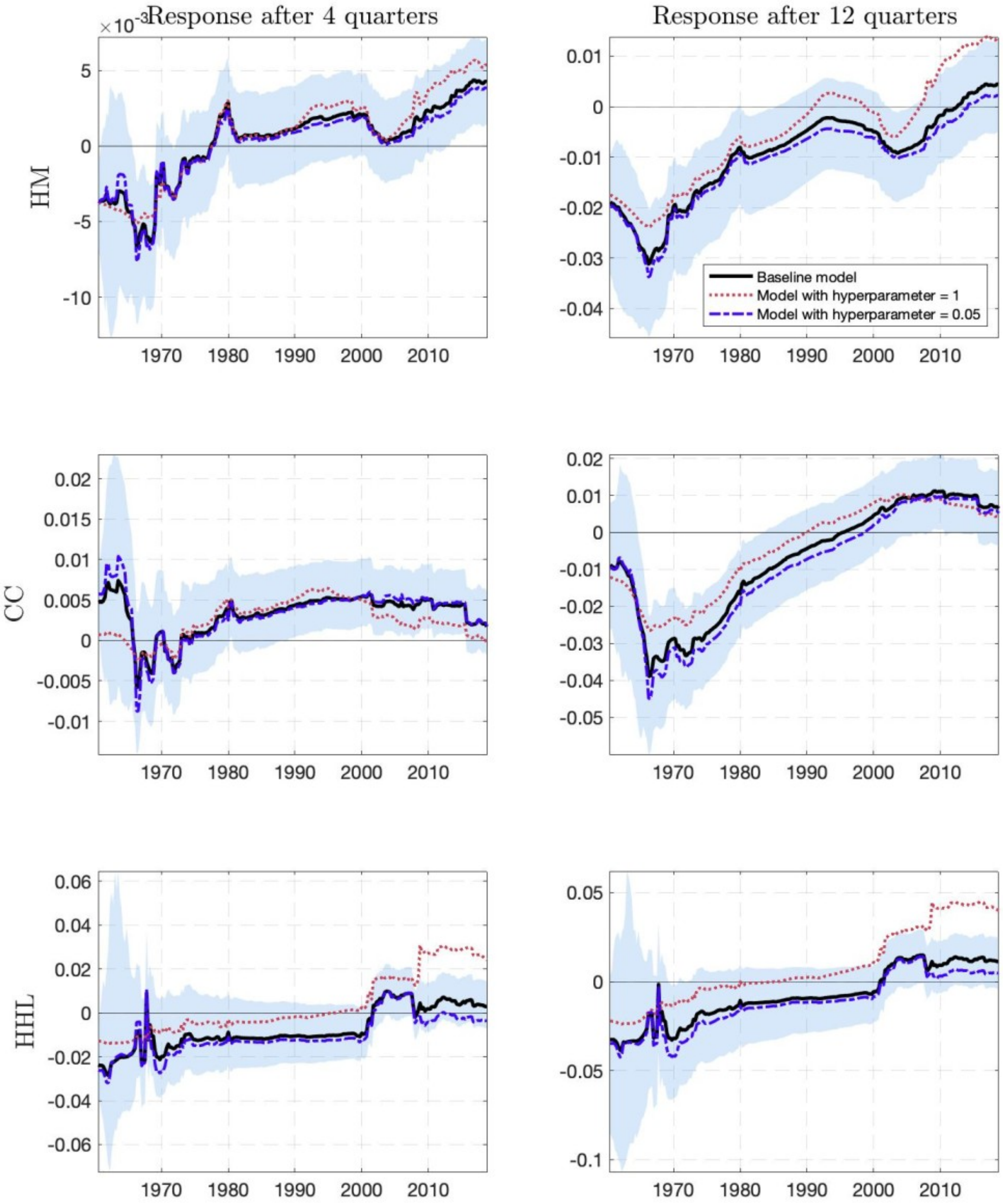


FIGURE B.6: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSEHOLD DEBT: SENSITIVITY TO k_Ω

Notes: this figure shows the cumulative average responses of household debt for different values of the hyperparameter of VAR variance-covariance matrix $k_\Omega = 0.1$ for the baseline model, $k_\Omega = 1$ and $k_\Omega = 0.05$. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

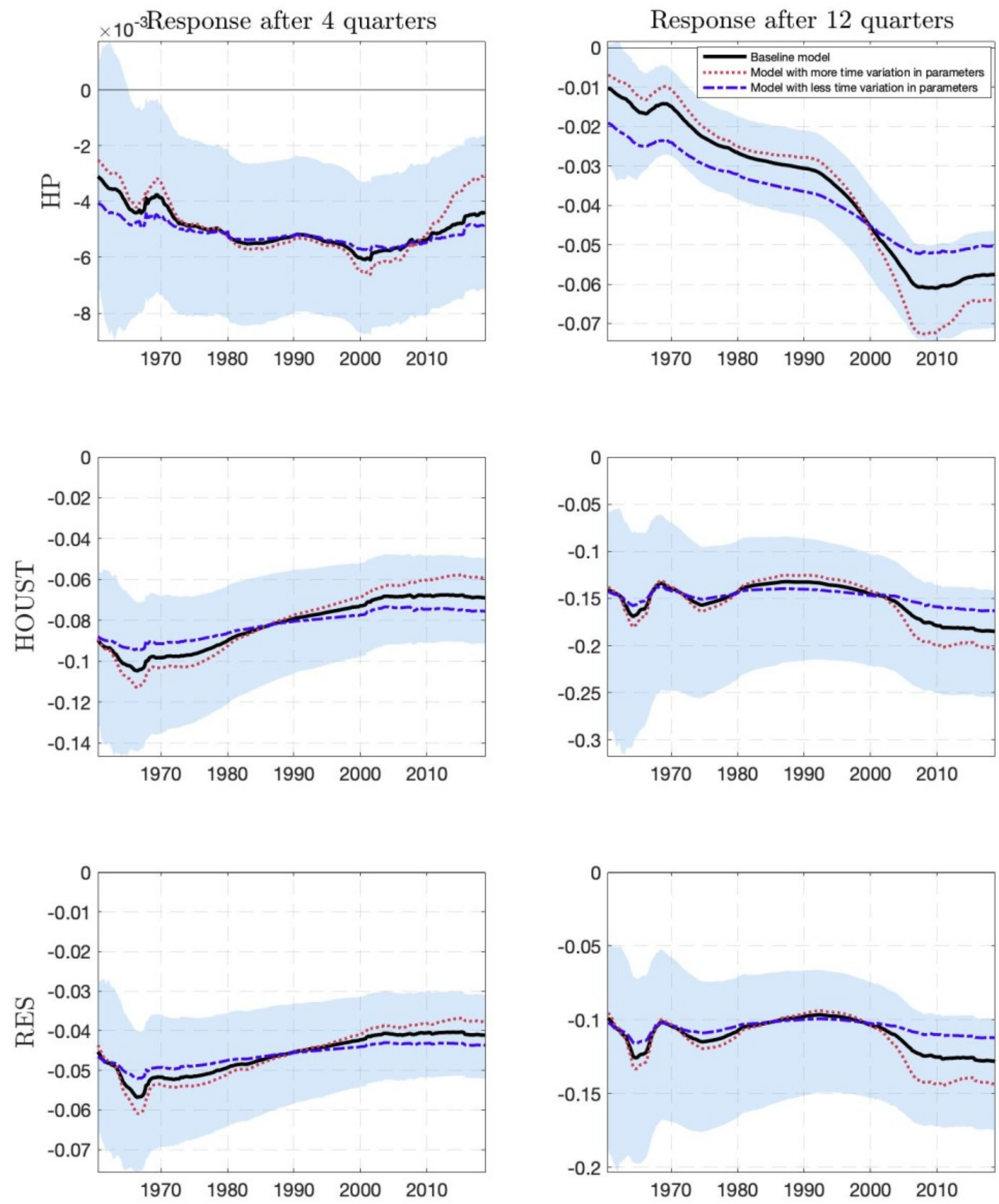


FIGURE B.7: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSING: SENSITIVITY TO λ

Notes: this figure shows the cumulative average responses of the housing sector for different values of the forgetting factor: $\lambda = 0.99$ for the baseline model, $\lambda = 0.985$ for the model with more time variation in the parameters and $\lambda = 0.995$ for the model with less time variation in the parameters. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

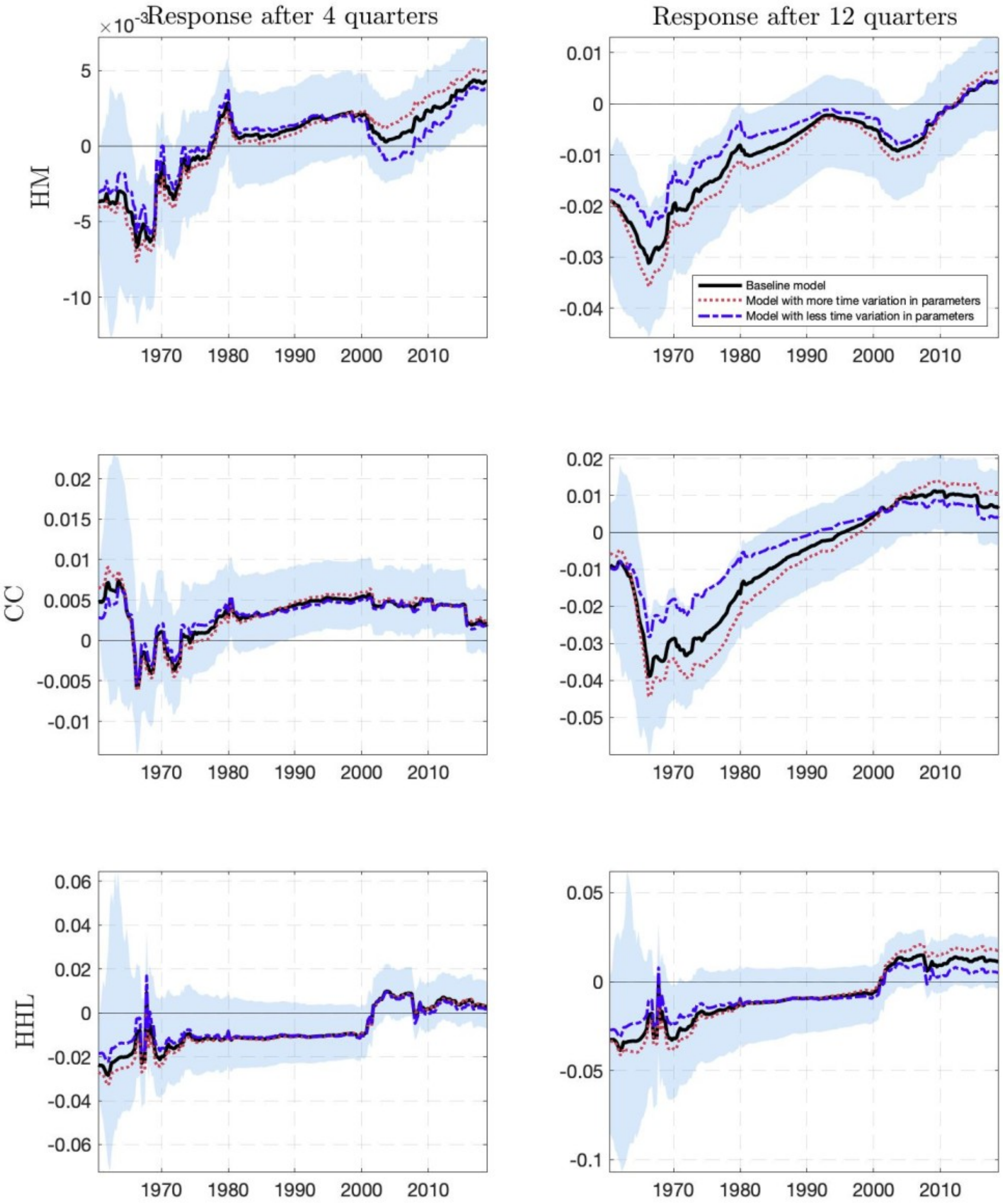


FIGURE B.8: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSEHOLD DEBT: SENSITIVITY TO λ

Notes: this figure shows the cumulative average responses of the housing sector for different values of the forgetting factor: $\lambda = 0.99$ for the baseline model, $\lambda = 0.985$ for the model with more time variation in the parameters and $\lambda = 0.995$ for the model with less time variation in the parameters. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

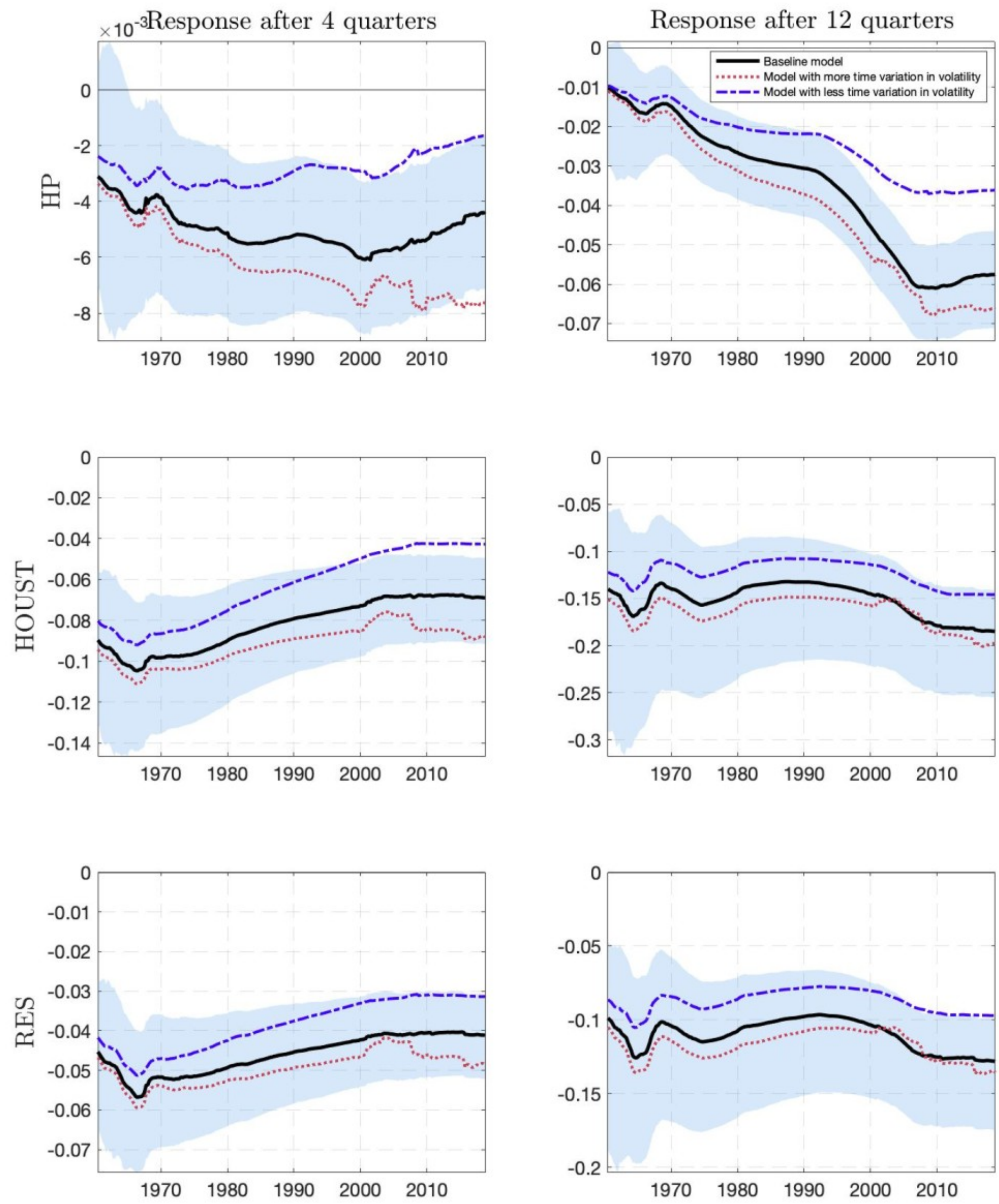


FIGURE B.9: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSING: SENSITIVITY TO κ

Notes: this figure shows the cumulative average responses of the housing sector for different values of the decay factor: $\kappa = 0.96$ for the baseline model, $\kappa = 0.95$ for the model with more time variation in volatility and $\lambda = 0.98$ for the model with less time variation in volatility. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

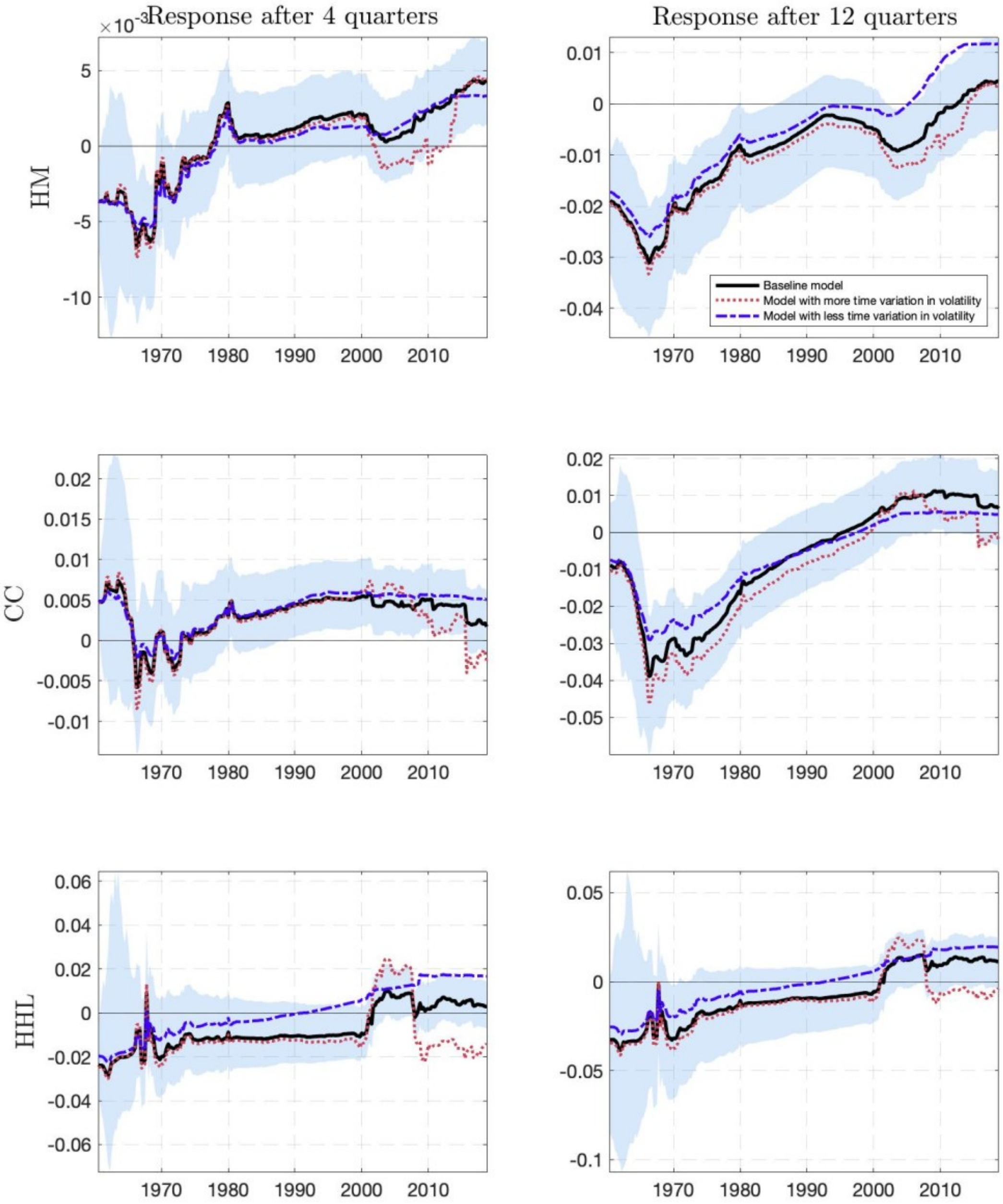


FIGURE B.10: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSEHOLD DEBT: SENSITIVITY TO κ

Notes: this figure shows the cumulative average responses of household debt for different values of the decay factor: $\kappa = 0.96$ for the baseline model, $\kappa = 0.95$ for the model with more time variation in volatility and $\lambda = 0.98$ for the model with less time variation in volatility. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

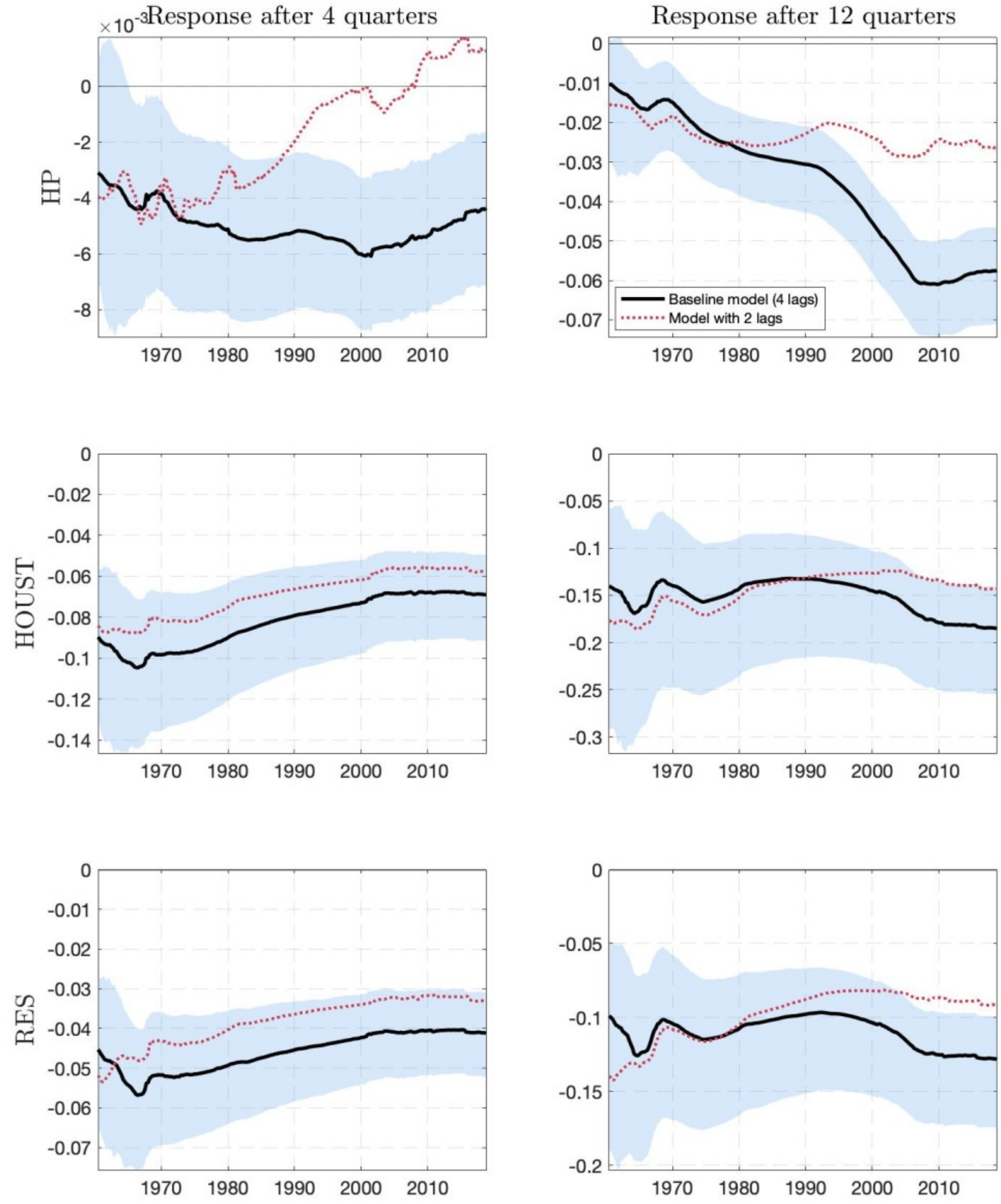


FIGURE B.11: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSING: SENSITIVITY TO p

Notes: this figure shows the cumulative average responses of the housing sector for $p = 4$ and $p = 2$ lags. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

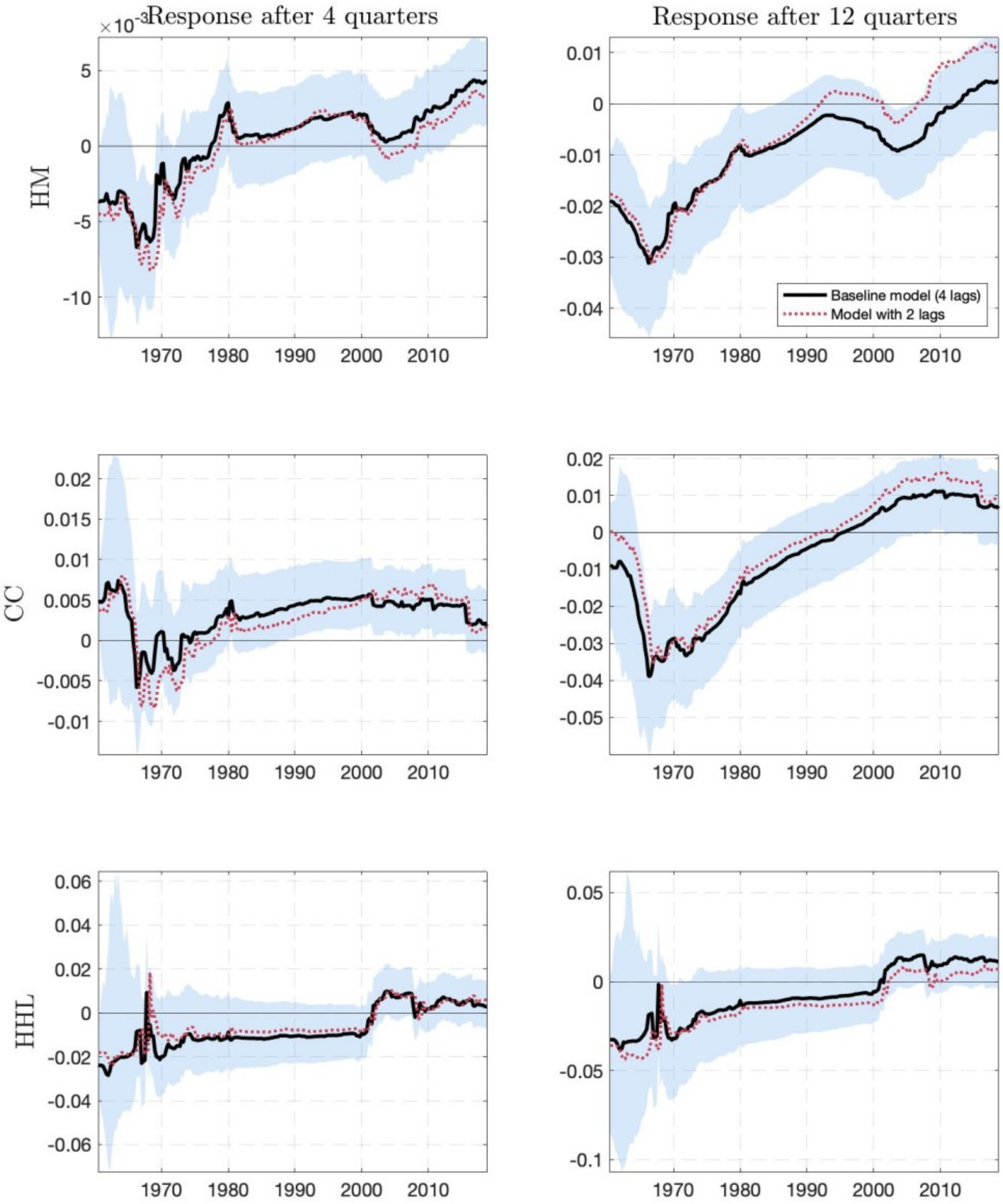


FIGURE B.12: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSEHOLD DEBT: SENSITIVITY TO p

Notes: this figure shows the cumulative average responses of household debt for $p = 4$ and $p = 2$ lags. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

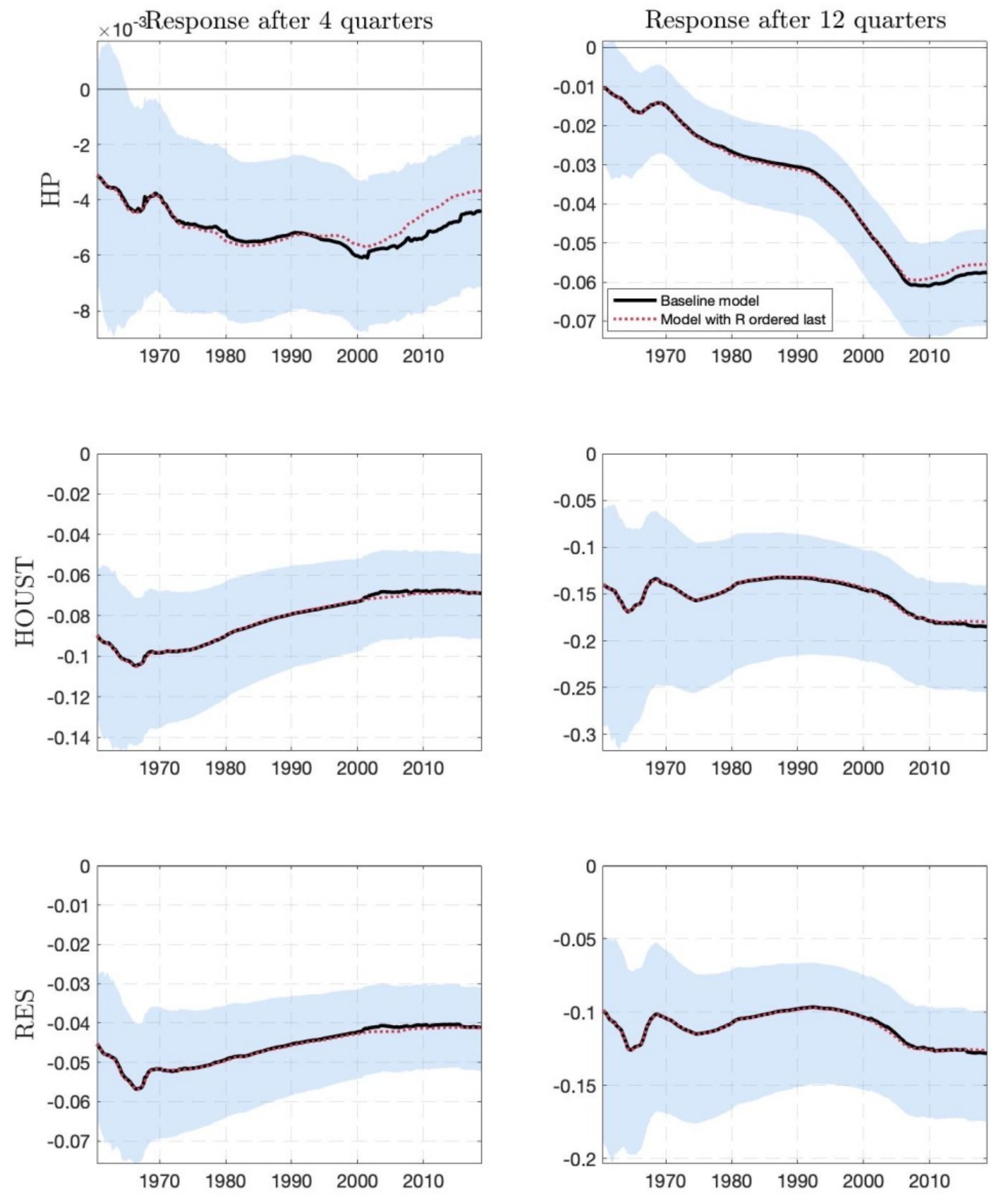


FIGURE B.13: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSEHOLD DEBT: SENSITIVITY TO ORDERING

Notes: this figure shows the cumulative average responses of the housing sector for the baseline model and for a version of the model with the effective federal funds rate order last. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

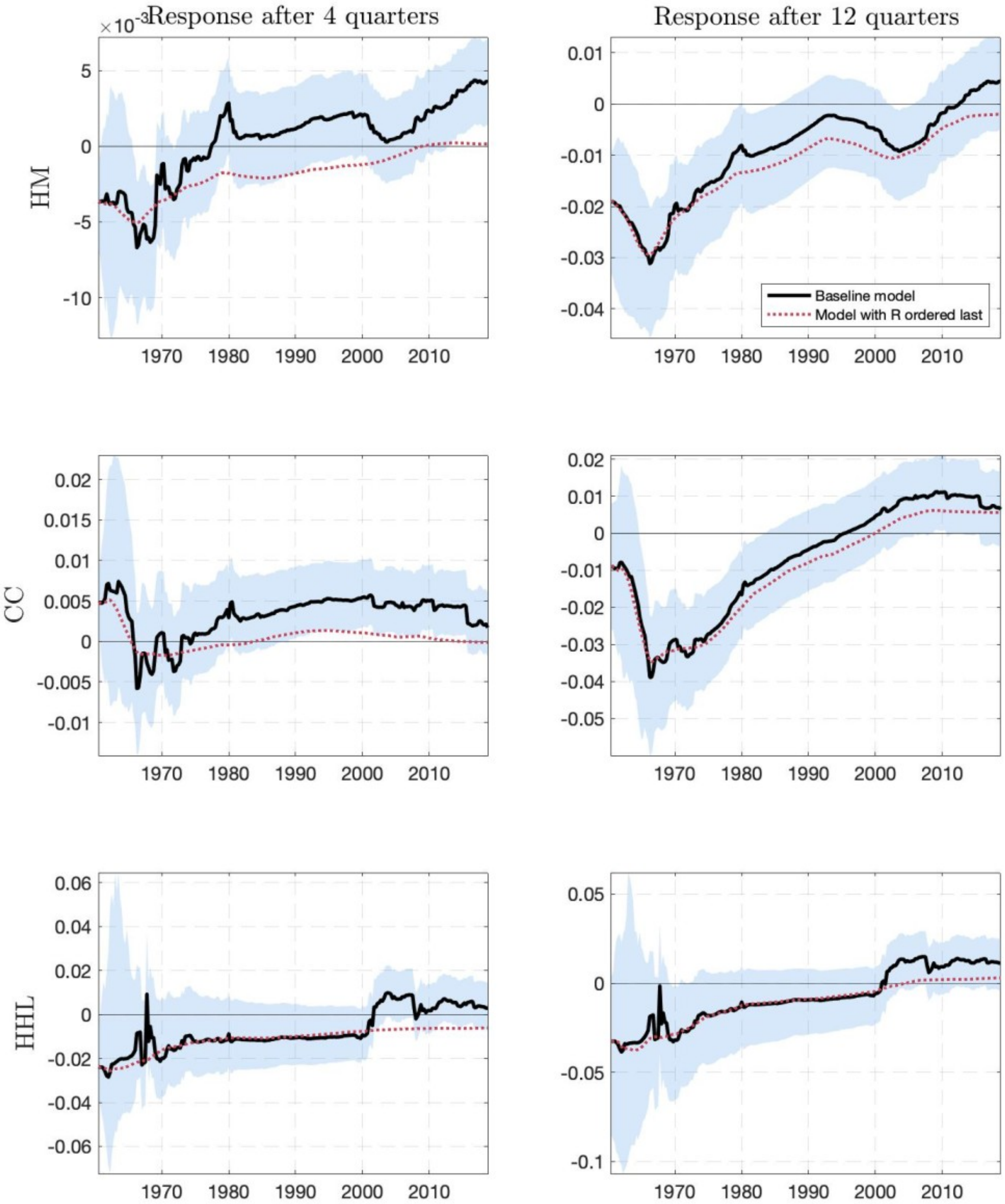


FIGURE B.14: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSEHOLD DEBT: SENSITIVITY TO ORDERING

Notes: this figure shows the cumulative average responses of the housing sector for the baseline model and for a version of the model with the effective federal funds rate order last. Shaded areas are 68 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

B.4 Other figures

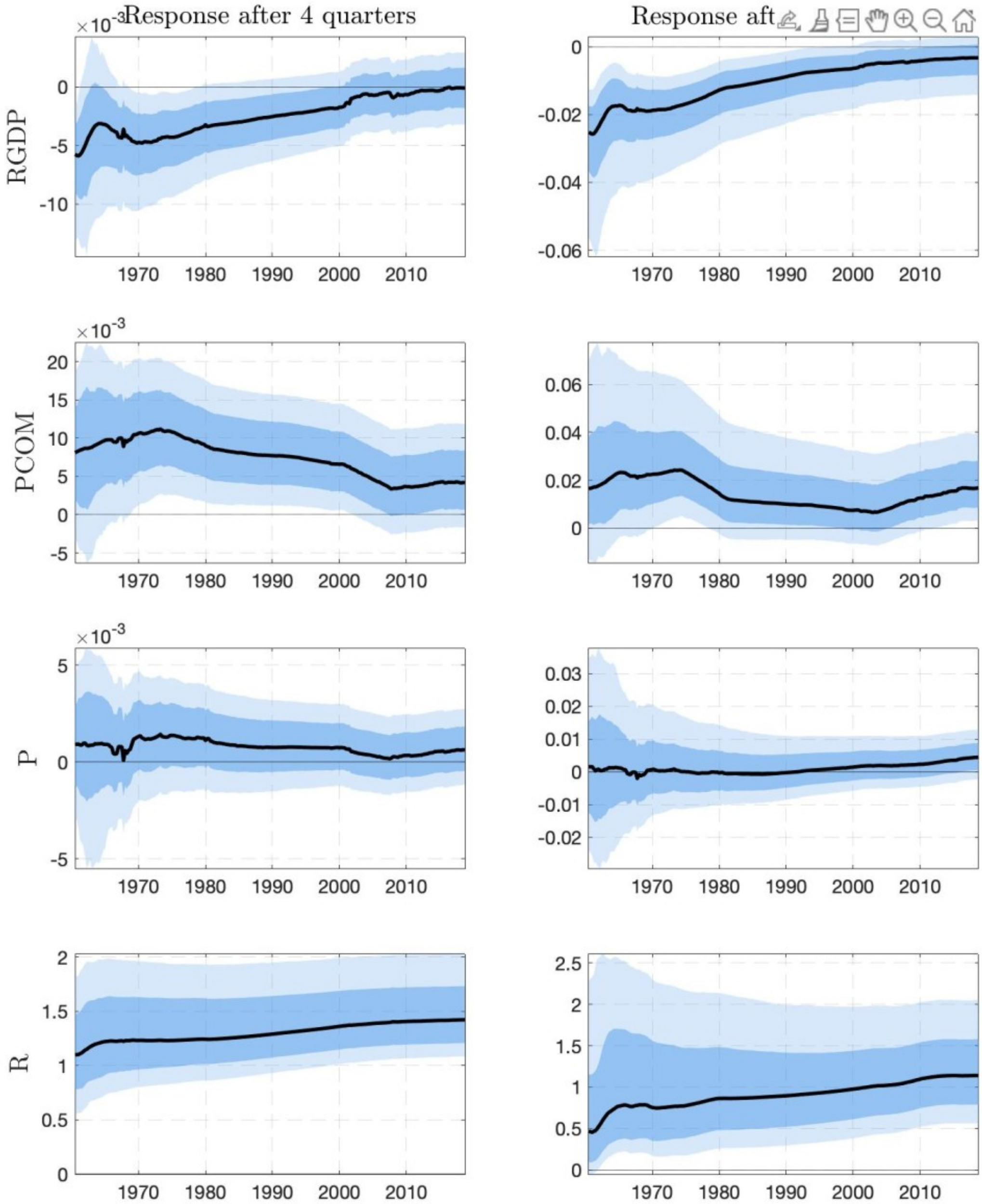


FIGURE B.15: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON AGGREGATE ECONOMY AND POLICY

Notes: this figure shows the cumulative impulse responses to a contractionary monetary policy shock that increases the effective federal funds rate by 1 % on impact. The short-run is 4 quarters after the shock while the medium-run is 12 quarters after the shock. The black solid line is the average response while shaded areas are 68 and 90 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

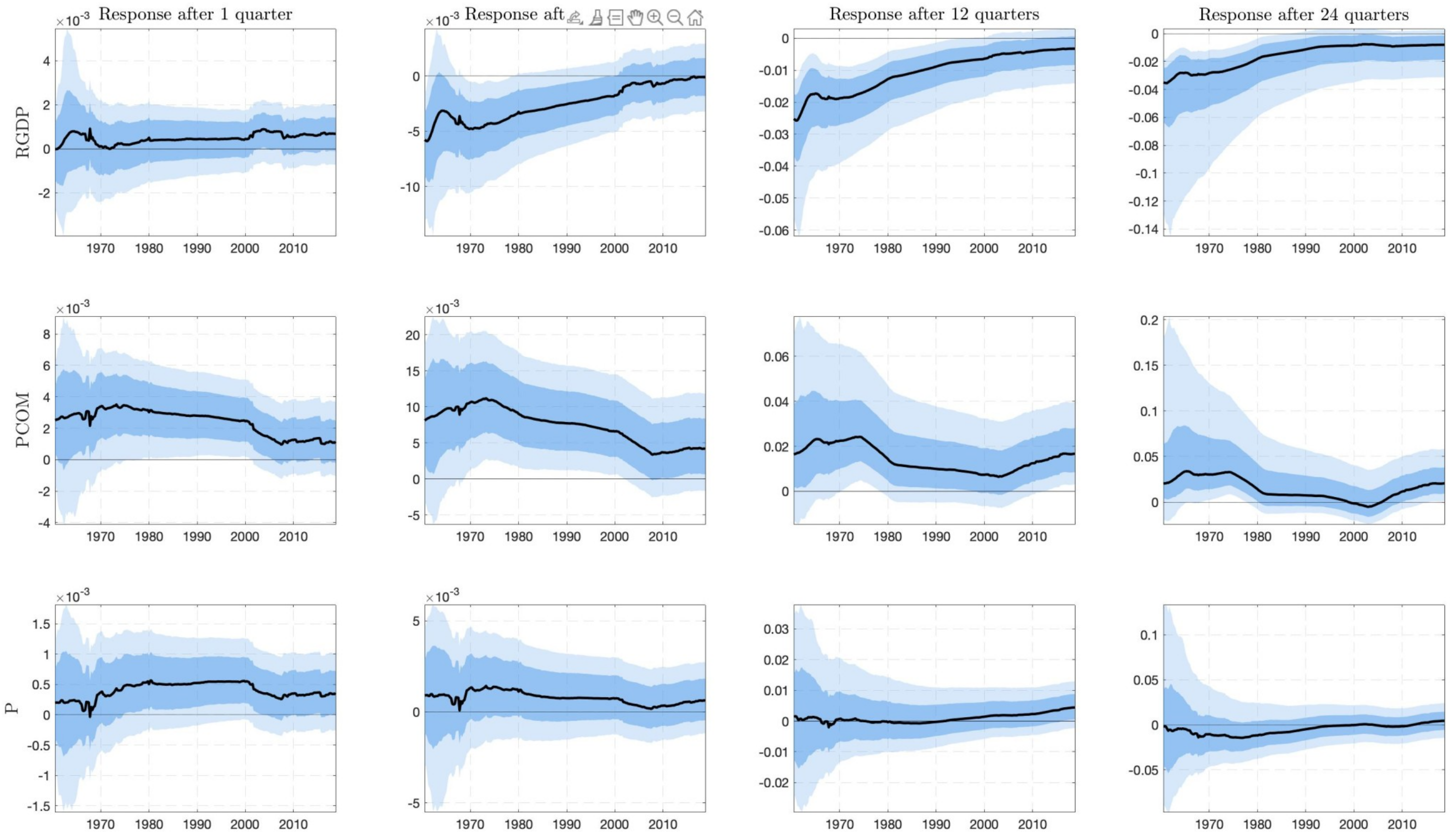


FIGURE B.16: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON AGGREGATE ECONOMY AT DIFFERENT HORIZONS

Notes: this figure shows the cumulative impulse responses to a contractionary monetary policy shock that increases the effective federal funds rate by 1 % on impact. The black solid line is the average response while shaded areas are 68 and 90 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

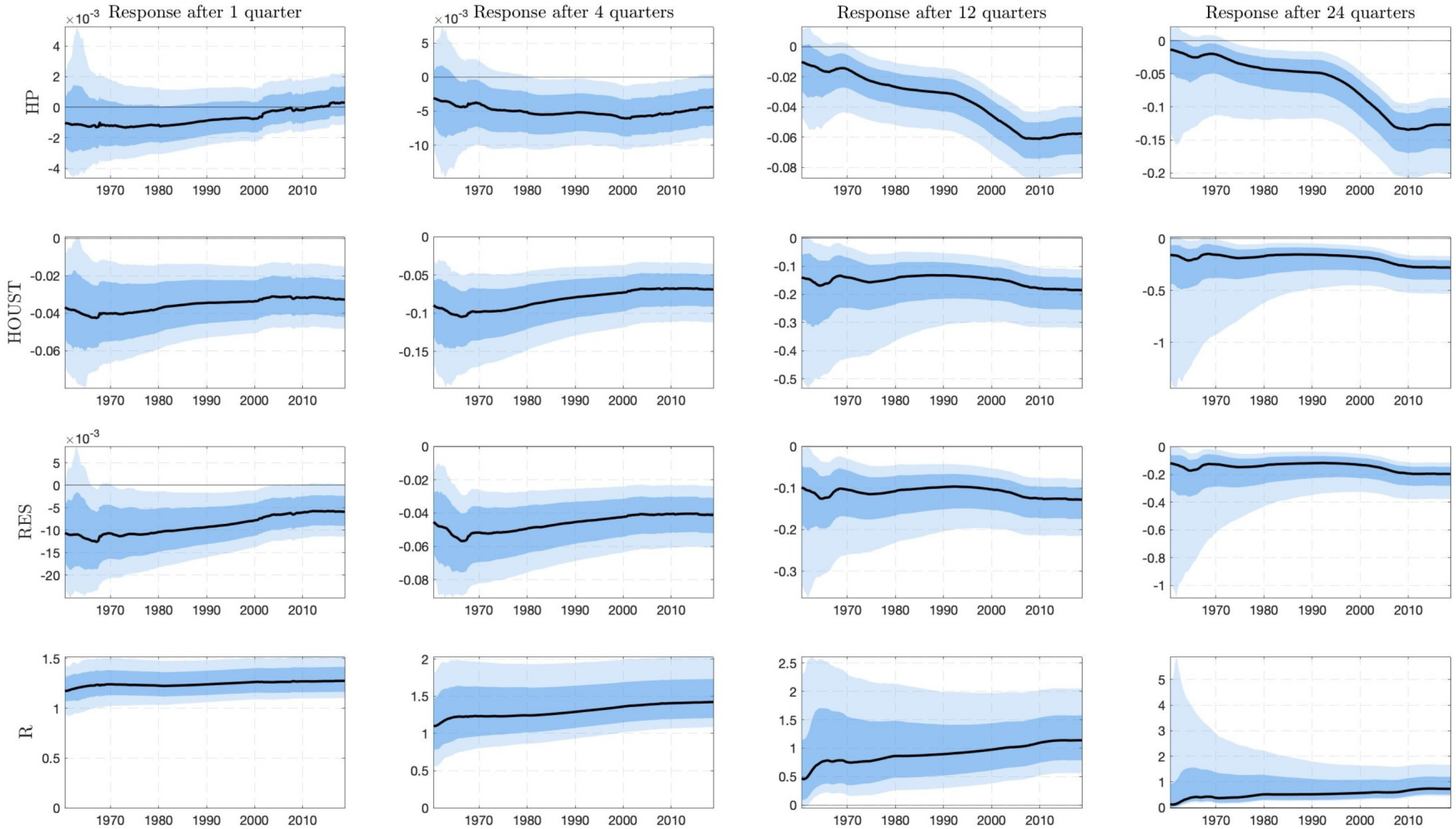


FIGURE B.17: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSING AND POLICY BLOCKS AT DIFFERENT HORIZONS

Notes: this figure shows the cumulative impulse responses to a contractionary monetary policy shock that increases the effective federal funds rate by 1 % on impact. The black solid line is the average response while shaded areas are 68 and 90 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

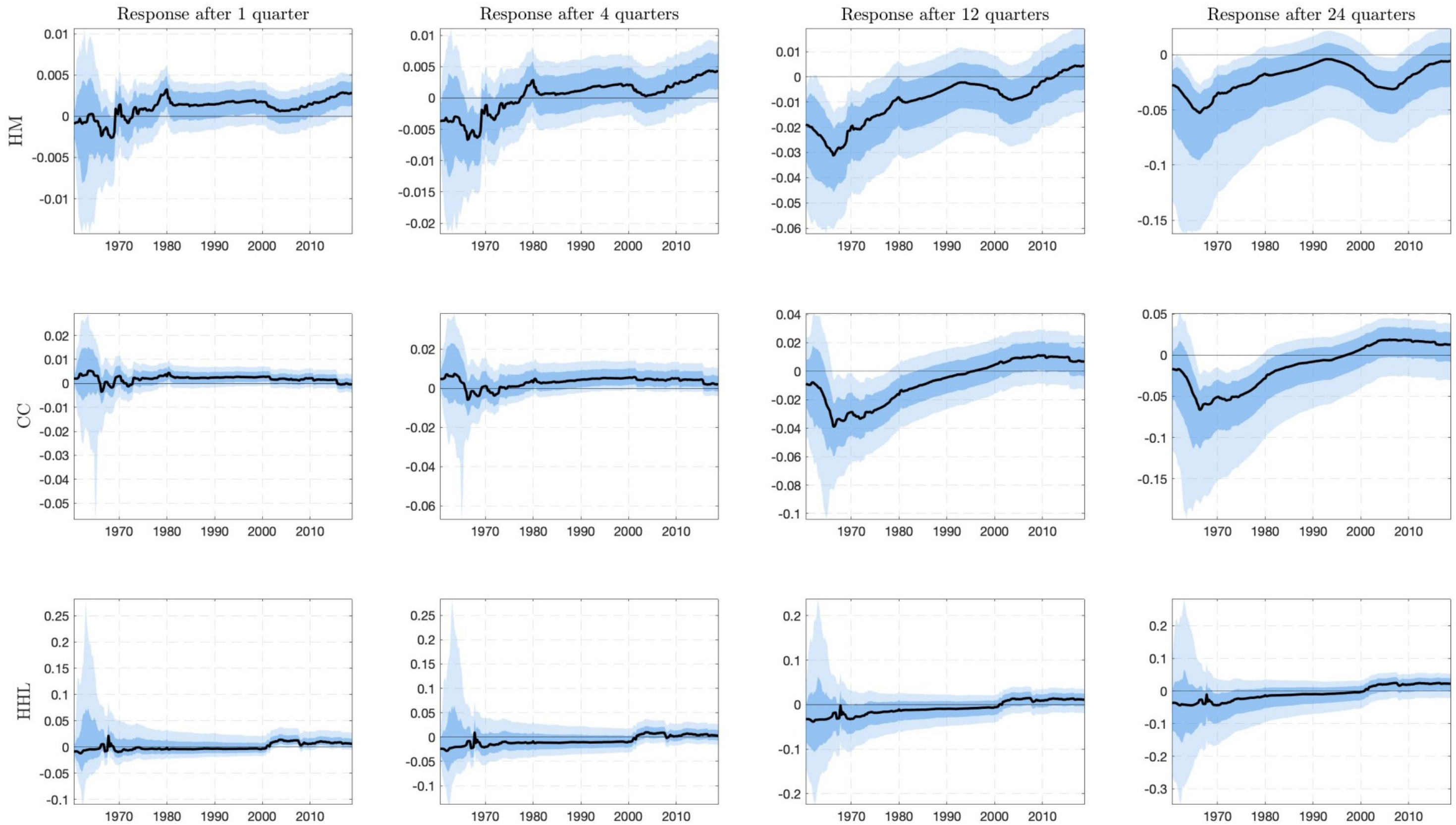


FIGURE B.18: TIME-VARYING EFFECTS OF MONETARY POLICY SHOCKS ON HOUSEHOLD DEBT AT DIFFERENT HORIZONS

Notes: this figure shows the cumulative impulse responses to a contractionary monetary policy shock that increases the effective federal funds rate by 1 % on impact. The black solid line is the average response while shaded areas are 68 and 90 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

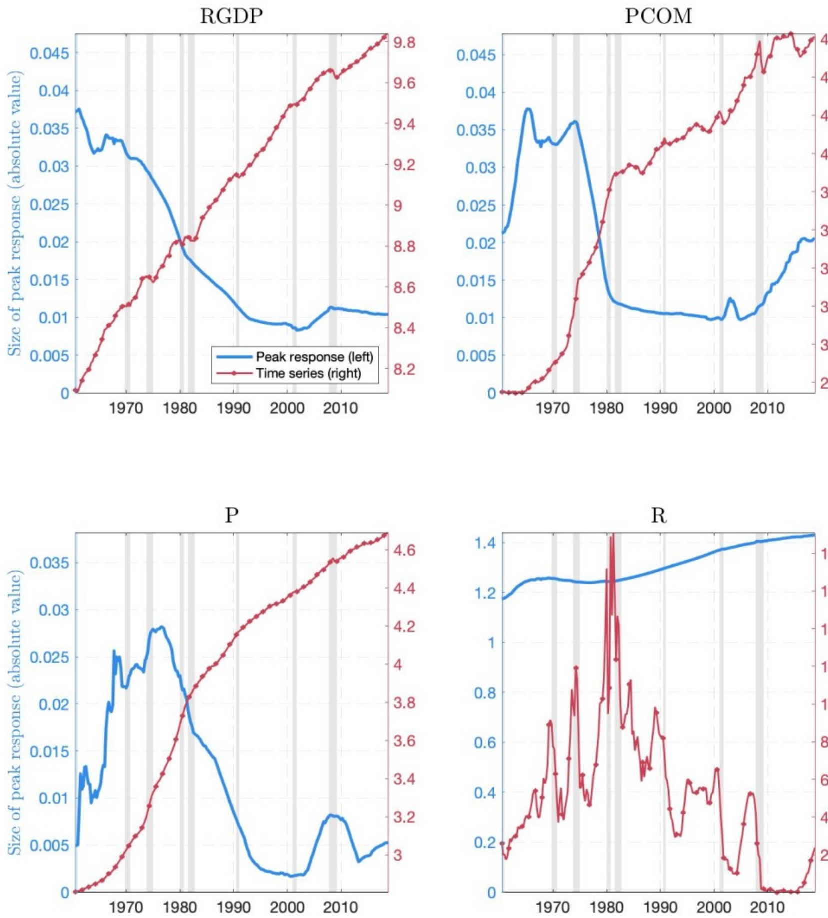


FIGURE B.19: TIME-VARYING PEAK RESPONSES OF AGGREGATE ECONOMY AND BLOCKS

Notes: this figure shows the time-varying peak responses of real GDP (RGDP), the commodity price index (PCOM), the PCE price index (P) and the effective federal funds rate (R). The blue solid line is the size of the peak average response in absolute value and it is measured on the left axis. The red line with markets is the natural logarithm of the variable of interest and it is measured on the right axis. The yellow dots are selected turning points in the time-varying peak responses. Shaded areas are NBER recessions.

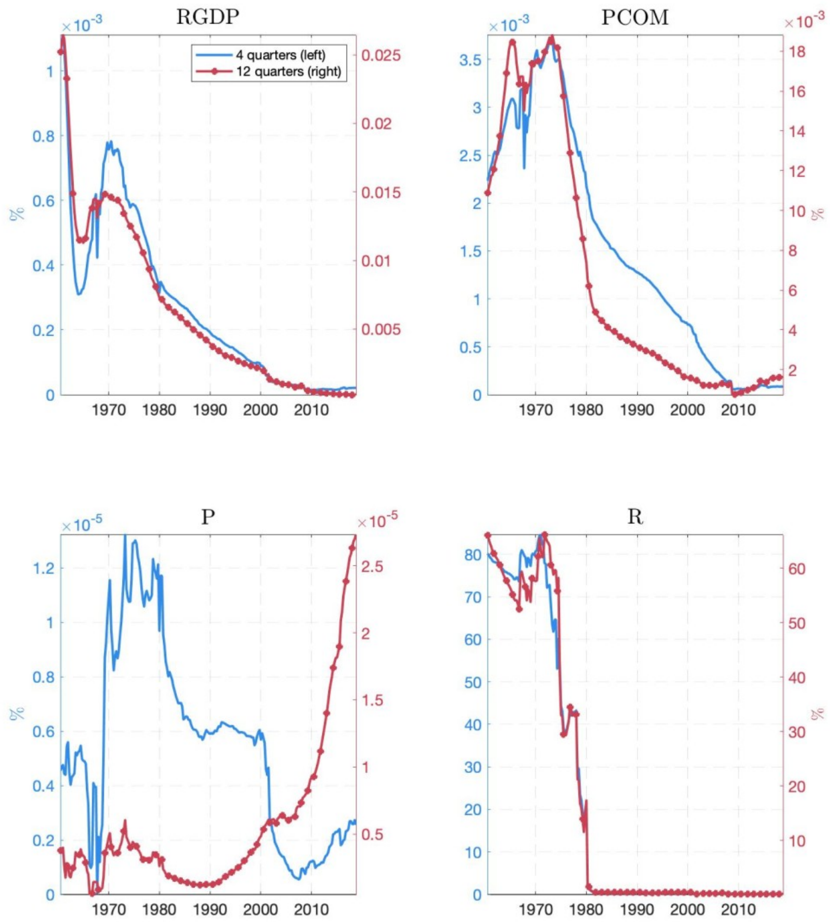


FIGURE B.20: TIME-VARYING CONTRIBUTION OF MONETARY POLICY SHOCKS: AGGREGATE ECONOMY AND POLICY BLOCKS

Notes: this figure shows the time-varying contribution of monetary policy shocks to the variables in the aggregate economy and policy blocks. The blue solid line is the contribution of monetary policy shocks after 4 quarters (or short-run contribution) and it is measured on the left axis. While the red line with markers is the contribution after 12 quarters (or medium-run contribution) and it is measured on the right axis.

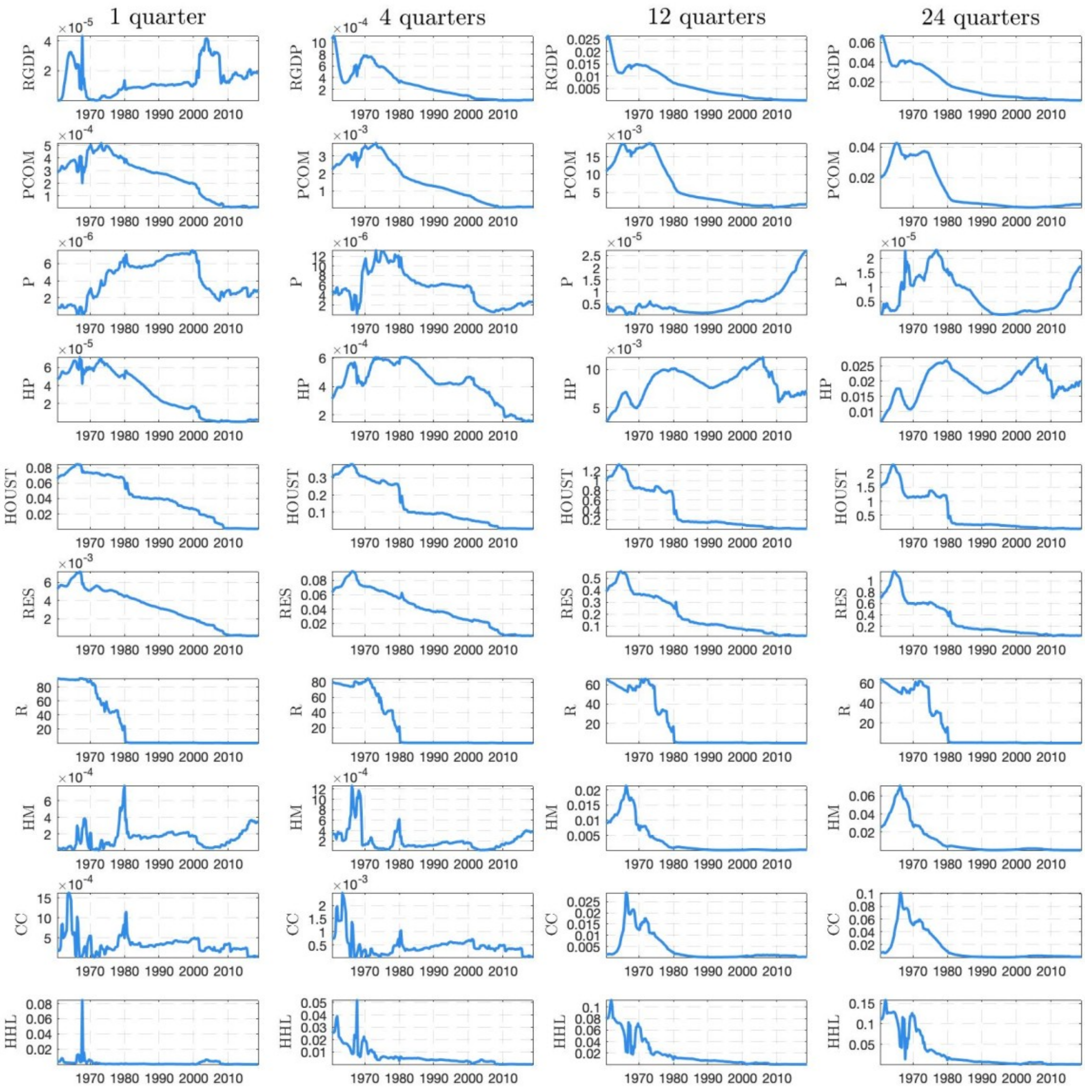


FIGURE B.21: TIME-VARYING CONTRIBUTION OF MONETARY POLICY SHOCKS: ALL VARIABLES

Notes: this figure shows the contribution of monetary policy shocks to the forecast error variance of all variables after 1, 4, 12 and 24 quarters.

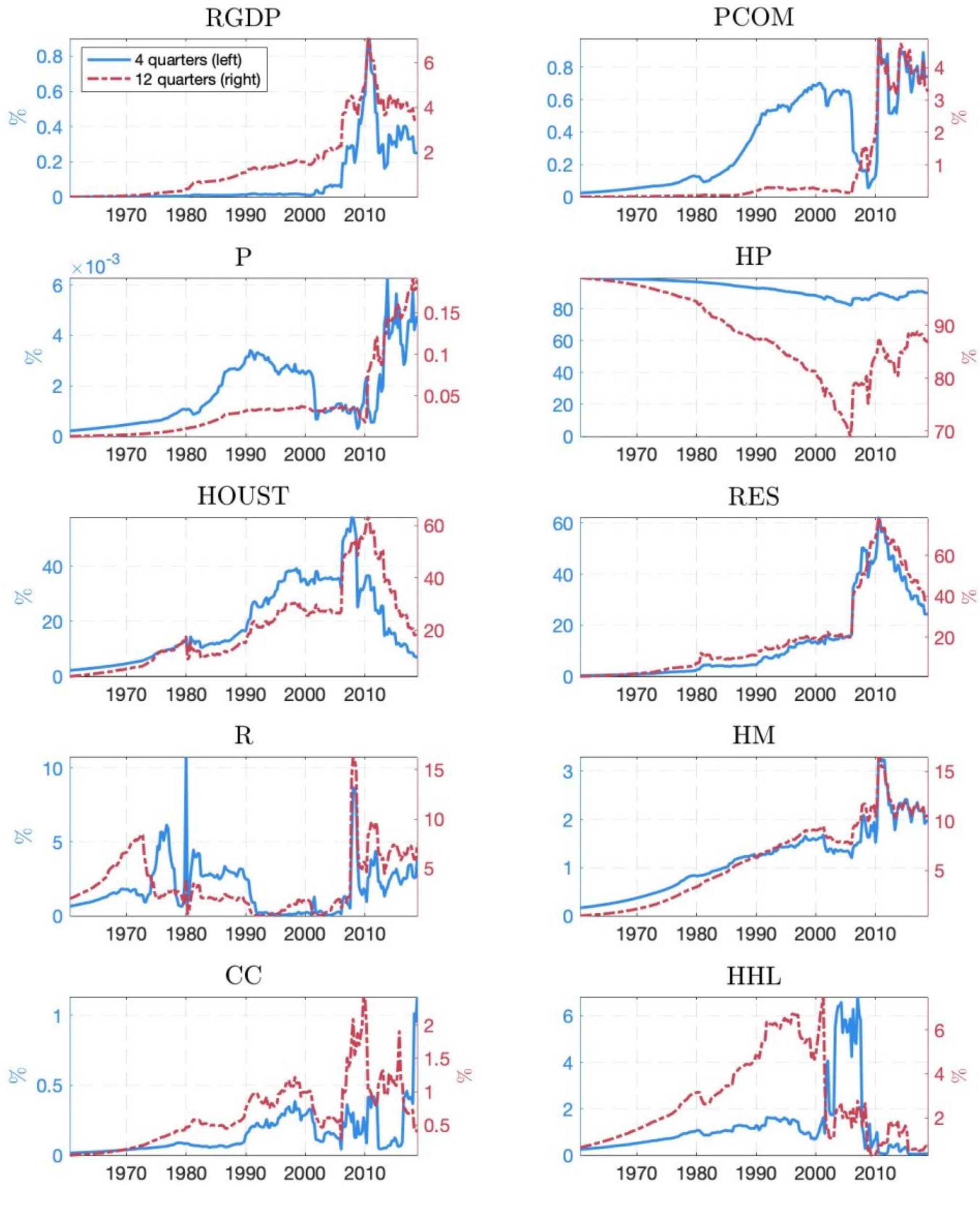


FIGURE B.22: TIME-VARYING CONTRIBUTION OF SHOCKS TO HOUSE PRICES: ALL VARIABLES

Notes: this figure shows the time-varying contribution of shocks to the real house price index equation to the forecast error variance of all variables. The blue solid line is the contribution of after 4 quarters (or short-run contribution) and it is measured on the left axis. While the red line with markers is the contribution after 12 quarters (or medium-run contribution) and it is measured on the right axis.

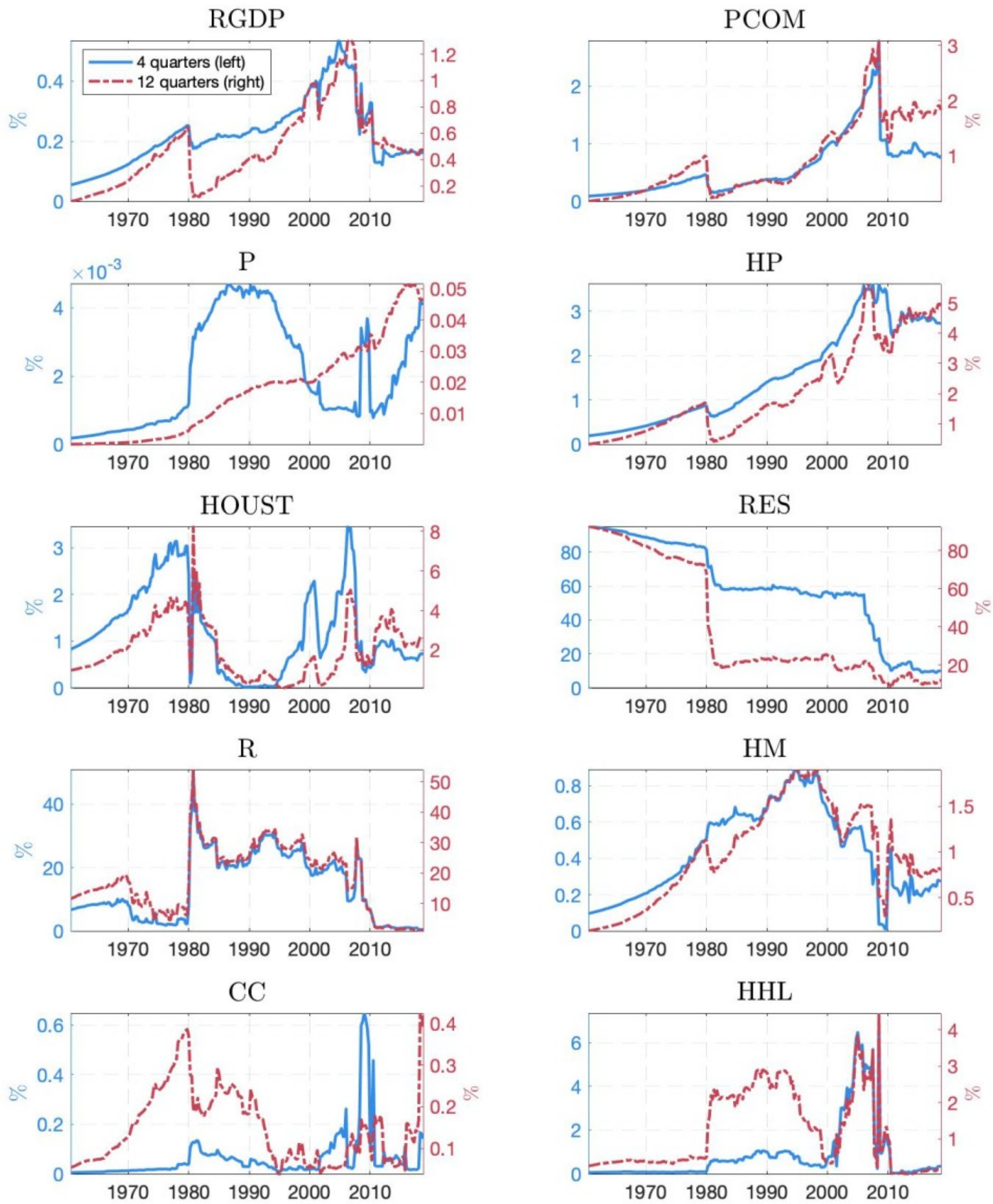


FIGURE B.23: TIME-VARYING CONTRIBUTION OF SHOCKS TO RESIDENTIAL INVESTMENT: ALL VARIABLES

Notes: this figure shows the time-varying contribution of shocks to the real residential investment equation to the forecast error variance of all variables. The blue solid line is the contribution of after 4 quarters (or short-run contribution) and it is measured on the left axis. While the red line with markers is the contribution after 12 quarters (or medium-run contribution) and it is measured on the right axis.

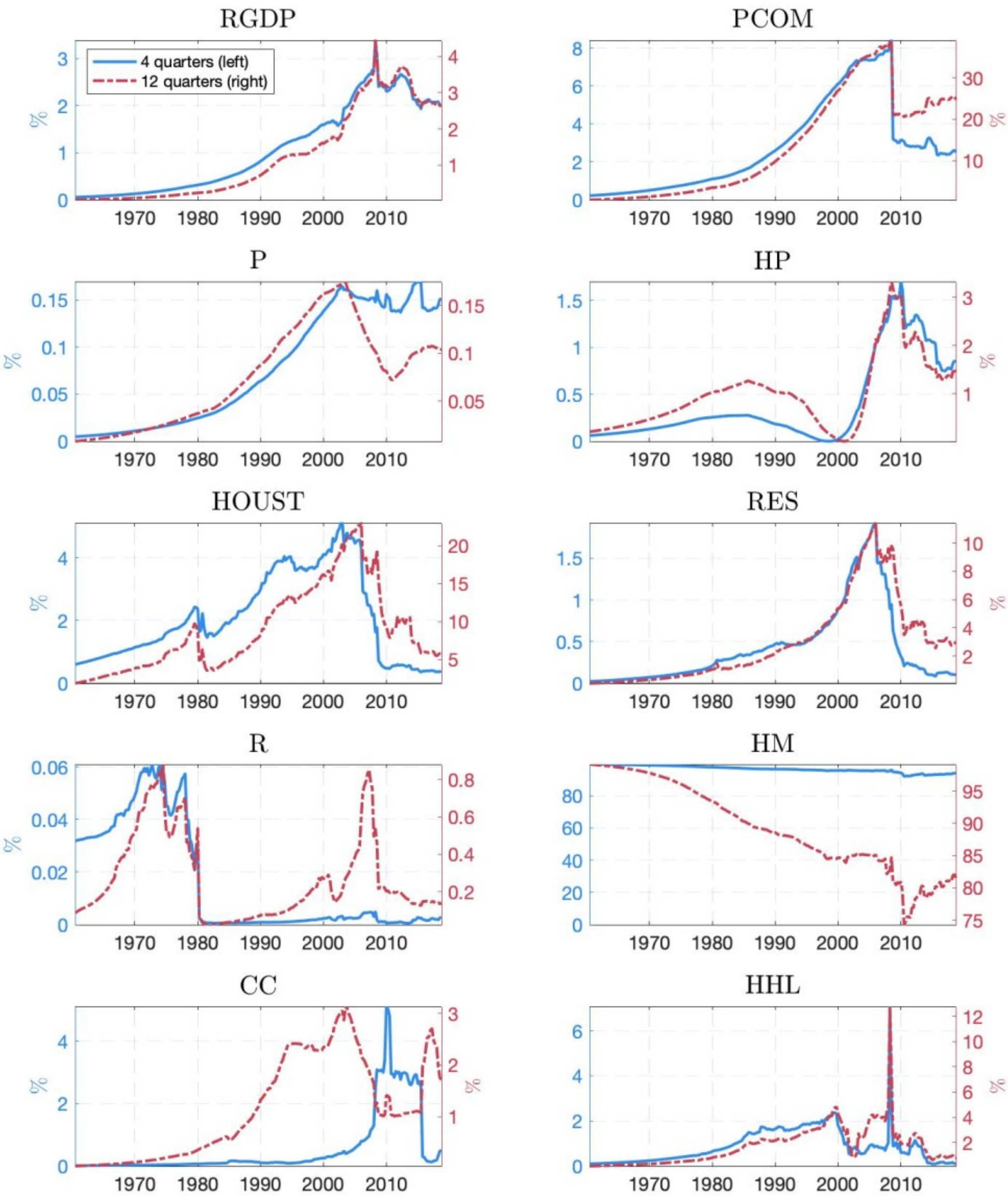


FIGURE B.24: TIME-VARYING CONTRIBUTION OF SHOCKS TO HOME MORTGAGES: ALL VARIABLES

Notes: this figure shows the time-varying contribution of shocks to the real home mortgages equation to the forecast error variance of all variables. The blue solid line is the contribution of after 4 quarters (or short-run contribution) and it is measured on the left axis. While the red line with markers is the contribution after 12 quarters (or medium-run contribution) and it is measured on the right axis.

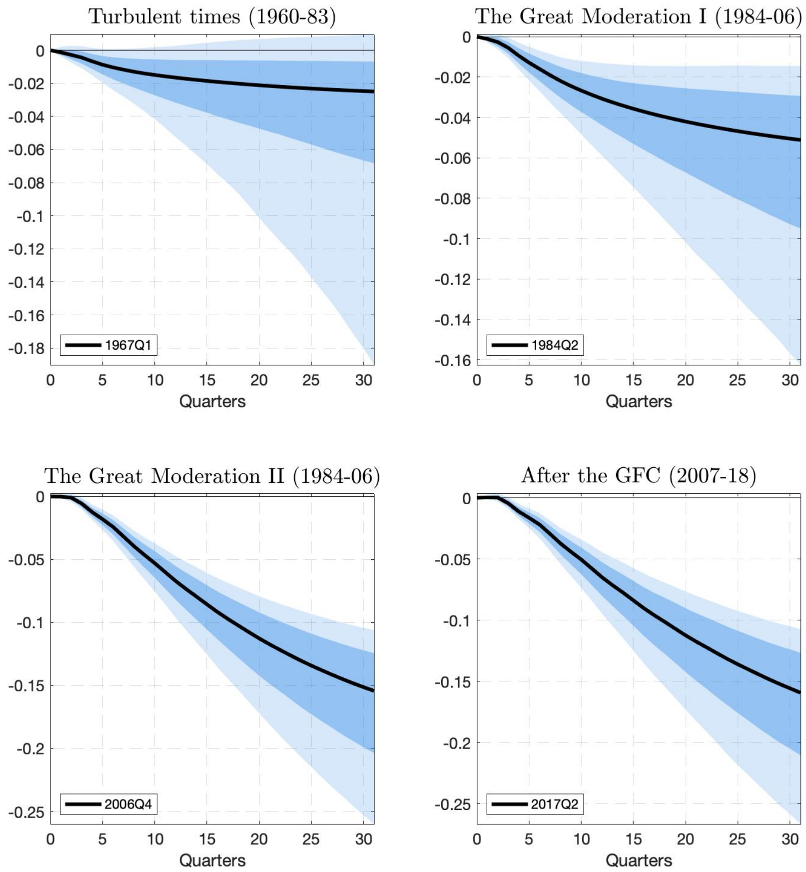


FIGURE B.25: THE RESPONSE OF THE REAL HOUSE PRICE INDEX (HP) TO MONETARY POLICY SHOCKS ARISING IN SELECTED PERIODS

Notes: this figure shows the response of the real house price index in some selected dates. The selected dates are 1967Q1 for the Turbulent Times, 1984Q2 and 2006Q4 for the Great Moderation, and 2017Q2 for After the Great Financial Crisis. The black line is the average response while shaded areas are 68 and 90 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

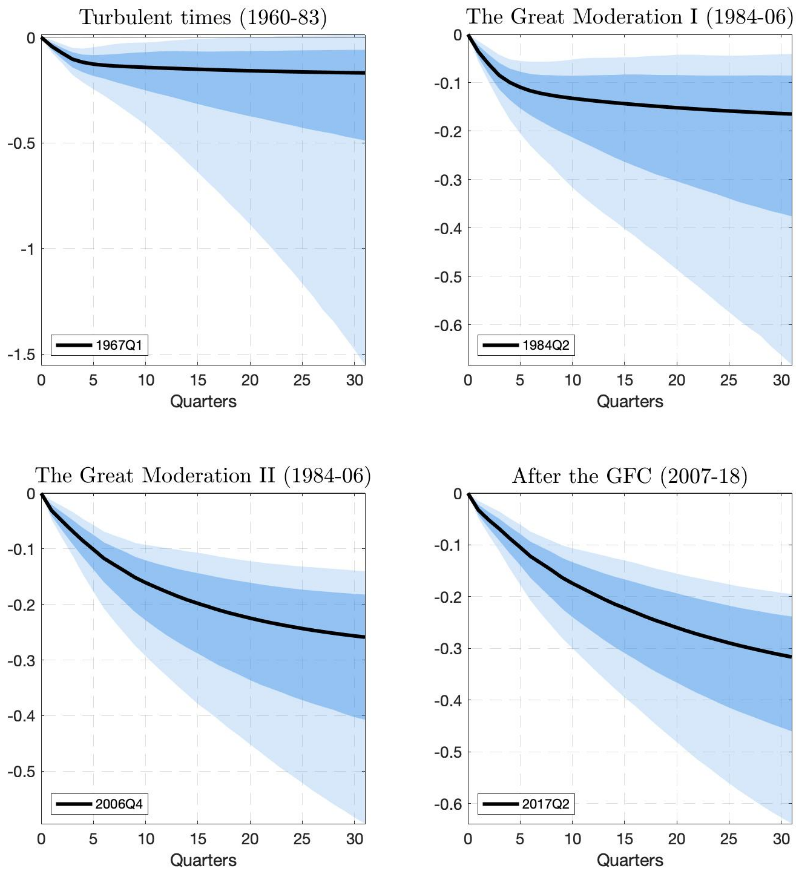


FIGURE B.26: THE RESPONSE OF NEW HOUSING STARTS (HOUST) TO MONETARY POLICY SHOCKS ARISING IN SELECTED PERIODS

Notes: this figure shows the response of new housing starts in some selected dates. The selected dates are 1967Q1 for the Turbulent Times, 1984Q2 and 2006Q4 for the Great Moderation, and 2017Q2 for After the Great Financial Crisis. The black line is the average response while shaded areas are 68 and 90 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

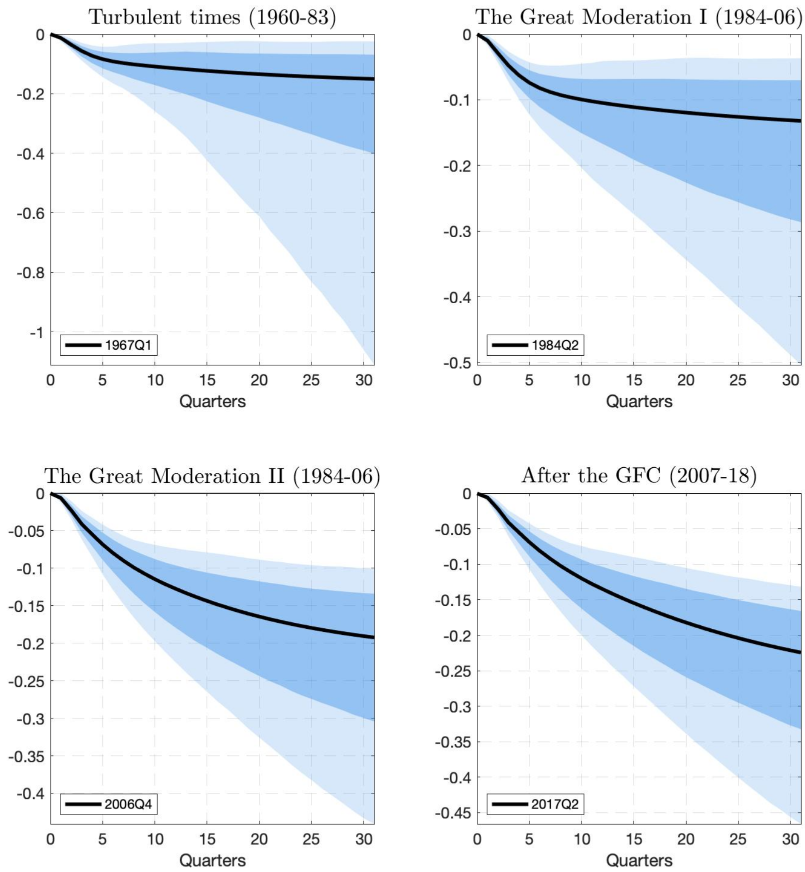


FIGURE B.27: THE RESPONSE OF THE REAL RESIDENTIAL INVESTMENT (RES) TO MONETARY POLICY SHOCKS ARISING IN SELECTED PERIODS

Notes: this figure shows the response of real residential investment in some selected dates. The selected dates are 1967Q1 for the Turbulent Times, 1984Q2 and 2006Q4 for the Great Moderation, and 2017Q2 for After the Great Financial Crisis. The black line is the average response while shaded areas are 68 and 90 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

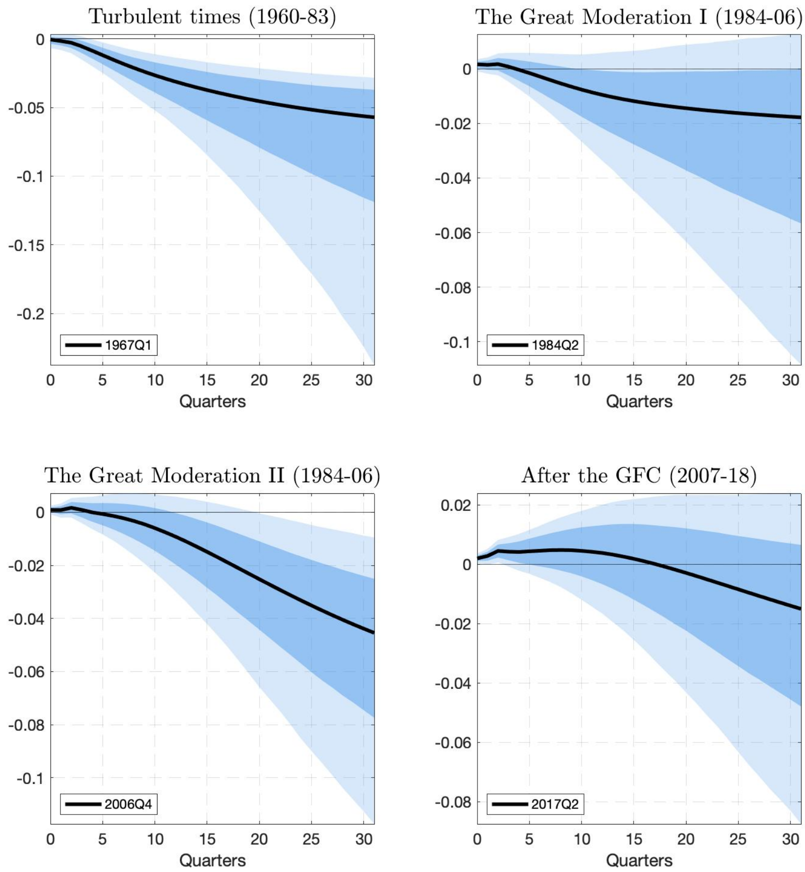


FIGURE B.28: THE RESPONSE OF THE REAL HOME MORTGAGES (HM) TO MONETARY POLICY SHOCKS ARISING IN SELECTED PERIODS

Notes: this figure shows the response of real home mortgages in some selected dates. The selected dates are 1967Q1 for the Turbulent Times, 1984Q2 and 2006Q4 for the Great Moderation, and 2017Q2 for After the Great Financial Crisis. The black line is the average response while shaded areas are 68 and 90 percent confidence bands. Confidence bands are constructed using a residual-based block bootstrap algorithm and 10000 bootstrap replications (Brüggemann et al., 2016).

Chapter 3

REAL AND FINANCIAL EFFECTS OF NON-FINANCIAL CORPORATE DEBT*

WITH
LEILA E. DAVIS,
JOAO PAULO A. DE SOUZA,
YUN K. KIM

ABSTRACT

Recent studies have shown that expansions of non-financial corporate debt have a weak correlation with the subsequent trajectory of aggregate demand. This finding raises the question: what is the non-financial corporate sector borrowing for? Using flow of funds data for the non-financial corporate sector in sixteen advanced economies over the 1970-2018 period, we show that new borrowing is strongly associated with a rise in holdings of financial assets net of non-debt liabilities, while being only weakly associated with an increase in capital expenditure. Moreover, by combining sector-level flow of funds data with country-level balance of payment data, we find that new borrowing by non-financial corporations is associated with residents obtaining large-stake equity holdings in foreign entities. Our results suggest that the weak correlation between non-financial corporate debt and aggregate demand can be explained by considering that corporate borrowing provides funds which can be given alternative uses besides the financing of capital investment in the domestic economy.

Keywords: corporate sector, corporate debt, financialization, financial globalization
JEL codes: E22, E44, G31, F60

3.1 Introduction

Recent studies have unveiled a puzzling pattern among advanced economies: expansions of non-financial corporate debt have a muted correlation with the subsequent trajectory of aggregate demand. For example, using sectoral data for a sample of advanced economies since the 1960s, Mian et al. (2017) find that increases in the stock of non-financial corporate debt have weak (and even negative) effects on future GDP. Drehmann et al. (2018), similarly, find that

*We wish to thank Daniele Girardi (discussant) for suggestions and comments on an earlier draft of this chapter. We thank the participants at the 2020 Pontignano PhD (Virtual) Annual Meeting for useful comments and suggestions. We are thankful to Monnet and Puy (2019) for making their data available for the research community.

increases in the flow of new borrowing by non-financial corporations also have little impact on GDP.

At first sight, these findings are counterintuitive. Alongside equity and internal funds, debt has traditionally been considered a key source of finance for capital investment. In spite of the Modigliani and Miller (1958) irrelevance result, the capital structure, namely the mix of internal funds, debt and equity that a firm uses to finance its assets, matters (Myers, 2001). A leading explanation of the capital structure is the *pecking order theory* (Myers and Majluf, 1984). According this theory, in financing capital investment, firms prefer internal funds to raising external finance. However, if external finance is needed, firms will issue debt in the first place, and then shares. Hence, the pecking order theory predicts that the accumulation of corporate debt mirrors the need for external finance in financing investment.[1] Although the importance of debt in financing investment varies across firms and industries, one would expect that, if capital investment is a prime reason for borrowing, higher borrowing would be associated with an increase in aggregate demand.

The relationship between corporate borrowing and aggregate demand also stands in contrast with the relationship between household borrowing and aggregate demand. Both Mian et al. (2017) and Drehmann et al. (2018) find that household debt expansions have significant positive correlations with GDP in the short-run (4-5 years), although these authors also find that the correlation subsequently turns negative. This cyclical pattern between household borrowing and aggregate demand, however, has an intuitive explanation. If households borrow to finance durable consumption and residential investment, aggregate demand is likely to initially increase. As indebtedness generates debt service commitments and possibly lower future inflows of credit, the transfer of financial resources from households to creditors eventually increases, contributing to a decline in future spending (Drehmann et al., 2018).

The muted and largely a-cyclical relationship between corporate borrowing and real spending, by comparison, remains puzzling. It raises the question: what is the non-financial corporate sector borrowing for? Indeed, non-financial corporate debt-to-GDP ratios have increased almost everywhere in advanced economies (see Figure 3.1). In this chapter, we contribute to answering this question with an explanation based on the observation that new borrowing provides funds that can be given alternative uses besides the financing of capital investment in the domestic economy. These alternative uses include the repayment of existing debt, foreign direct investment, and the accumulation of a portfolio of financial assets.

Using flow of funds data for the non-financial corporate sector in sixteen advanced economies over the 1970-2018 period, in combination with a consistent set of accounting relationships, we find that new borrowing is strongly associated with a rise in holdings of fi-

[1] The reason why firms prefer debt to equity is that issuing new shares signals to outside investors that managers, which have an information advantage over new investors about the conditions of the firm, believe that shares of their firm are overvalued. As a result, announcements of equity (debt) issuance are associated with larger (smaller) declines in share prices.

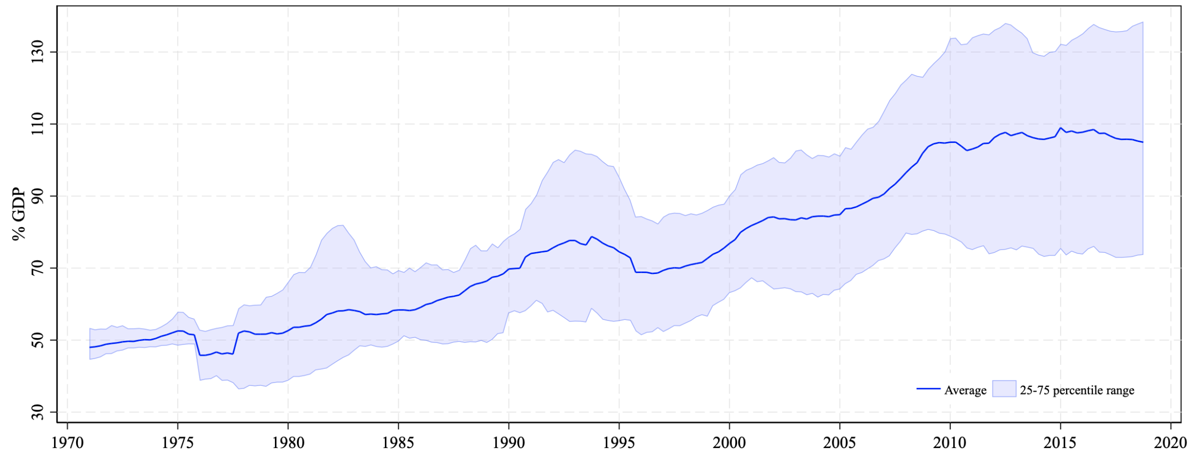


FIGURE 3.1: NON-FINANCIAL CORPORATE DEBT

Notes: this figure plots the average non-financial corporate debt-to-GDP ratio using quarterly data on the stock of debt from the Bank of International Settlements for the following countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain, Sweden, UK, US.

nancial assets net of non-debt liabilities, while being only weakly associated with an increase in capital expenditure. Our baseline estimates from a dynamic panel data model suggest that when new borrowing-to-GDP increases by 1 percentage point, the acquisition of financial assets by non-financial corporations, net of non-debt liabilities and as share of GDP, rises by 0.82 percentage points, while capital expenditure-to-GDP rises by only 0.03 percentage points. We find, moreover, that the initial infusion of cash that follows upon the settlement of a borrowing transaction accounts for only a small fraction of the increase in financial assets holdings, with the majority of the increase being accounted for non-cash assets. Finally, we combine sector-level flow of funds data with country-level balance of payment data to examine the extent to which the rise in financial assets net of non-debt liabilities is accounted for by foreign direct investment (i.e. the accumulation of large-stake equity holdings against foreign entities). While we do estimate a sizable relationship between new borrowing and foreign direct investment - a 1 percentage point increase in new borrowing-to-GDP by non-financial corporations leads to a 0.12 percentage point increase in net direct equity investment abroad as share of GDP - our findings still suggest that the main use of borrowed funds is the accumulation of financial assets as portfolio holdings in their own right.

Our findings have several implications for different strands of literature on the macroeconomic effects of non-financial corporations' uses and sources of funds. The result that part of borrowed funds may be channeled into the acquisition of financial assets provides an answer to the puzzle that, in aggregate data, corporate debt expansions do not predict significant boom-and-bust cycles in aggregate demand (Drehmann et al., 2018; Jordà et al., 2020, 2016; Mian et al., 2017). The muted correlation between corporate debt booms and economic activity contrasts with the importance of the *corporate debt overhang hypothesis* in the corporate finance literature (Lamont, 1995; Myers, 1977). According to the debt overhang hypothesis, high levels of debt can hold back investment because profits from new investments would benefit existing creditors rather than new shareholders. The empirical literature on the effects of corporate debt overhangs remains mixed. Most of the recent evidence comes from firm-level studies during the Great Recession in US (Giroud and Mueller, 2017) and in Europe (Kalemli-Özcan et al., 2019). However, during the Great Recession, corporate investment may have fallen for disparate reasons, in addition to or instead of debt overhang. Our emphasis on the accumulation of financial assets is complementary to Jordà et al. (2020) which rejects the corporate debt overhang hypothesis in aggregate data. They argue that corporate debt and future aggregate demand are weakly correlated because corporate debt, differently from household debt, can be easily restructured and this would prevent episodes of macroeconomic instability.

Our findings are related to the literature on the rise of corporate saving in advanced economies. Numerous studies document that, since the early 2000s, the non-financial corporate sector in many advanced economies accumulated substantial surpluses of saving relative to investment (*corporate saving glut*). As a result, non-financial corporations turned from being net borrowers, as they have historically been, to net lenders, with financial assets growing more than liabilities. This literature identifies several factors driving the rise of corporate net lending. Some of these factors are cyclical (Gruber and Kamin, 2016), while others are structural, such as rising profit share (Behringer, 2020), falling wage share (Villani, 2021), increasing profitability, falling cost of capital and corporate tax rates (Chen et al., 2017; Dao and Maggi, 2018), and growing investment abroad by non-financial corporations (Cesaroni et al., 2018).

Finally, our results contribute to the literature on the *financialization* of non-financial corporations with new insights on the relationship between debt, business investment and the accumulation of financial assets.[2] In this literature, rising holdings of financial assets on the balance sheets of non-financial corporations have ambiguous implications for business investment. Some studies argue that investment in financial assets or growing profit opportunities from financial investment may have crowded-out capital investment in US (Orhangazi, 2008), UK (Tori and Onaran, 2018) and in emerging economies (Demir, 2009). Instead, other studies argue that rising holdings of financial assets may support capital investment (see Davis, 2018, for the US). Indeed, large non-financial corporations are increasingly complex organizations which are often involved in the provision of financial services to their customers and, therefore, may create complementarities between real and financial capital. Rather, the rise of shareholder value orientation and *short-termism* are found to be important factors driving the post-1980s steep decline in the correlation between new borrowing and capital accumulation on the one hand, and, on the other hand, the rising correlation between new borrowing and

[2]According to Epstein (2005, p. 3), *financialization* can be defined as the "increasing role of financial motives, financial markets, financial actors and financial institutions in the operation of domestic and international economies". Davis (2017) provides a comprehensive survey of the empirical literature on financialization and corporate investment.

shareholder payouts in US (Davis, 2018; Mason, 2015).

ROAD MAP. The chapter is organized as follows. Section 3.2 provides motivating evidence that non-financial corporate debt expansions are weakly correlated with future aggregate demand. In Section 3.3, we describe the data and introduce the accounting and estimation framework. Section 3.4 presents and discusses the results. In Section 3.5, we discuss the robustness of our findings. Section 3.6 concludes.

3.2 Non-financial corporate debt and aggregate demand

We begin by showing that non-financial corporate debt expansions are weakly correlated with the future level of GDP as well as with the business investment share (Drehmann et al., 2018; Jordà et al., 2020, 2016; Mian et al., 2017). This evidence will serve as motivation for the main analysis that we introduce in the next section.

As in Mian et al. (2017), we estimate the dynamic response of GDP and of the business investment share to an impulse to non-financial corporate debt-to-GDP using the method of local projections (Jordà, 2005).[3] For each country $i = 1, \dots, n$, we let z_{it+h} be the logarithm of real GDP (y_{it+h}), or alternatively the business investment share (I_{it+h}/Y_{it+h}). The debt-to-GDP ratios, $d_{it}^{j} = \left(D_{it}^{j,BIS} / \sum_{l=0}^{4} Y_{it-l-1} \right)$ with $j = \{F, HH\}$, are obtained by normalizing the stock of debt (D^{BIS}) in the reference quarter by the sum of nominal GDP (Y) in the four quarters to the reference quarter. We distinguish between the non-financial corporate sector (F) and the household sector (HH), and lag the denominator. Data on the stock of sectoral debt are assembled from the Bank of International Settlements (BIS) *Long series of total credit to the non-financial sector*. These series record all outstanding debt of non-financial corporations and households borrowed from banks and other non-bank lenders. On average, non-financial corporate debt-to-GDP ratios increased over time at a roughly constant pace (see Figure 3.1).[4]

For each horizon $h = 0, \dots, H$, equation 3.1 regresses the variable of interest z on the lagged non-financial corporate and household debt-to-GDP ratios as well as on lags of the dependent variable:

$$z_{it+h} = \alpha_i^h + \theta_t^h + \sum_{p=1}^{P} \beta_{Fp}^h d_{it-p}^F + \sum_{p=1}^{P} \beta_{HHp}^h d_{it-p}^{HH} + \sum_{p=1}^{P} \gamma_p^h z_{it-jp} + \boldsymbol{\lambda}^h(L)' \mathbf{x}_{it} + \varepsilon_{it+h} \tag{3.1}$$

where α_i^h and θ_t^h are country and time fixed effects, respectively. The former controls for country-specific unobserved heterogeneity while the latter captures unobserved global factors which may explain variations in both GDP and the business investment share. For the

[3] Local projections are analogous to performing a series of direct forecasts and provide a simple way to estimate impulse response functions without assuming a VAR structure (Ramey, 2016). We stress that the impulse responses presented in this section should not be interpreted as representing causal effects. However, they can be used to shed light on the dynamic relationship between non-financial corporate debt expansions and aggregate demand.

[4] Data frequency is quarterly, from 1970Q1 to 2018Q4. Real GDP is from Monnet and Puy (2019). Business investment (I) is gross fixed capital formation of the non-financial corporate sector and Y is nominal GDP. Countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain, Sweden, UK, US.

specification where z is the business investment share, we include a vector of macroeconomic controls ($\mathbf{x}_{it}$) which are generally known to influence business investment while $\boldsymbol{\lambda}^h(L)$ is a vector of polynomials in the lag operator. We set a rather long horizon of 10 years for the local projections ($H = 40$) to ensure that our results are comparable to other studies using annual data and specifications similar to our own. In choosing the maximum lag length, we follow the recommendations in Montiel and Plagborg-Møller (2020) and set $J = 8$ quarters. They advocate for the use of lag-augmented local projections with many lags and controls when data are persistent, as our debt-to-GDP ratios, and the largest forecast horizon H is a non negligible fraction of the sample.

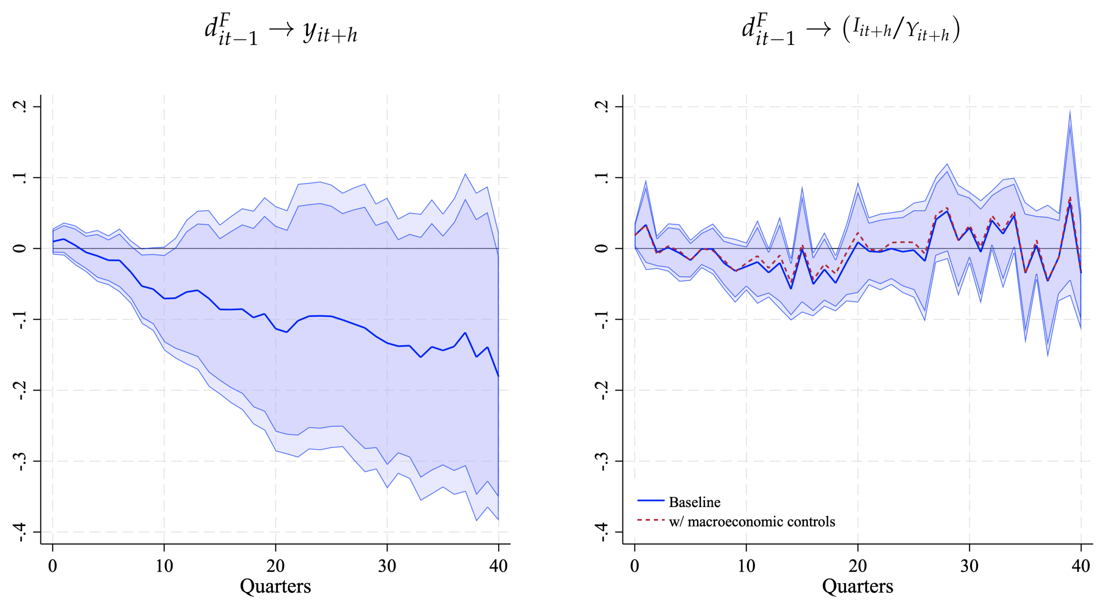
The estimated coefficient of interest is $\hat{\beta}^h_{F1}$ which traces out the response of the variable z at horizon $h = 0, \ldots, H$ to a temporary 1 percentage point (or unit change) shock to the non-financial corporate debt-to-GDP ratio in $t-1$ (d^F_{it-1}). These dynamic responses are estimated using a two-way fixed effects OLS estimator. Jordà (2005) warns that the residuals in local projections (ε_{it+h}) are serially correlated for $h \geq 1$ and that the order of the moving average structure in the residuals depends on the horizon h. Therefore, we obtain (HAC) robust standard errors (robust to cross-country heteroskedasticity and within-country serial correlation) and cluster them by country. We use these standard errors to produce confidence bands for impulse responses.[5]

Figure 3.2 plots the response of log real GDP (panel A) and of the business investment share (panel B) to a 1 percentage point temporary increase in the non-financial corporate debt-to-GDP ratio in $t-1$. Panel A shows that an increase in non-financial corporate debt is associated with lower GDP in the future. However, the estimated impulse response is almost never statistically different from zero at conventionally accepted confidence levels.[6]

In Panel B, the (blue) solid line plots the estimated response of the business investment share when we omit the vector of macroeconomic controls. Instead, the (red) dashed line is the response from a version of equation 3.1 with macroeconomic controls. The vector of controls ($\mathbf{x}_{it}$) includes corporate saving-to-GDP, the flow of corporate equity issued by non-financial corporations as share of GDP, and the level of medium to long term government bond yields. We include up to four lags of each control. The inclusion of corporate saving and equity issuance controls for the corporate financing mix (Myers, 2001). Instead, government bond yields are included to control for general financing conditions. The correlation between non-financial

[5]The OLS estimates may be biased. The inclusion of lags of the dependent variable on the right hand side of equation 3.1 exposes the model to the standard problem that the OLS estimator is biased and inconsistent in dynamic panel data models (Nickell bias). However, the Nickell bias is a large in "small T, large n context" which is not the case of our dataset. In fact, the importance of the bias decreases as T grows relative to n. Our dataset has a minimum of 79 time-observations per country at the highest horizon of the local projection and $n = 16$. Moreover, because debt-to-GDP ratios are unlikely to be exogenous to disturbances to GDP and to the business investment share, the impulse response functions estimated with local projections are not directly comparable to the impulse responses from an identified structural VAR.

[6]In contrast, an increase in the household debt-to-GDP ratio is associated with a temporary rise in GDP which returns back to the initial level within five years. We report this result in Figure C.1 in Appendix C.2.



(A)

(B)

FIGURE 3.2: LOCAL PROJECTIONS: REAL GDP (y_{it+h}) AND BUSINESS INVESTMENT $\left({}^{I_{it+h}}/_{Y_{it+h}}\right)$

Notes: this figure plots the response of log real GDP (y_{it+h}, panel A) and of the business investment share (${}^{I_{it+h}}/_{Y_{it+h}}$, panel B) to a one percentage point increase in the non-financial corporate debt-to-GDP ratio in $t-1$ (d^F_{it-1}). The (blue) solid line is the estimated coefficient. Dark and light shaded regions are 90% and 95% confidence intervals constructed using HAC standard errors clustered by country. In panel B, the (red) dashed line is the response of the business investment share when the extended set of controls $\mathbf{x}_{it}$ in equation 3.1 is considered.

corporate debt-to-GDP ratios and the future level of the business investment share is weak. Although the estimates are imprecise, non-financial corporate debt expansions are more likely to be associated with lower, though small, than with higher future levels of the business investment share.[7]

To sum-up, local projections show that shocks that raise the non-financial corporate debt-to-GDP ratio have weak and even negative effects on the future path of log real GDP. In absolute value, the correlation between corporate debt booms and future GDP is extremely smaller than the correlation between corporate debt booms and future GDP (see Figure C.1 in Appendix C.2). Similarly, non-financial corporate debt expansions are weakly correlated with the future level of the business investment share. The response of real activity to a shock to non-financial corporate debt is somewhat at odds with the conventional wisdom according to which firms

[7]In Appendix C.2, we show that the relationship between non-financial corporate debt and aggregate demand is robust to different specification choices. The effects of non-financial corporate debt-to-GDP on log real GDP (Figure C.1, panel A) and on the business investment share (Figure C.3, panel A) are qualitatively unchanged when we omit time fixed effects from equation 3.1, as most of the literature does (see for example Drehmann et al., 2018; Mian et al., 2017). In contrast, the response of log real GDP to household debt expansions is dramatically sensitive to the inclusion/exclusion of time fixed effects (Figure C.1, panel B). Figure C.2 and Panel B in Figure C.3 show that all results are qualitatively unchanged for a specification in which the non-financial corporate debt-to-GDP ratio enters in first difference and the dependent variables are expressed as cumulative changes or cumulative changes in logarithms. Moreover, the results on the business investment share are robust to a specification in which we use capital expenditure rather than gross fixed capital formation to proxy business investment (Figure C.3, panel C).

borrow to finance investment expenditure which, in turn, would be associated with an increase in aggregate demand.

3.3 Data and empirical strategy

We have established that non-financial corporate debt-to-GDP does not correlate neither with higher GDP nor with growth in the domestic business investment in the future. Rather, a temporary increase of non-financial corporate debt relative to GDP leads to a mild decline in economic activity, all else equal. However, if debt does not finance the accumulation of physical capital in any meaningful magnitude, the question of what is the non-financial corporate sector borrowing for remains unanswered.

In this chapter, we use data on sources and uses of funds to explore whether firms' other uses of borrowed funds may explain the low responsiveness of real activity to increases in non-financial corporate debt. More specifically, we ask whether an increase in borrowing by non-financial corporations is associated with a rise in the accumulation of financial assets on their balance sheets. We begin by motivating the plausibility that non-financial corporations channel part of borrowed funds into the acquisition of financial assets. To this end, we present some descriptive evidence of a link between new borrowing and holdings of financial assets on the non-financial corporate sector's balance sheet. Then, we use a set of regressions to support this hypothesis.

3.3.1 Data

We assemble quarterly data on non-financial corporate debt, household debt, business investment, uses and sources of funds by the non-financial corporate sector, interest rates and stock prices for an unbalanced panel of sixteen advanced economies (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain, Sweden, United Kingdom, United States) from 1970 to 2018. We focus on a narrow cross-section of countries in order to keep the sample as homogeneous as possible relative to country-specific institutional factors. Table 3.1 lists some of the key variables used along the chapter with summary statistics while Appendix C.1 provides more details on the construction of variables, sources and definition.

NON-FINANCIAL CORPORATIONS' SOURCES AND USES OF FUNDS. We collect time series of transactions (or flows) in financial assets and liabilities for the non-financial corporate sector. The main sources of data are the national accounts and, in particular, the financial and capital account. For what concerns the financial flows, we narrow our focus on transactions in order to exclude changes in sources and uses of funds driven by price changes (e.g. changes in share prices that impact on the value of equity or changes in interest rates that impact on the value of corporate bonds) and by other changes (e.g. reclassification of institutional units). Non-financial corporations' sources and uses of funds cover data on gross fixed capital formation, capital expenditure, corporate saving net of capital transfers, equity issuance, new borrowing (bonds and loans), and holdings of different types of financial assets (e.g. cash-like and non-cash financial assets).[8]

COUNTRY-WIDE VARIABLES. We collect data on macroeconomic and financial conditions at country-level. We retrieve data on quarterly log real GDP, medium-long term government bond yields (seven to ten years), and stock price indexes from the dataset by Monnet and Puy (2019).[9] Moreover, we collect data on new direct and portfolio investment abroad from the Balance of Payment Statistics.

TABLE 3.1: SUMMARY STATISTICS

Symbol	Name	Obs.	Mean	Std. dev.	Source
STOCK VARIABLES AS SHARE OF GDP					
d^F	Non-financial corporate debt (% GDP)	2022	84.95	31.59	BIS
A/Y	Non-financial corporate financial assets (% GDP)	1421	146.40	86.01	FA
L/Y	Non-financial corporate liabilities, net of corporate equity (% GDP)	1425	120.29	42.79	FA
d^{HH}	Household debt (% GDP)	2042	60.90	25.58	BIS
NON-FINANCIAL CORPORATIONS' SOURCES AND USES OF FUNDS (FLOWS)					
I/Y	Business investment share (% GDP)	1474	10.46	3.34	CA
k/Y	Capital expenditure (% GDP)	1474	10.85	3.54	CA
S/Y	Corporate saving (% GDP)	1474	11.25	4.19	CA
$(S-K)/Y$	Net lending, from Capital Account (% GDP)	1474	0.34	3.30	CA
b/Y	New borrowing (% GDP)	1455	4.07	6.46	FA
$(a-l)/Y$	Net accumulation of financial assets (% GDP)	1455	3.27	7.22	FA
$(a^{Cash}-l)/Y$	Net accumulation of cash-like financial assets (% GDP)	1455	-2.62	6.89	FA
$(a^{Non-cash}-l)/Y$	Net accumulation of non-cash financial assets (% GDP)	1455	2.33	7.07	FA
E/Y	Equity issuance (% GDP)	1455	2.37	4.96	FA
COUNTRY-WIDE VARIABLES					
DI/Y	Net direct equity investment abroad (% GDP)	1337	0.68	6.07	BoP
PI/Y	Net portfolio equity investment abroad (% GDP)	1409	-0.15	4.33	BoP

All summary statistics are computed by pooling observations from all countries. BIS = Bank of International Settlements, FA = Financial Accounts, CA = Capital Account, BoP = Balance of Payment Statistics.

3.3.2 National accounting framework

We begin by looking at the aggregate sector-level statistics on the financing of physical and financial assets growth. Conventionally, the financing gap is determined by the investment-saving balance, namely by the difference between capital expenditure and retained earnings or corporate saving. The balance of the capital account determines if internally generated funds (saving, S) finance the accumulation of non-financial assets (capital accumulation or invest-

[8] In order to ensure consistency between data published by different statistical offices, we use national account data organized under the common framework of the System of National Accounts (SNA) 2008. Therefore, our primary source of data are the Quarterly Sector Accounts available at the ECB Statistical Data Warehouse, the Finance and Wealth Accounts published by the Australian Bureau of Statistics, the Financial and Wealth Accounts published by Statistics Canada, and the Integrated Macroeconomic Accounts of the United Stated published by the Federal Reserve Board in the Z.1 Financial Accounts release.

[9] In Monnet and Puy (2019), bond yields data are not available for Austria, Finland, Greece, Spain; likewise, stock price indexes are not available for Greece and Portugal. Therefore, we replace missing observations with an average bond yields and average stock price indexes computed using observations from all other countries.

ment, I). As a result, the sign of the financing gap determines if the sector is net lender or net borrower toward the rest of the economy. In principle, the net lending/borrowing position emerging from the capital account mirrors the balance of the financial account. If the expenditure for capital accumulation exceeds (falls behind) saving, the financing gap will result in liabilities (L) growing more (less) than financial assets (A). In other words, the non-financial corporate sector, lacking of internally generated funds, incurs into more liabilities and may do it eventually through a rise in debt-liabilities, namely by taking on debt.

The relationship between the investment-saving balance and the financial account position can be embedded in the following flow budget constraint for the non-financial corporate sector in country i:

$$I_{it} - S_{it} = l_{it} + b_{it} - a_{it} - \eta_{it}$$

where I_{it} is (gross) capital expenditure, S_{it} is gross saving less net capital transfers paid, $l_{it} \equiv \Delta L_{it} = L_{it} - L_{it-1}$ is the net change in non-debt liabilities, $b_{it} \equiv \Delta D_{it} = D_{it} - D_{it-1}$ is the net change in debt (loans and bonds) liabilities (D is the stock of debt), and $a_{it} \equiv \Delta A_{it} = A_{it} - A_{it-1}$ is the net change in financial assets.[10] For the sake of clarity and to not induce confusion with the variables used in the previous section, we will refer to b_{it} as new borrowing by non-financial corporations or simply new borrowing. The term $(l_{it} + b_{it})$ equals the net change in total (debt and non-debt) liabilities. The extra-term η_{it} is the statistical discrepancy that reconciles the financing gap from the capital account with the net borrowing/lending position from the financial account.[11]

After manipulating the previous identity and normalizing all quantities by country-level nominal GDP (Y_{it}), we can express new borrowing-to-GDP (b_{it}/Y_{it}) as the difference between the financing gap from the capital account ($(S_{it}-I_{it})/Y_{it}$) and (net of debt) net lending/borrowing position from the financial account ($(a_{it}-l_{it})/Y_{it}$), corrected by the discrepancy (η_{it}):

$$\underbrace{\underbrace{\frac{(S_{it} - I_{it})}{Y_{it}}}_{\text{Capital Account}} - \underbrace{\frac{(a_{it} - l_{it})}{Y_{it}}}_{\text{Financial Account}}}_{\text{Balance from}} - \underbrace{\frac{\eta_{it}}{Y_{it}}}_{\text{Discrepancy}} = \underbrace{-\frac{b_{it}}{Y_{it}}}_{\text{New borrowing}} \tag{3.2}$$

[10]Note the change of notation. While in the previous section, lowercase letters refer to stock of debt-to-GDP ratios, from now on we use the lowercase letter to identify flows.

[11]The discrepancy is due to measurement errors and because the capital account and the financial account use different source of data. When the discrepancy is not reported, we follow the method used in the Z.1 Financial Account of US and obtain the discrepancy as the difference between the aggregate value of the sector's sources of funds and the value of its uses of funds, namely:

$$\begin{aligned} & S + l^{tot} - (I + a) \\ =& S - I - a + l^{tot} \\ =& (S - I) - (a - l^{tot}) \\ =& \underbrace{\text{Financing gap}}_{\text{Capital Account}} - \underbrace{\text{Net lending}}_{\text{Financial Account}} = \eta \end{aligned}$$

where l^{tot} is the change in total (debt and non-debt) liabilities.

Positive values of net lending from the financial account ($(a_{it}-l_{it})/Y_{it} > 0$) suggest that the non-financial corporate sector is acquiring financial assets over non-debt liabilities, as share of GDP. Therefore, from now on, we will refer to the term $(a_{it} - l_{it})$ as the accumulation of financial assets net of non-debt liabilities, or simply net accumulation of financial assets.[12]

In Table 3.2, we use our dataset to give a sense of the quantities in equation 3.2. More specifically, we split the sample in ten sub-samples each of equal length of 20 quarters and, for each sub-period, average the quantities across countries (standard deviations are reported in brackets). These quantities reveal three relevant patterns or *stylized facts* on the sources and uses of funds by the non-financial corporate sector.

THE CORPORATE SAVING GLUT. The balance from the capital account, namely the financing gap $(S - I)$, suggests that the need for external funds to finance the accumulation of non-financial assets has become smaller. Until the late 1990s, non-financial corporations were, on average, net borrowers toward the rest of the economy as investment expenditure exceeded corporate saving. However, starting from the early of 2000s, non-financial corporations have systematically saved more than what they have invested, on average. This excess of corporate saving over investment made the non-financial corporate sector net lender toward the rest of the economy. In the literature, the rise of corporate saving over investment is known as the *corporate saving glut*, a well documented phenomenon in advanced economies (Behringer, 2020; Chen et al., 2017; Dao and Maggi, 2018; Gruber and Kamin, 2016).

RISING ACQUISITION OF FINANCIAL ASSETS. In part as direct consequence of the corporate saving glut, during the same period the non-financial corporate sector increased its holdings of currency, deposits, equities and other financial assets, net of non-debt liabilities. Between 1995 and 2018, the quarterly net accumulation of financial assets by the whole sector was about 3.5% of GDP, on average. Ultimately, continuous positive rates of net accumulation of financial assets contributed to raise the stock of financial assets on the balance sheet of the non-financial corporate sector. The average stock of financial assets-to-GDP ratio in our sample was 128% in 1995, 136% in 2010 and 171% in 2018. A similar trend for the rise of financial assets has been documented by Davis (2018) for a sample of US non-financial firms.[13]

GROWING NON-FINANCIAL CORPORATE DEBT. On average, the non-financial corporate sector has been running-up debts during all sub-samples. Between 1995 and 2018, new borrowing in corporate bonds and loans was about 4% of GDP. Between 2005 and 2009, the average quarterly increase of non-financial corporate debt stood at about 6.2% of GDP. The high value for the average standard deviation in this period is likely to reflect the increase in leverage and

[12] Along the chapter, we use net accumulation, net acquisition and net growth of financial assets interchangeably. In all cases, and unless differently specified, they indicate the flow of financial assets, net of changes in non-debt liabilities.

[13] Davis (2018) documents a shift in the composition of balance sheets using firm-level data for the US between 1971 and 2013. Total financial assets as share of sales has risen from 28.6% (1971) to 50.0% (2013) for small firms and from 28.8% (1971) to 42.4% (2013) for large firms. Similarly, fixed capital as share of sales declines from 17.5% (1971) to 7.1% (2013) for small firms and from 49.3% (1971) to 30.7% (2013) for large firms.

de-leverage of corporate debt during the crisis. As with the accumulation of financial assets, the stock of non-financial corporate debt increased too, as it shown in Figure 3.1.

TABLE 3.2: SOURCES AND USES OF FUNDS IN THE NON-FINANCIAL CORPORATE SECTOR

T_α	(1) 1970-74	(2) 1975-1979	(3) 1980-84	(4) 1985-89	(5) 1990-94	(6) 1995-99	(7) 2000-04	(8) 2005-09	(9) 2010-15	(10) 2015-18
$(S-I)/Y$	-1.25	-0.35	-0.78	-1.09	-0.52	-0.79	0.35	0.058	1.52	0.67
	(0.86)	(0.87)	(0.97)	(1.93)	(1.33)	(3.77)	(4.54)	(4.98)	(4.66)	(4.79)
$(a-l)/Y$	1.80	0.38	1.87	2.60	-0.95	3.56	3.80	4.89	2.82	2.63
	(2.17)	(1.35)	(2.41)	(3.63)	(3.66)	(6.03)	(8.09)	(7.93)	(8.00)	(9.82)
η/Y	0.63	2.02	0.73	1.51	1.25	0.89	1.49	1.36	0.69	0.63
	(2.08)	(1.13)	(1.53)	(2.94)	(3.04)	(3.94)	(6.17)	(5.37)	(5.24)	(4.54)
b/Y	3.68	2.75	3.37	5.19	0.82	5.25	5.22	6.20	1.99	2.69
	(1.34)	(1.05)	(1.49)	(3.66)	(2.94)	(4.86)	(5.97)	(7.27)	(6.56)	(7.92)
Observations	20	20	20	26	60	117	320	320	320	256

All quantities are normalized by country-level GDP (Y_{it}). For each sub-sample $\alpha = 1, \ldots, 10$, the averages are obtained as:

$$\frac{(S-I)}{Y} = \frac{1}{nT_\alpha}\sum_{i=1}^{n}\sum_{t=1}^{T_\alpha}\frac{(S-I)_{it}}{Y_{it}}, \quad \frac{(a-l)}{Y} = \frac{1}{nT_\alpha}\sum_{i=1}^{n}\sum_{t=1}^{T_\alpha}\frac{(a-l)_{it}}{Y_{it}}, \quad \frac{\eta}{Y} = \frac{1}{nT_\alpha}\sum_{i=1}^{n}\sum_{t=1}^{T_\alpha}\frac{\eta_{it}}{Y_{it}}, \quad \frac{b}{Y} = \frac{1}{nT_\alpha}\sum_{i=1}^{n}\sum_{t=1}^{T_\alpha}\frac{b_{it}}{Y_{it}}$$

The series used to obtain this table are not seasonally adjusted.

3.3.3 Interpreting the stylized facts

The stylized facts in Table 3.2 suggest that the non-financial corporate sector accumulated debt while having, at the same time, an excess of corporate saving over investment spending. How can we interpret these stylized facts? The stylized facts, in combination with the accounting framework introduced above, suggest that rising non-financial corporate debt may have been channeled into the accumulation of financial assets. Indeed, the sign of the financing gap suggests that, after the early 2000s, corporate saving was enough to pay for investment expenditure. From the outset, we stress that our interpretation is based on accounting relationships and therefore it does not necessarily implies a behavioral interpretation of firms' uses and sources of funds.

To motivate our interpretation of the stylized facts, let's start from a scenario in which the only asset in which the non-financial corporate sector invests is a physical asset which accumulation is I. In this case, the relationship between sources and uses of funds is represented by the following identity:

$$I = S + l + b$$

where we omitted time and country indexes as well as the statistical discrepancy. We also assume that investment spending (I) is primarily financed with corporate saving (S). This assumption is consistent with firms facing a menu of financing choices when deciding about the capital structure in which internal funds are preferred to external finance (Myers, 2001). If the non-financial corporate sector as a whole invests more than what it saves, then $I > S$. Accordingly, the excess of investment spending over saving is met by issuing more liabilities. One the one hand, the sector may finance the difference between investment spending and corporate saving by issuing debt (corporate bonds and loans, $b > 0$), and, therefore, making the stock of debt growing. On the other hand, the discrepancy between investment spending and corporate saving may be financed by issuing corporate equities ($l > 0$).[14] Alternatively, both b and l can grow if firms finance investment using a mix of debt and equity. Therefore, the financing gap from the capital account results in the non-financial corporate sector being net borrower toward other sectors in the economy, e.g. toward the financial and household sectors. It is important to stress that, in this oversimplified example, corporate debt increases because the non-financial corporate sector, lacking of internally generated funds, borrows in order to finance investment spending. Similarly, if investment spending equals or falls short of corporate saving ($I \leq S$), the accounting identity above implies that debt and non-debt liabilities have to (jointly) decrease by the same amount of excess saving.[15]

To sum up, if non-financial corporations can only invest in physical assets, and borrowing occurs because of a lack of internally generated funds to finance investment spending, debt accumulation ($b > 0$) can only be associated with investment spending exceeding corporate saving ($I > S$). However, Table 3.2 suggests that investment spending exceeding corporate saving was not been a feature of the data since the early 2000s. Meanwhile, non-financial corporate debt accumulated.

Imagine now that non-financial corporations can also invest in financial assets, in addition to physical assets, and that a is the financial investment. In this case, the accounting identity that connects sources to uses of funds is:

$$I + a = S + l + b$$

If corporate saving exceeds investment spending ($S \geq I$), as Table 3.2 suggests to be the case since the early 2000s, then it is reasonable to think that the accumulation of debt *finances* the net acquisition of financial assets (at least in an accounting sense). Indeed, if there is no need for external funds to finance investment expenditure as the balance from the capital account suggests and if here is a *finance motive* to borrow (namely, if firms borrow to finance investment spending), then additional debt would channel into the net accumulation of financial assets. Therefore, the accounting framework suggests that, if non-financial corporations invest in financial assets in addition to physical assets, the stylized facts from Table 3.2 can consistently coexists: *(i)* negative financing gap ($S \geq I$), *(ii)* acquisition of net financial assets ($a - l \geq 0$), and *(iii)* growing non-financial corporate debt (persistent $b > 0$).

This simple interpretation of the stylized facts yields a testable prediction regarding the

[14] Although we define l to be non-debt liabilities, most of these liabilities are corporate equities and shares. See Figure C.5 in Appendix C.5.

[15] In reality, the non-financial corporate sector becomes net lender whenever $I \leq S$. However, in this example, excess saving does not imply the automatic accumulation of financial assets and the emergence of a net lending position. Without financial assets (not even cash) in which park excess saving, excess saving over investment implies a reduction of liabilities (e.g. repayment of existing debts) by the same amount of the difference between I and S.

relationship between rising non-financial corporate debt and the accumulation of financial assets. We present this test in Table 3.3. The table reports estimates from a simple model that regresses the net accumulation of financial assets-to-GDP on new borrowing-to-GDP (panel A). In panel B, we report the results from a similar model but with capital expenditure-to-GDP as dependent variable. We interpret the estimated coefficient as representing the contemporaneous partial correlation between new borrowing and the net accumulation of financial assets (panel A), and between new borrowing and capital expenditure (panel B). In estimating the contemporaneous correlations, we control for country-level heterogeneity and time-varying global shocks. We normalize new borrowing by lagged GDP in order to avoid that the ratios are driven by disturbances to contemporaneous GDP. Although our main source of data for new borrowing are flows from the financial accounts, we also use measures of new borrowing obtained from the BIS dataset.[16]

Panel A in Table 3.3 shows that an increase in new borrowing is positively associated with a rise in the net accumulation of financial assets. The partial correlation is statistically significant and robust to changing data source and to the inclusion of time fixed effects. For the case of BIS-based new borrowing, we find that the estimated correlation is lower in magnitude but still statistically significant.[17] Turning to the accumulation of non-financial assets, Panel B indicates that a rise in new borrowing is positively associated with an increase in capital expenditure but the magnitude of the correlation is dramatically smaller relative to the estimates in Panel A.

3.3.4 Estimation framework

IWe established that an increase in new borrowing is positively correlated with a rise in the net accumulation of financial assets by non-financial corporations. On the contrary, capital expenditure moves very little in response to changes in new borrowing. We now expand the simple specification used to obtain the correlations in Table 3.3 in two directions. First, we explore how robust is the relationship between new borrowing and net growth of financial assets to a richer model that controls for persistence in financial variables and for macroeconomic conditions. Second, since *financial assets* is a rather heterogeneous family of financial instruments, we explore which category of financial assets effectively drives the correlations reported in Panel

[16] We use both transaction-based and BIS-based series for new borrowing because estimates using financial accounts data may reflect some built-in correlation since many items in the financial accounts are computed as residuals. As a robustness check, we estimate the contemporaneous correlations reported in Panel B of Table 3.3 using gross fixed capital formation instead of capital expenditure. We do not report these estimates but they are very similar to these in Table Table 3.3.

[17] We obtain qualitatively similar results when we use BIS-based series. However, the quantitative differences between columns (1) and (2) and columns (3) and (4) are substantial and can be explained by the fact that changes in the BIS stock of debt do not necessarily reflect transactions. The new borrowing series, b_{it}, correctly trace out transactions in loans and debt securities on the liability side of the balance sheets because they are retrieved from the transaction account of the financial accounts. While, the BIS-based new borrowing series, b_{it}^{BIS}, are obtained as the change in stock of debt and this change is affected by transactions, revaluations, and other changes. Therefore, the presence of revaluations and other changes may explain why using b_{it} and b_{it}^{BIS} yields results which are qualitatively analogous but quantitatively different.

TABLE 3.3: CORRELATION BETWEEN NEW BORROWING AND ASSETS ACCUMULATION

Panel A: *Net accumulation of financial assets*				
	Dependent variable: $(a_{it}-l_{it})/Y_{it}$			
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.778***	0.827***		
	(0.061)	(0.054)		
b_{it}^{BIS}/Y_{it-1}			0.512***	0.516***
			(0.062)	(0.075)
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects		✓		✓
within-R^2 (adj.)	0.557	0.604	0.313	0.374
Observations	1455	1455	1454	1454

Panel B: *Accumulation of non-financial assets*				
	Dependent variable: k_{it}/Y_{it}			
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.069**	0.036**		
	(0.024)	(0.019)		
b_{it}^{BIS}/Y_{it-1}			0.054***	0.031**
			(0.014)	(0.012)
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects		✓		✓
within-R^2 (adj.)	0.092	0.336	0.076	0.335
Observations	1450	1450	1473	1473

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table shows the contemporaneous correlations between the new borrowing-to-GDP and the net accumulation of financial assets-to-GDP (panel A) and between new borrowing-to-GDP and capital expenditure-to-GDP (panel B). For a generic dependent variable z, the contemporaneous correlation, conditional on country and time fixed effects, is the OLS estimate of the coefficient β from the following regression:

$$z_{it} = \alpha_i + \theta_t + \beta\left(\frac{b_{it}}{Y_{it-1}}\right) + \varepsilon_{it} \quad \text{with} \quad z_{it} = \left\{\frac{(a_{it}-l_{it})}{Y_{it}}, \frac{k_{it}}{Y_{it}}\right\}$$

In columns (1)-(2), new borrowing is obtained using transaction-based data from the financial accounts, while in columns (3)-(4) new borrowing is obtained as first difference of the BIS stock of debt, that is $b_{it}^{F,BIS} = D_{it}^{F,BIS} - D_{it-1}^{F,BIS}$. All variables are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A of Table 3.3.

We postulate a standard dynamic two-way fixed-effects panel data model that regresses a generic variable of interest z_{it} on contemporaneous and lagged new borrowing-to-GDP (b_{it}/Y_{it-1}), on lags of z and on a vector of macroeconomic controls ($\mathbf{x}_{it}$):

$$z_{it} = \alpha_i + \theta_t + \beta \left(\frac{b_{it}}{Y_{it-1}} \right) + \sum_{p=1}^{P} \delta_p \left(\frac{b_{it-p}}{Y_{it-p-1}} \right) + \sum_{p=1}^{P} \gamma_p z_{it-p} + \boldsymbol{\lambda}' \mathbf{x}_{it} + \varepsilon_{it} \tag{3.3}$$

where α_i captures country-level unobserved heterogeneity and θ_t controls for time-varying global shocks. We include up to $P = 4$ lags of new borrowing and of the dependent variables. The choice of lags is consistent with studies using quarterly macroeconomic data. Moreover, we find that increasing the maximum lag length does not change the main results.[18]

For the generic dependent variable z, we consider proxies for the accumulation of financial assets at the level of the non-financial corporate sector as well as country-level. More specifically, the generic dependent variable z will be, alternatively:

- accumulation of total financial assets, net of non-debt liabilities and as share of GDP, or net accumulation of financial assets-to-GDP ($(a_{it}-l_{it})/Y_{it}$).
- accumulation of cash-like financial assets, net of non-debt liabilities and as share of GDP, or net accumulation of cash-like financial assets-to-GDP ($(a_{it}^{Cash}-l_{it})/Y_{it}$),
- growth of non-cash financial assets, net of non-debt liabilities and as share of GDP, or net accumulation of non-cash financial assets-to-GDP ($(a_{it}^{Non-cash}-l_{it})/Y_{it}$),
- country-level net direct equity investment abroad as share of GDP, DI_{it}/Y_{it},
- country-level net direct portfolio investment abroad as share of GDP, PI_{it}/Y_{it}.

For each country, net accumulation of financial assets, net accumulation of cash-like financial assets, and net accumulation of non-cash financial assets are constructed using data from the financial accounts of the non-financial corporate sector. Instead, data on investment abroad refer to the total economy. We will discuss the choice of the dependent variables when we discuss the results in Section 3.4.

The vector $\mathbf{x}_{it}$ contains macroeconomic variables which are likely to affect the dependent variables independently of new borrowing. In fact, the accumulation of financial assets by non-financial corporations, or alternatively investment abroad, is likely to depend on the growth of the economy and on the conditions in equity and bond markets. The macroeconomic controls are:

- Log real GDP growth (Δy_{it}) controls for the correlation between business cycles and financial assets growth. During recessions, firms may prefer to accumulate cash and other

[18] We provide unit root tests of the series used in the model in Table C.1 in Appendix C.3.

financial assets as current and expected demand contracts. This may be driven by a lack of investment opportunities or by precautionary saving. For example, as Gruber and Kamin (2016) show for a sample of OECD economies, non-financial corporations run substantially higher surpluses of saving over investment, and hence they accumulated financial assets, in countries that experienced large slowdowns in growth during the Great Recession.

- Quarterly changes in stock prices (Δp_{it}) from Monnet and Puy (2019) controls for conditions in equity markets. In general, large non-financial corporations are responsive to changes in equity market conditions (see Ma, 2019, for US non-financial corporations). Moreover, rising stock prices and equity valuations could represent an incentive for non-financial corporations to divert funds toward investment in financial markets.

- Government bond yields (g_{it}) from Monnet and Puy (2019) are included to capture general financing conditions in the economy as well as the level of interest rates.

We are interested in estimating the coefficient β which captures that contemporaneous response of each variable of interest z to a unit change in new borrowing-to-GDP ($^{b_{it}}/_{Y_{it-1}}$). An estimate of β provides a sense of the relationship between the accumulation of non-financial corporate debt and the growth of financial assets on the balance sheet of the non-financial corporate sector. We emphasize that we do not attach any causal interpretation to β. In fact, reverse causality and omitted variables may be serious biases. For example, firms may have plans about their financial policy and adjust borrowing accordingly. Moreover, we do not control for any factor related to expectations which can drive both borrowing and investment behavior. Having said that, the evidence of a weak correlation between new borrowing and investment spending from Table 3.3 as well as the accounting framework introduced above together motivate a potentially strong link between non-financial corporate debt and financial investment.

3.4 Results

In this section, we present the results from the estimation of equation 3.3. The model is estimated using a two-way fixed-effects OLS estimator and we obtain standard errors robust to cross-country heteroskedasticity and within-country serial correlation. We cluster robust standard errors at country-level. For each specification, we start by discussing a parsimonious model in which only lags of new borrowing and of the dependent variable of interest are included. Then, we enrich the model with macroeconomic controls. In the tables presented in this section, we report only the estimated coefficient associated with the new borrowing, namely $\hat{\beta}$. However, we report tables with all coefficients in Appendix C.3.

3.4.1 Does new borrowing lead to a rise in the acquisition of financial assets?

We begin by estimating a version of equation 3.3 in which the dependent variable is the net accumulation of total financial assets as share of GDP ($(a_{it}-l_{it})/Y_{it}$). In the financial accounts, total financial assets is the highest level of aggregation of financial instruments. Hence, a rise in total financial assets, net of the flow of non-debt liabilities, suggests that non-financial corporations increased holdings of financial claims, equity and cash, relative to changes in liabilities. Columns 1 in Table 3.4 shows that an increase in new borrowing is associated with a rise in the net accumulation of financial assets. The coefficient on new borrowing implies that a 1 percentage point increase in new borrowing-to-GDP leads to an increase in the net acquisition of financial assets by about 0.86 percentage points of GDP. The estimated coefficient is statistically significant and robust to the inclusion of macroeconomic controls (see Column 2). This finding confirms the intuitions from the accounting framework introduced above and suggests that non-financial corporations likely borrow to increase holdings of financial assets on their balance sheets.

New borrowing and the accumulation of financial assets during credit expansions

So far, we focused on new borrowing, namely on the cash flow from lenders to non-financial corporations. Our emphasis on the flow of credit makes our analysis similar to Drehmann et al. (2018) which focus on the real effects of new borrowing by households. To the extent that the correlations reported in columns (3)-(4) in Table 3.4 are determined by the choice of non-financial corporations to borrow to increase holdings of financial assets, this choice may depend on the (relative) level of debt. For example, it is possible that in periods of large private credit expansions, non-financial corporations may decide to shift the composition of their portfolio toward holding more financial assets (not necessarily at the cost of reducing real investment). This may occur for a number of reasons. First, large non-financial corporations are increasingly involved in the provision of financial services toward their customers and they expand their activities beyond the core business (Davis, 2017). During periods of credit expansions, when also demand grows, non-financial corporations may increase holdings of financial assets in order to meet higher demand for financial services connected to their core businesses. Another reason why the correlation between new borrowing and rising acquisition of financial assets may be higher during private credit expansions concerns speculation (Kindleberger, 1978; Minsky, 1986). During credit expansions, credit spreads squeeze and asset prices rise (Jordà et al., 2015; López-Salido et al., 2017). Hence, rising returns on financial investments may be an incentive for firms to hold more financial assets.

In Column 3 in Table 3.4, we explore whether the correlation between new borrowing and the acquisition of financial assets changes according to whether the economy is experiencing a private credit expansion. We create a dummy variable (LEV_{it}) that takes value 1 if the private sector (households and non-financial corporations) is in a high leverage state. On the contrary,

$LEV_{it} = 0$ if the private sector is in a low leverage state. We assume that the economy is experiencing an expansion in private credit if the private sector is in a high leverage state.[19] We identify periods of high and low leverage using a standard approach in the literature on credit gaps (Drehmann and Yetman, 2018). This approach consists in de-trending the non-financial private debt to-GDP-ratio using a Hodrick–Prescott filter. Then, a country-quarter observation is assigned to the high (low) leverage state if the private debt-to-GDP ratio is above (below) the trend.[20] The results are provided in Column 3 in Table 3.4. When country-quarter observations are not sorted according to the leverage state, the correlation between new borrowing-to-GDP and the net accumulation of financial assets as share of GDP is positive and statistically significant but slightly lower than in Column 1. How does the correlation change when the economy is experiencing a private credit boom? We look at the estimated coefficient associated with the interaction term (Column 3). The estimated coefficient, which is positive and (marginally) statistically significant, suggests that growth in the net accumulation of financial assets as share of GDP in response to a one percentage point rise in new borrowing-to-GDP is greater by about 0.06 percentage points when the country is experiencing a private credit expansion.

In sum, Table 3.4 confirms the contemporaneous correlations presented in the previous section and lend support to the idea that non-financial corporations may funnel (part of) debt accumulation into increasing their holdings of financial assets.

3.4.2 Are cash holdings driving the rise in financial assets acquisition?

The correlation between new borrowing by non-financial corporations and rising holdings of financial assets, net of non-debt liabilities, may reflect the initial infusion of cash that follows upon the settlement of a borrowing transaction. After all, cash and cash-like financial instruments account for a non-negligible share of total financial assets.[21] Moreover, in an environ-

[19]We obtain similar results if we condition the correlation between new borrowing and the acquisition of financial assets to high/low leverage of the non-financial corporate sector only.

[20]For the Hodrick–Prescott filter, we choose a very high smoothing parameter ($\lambda = 10^6$) in order to obtain a very smooth trend for private debt-to-GDP ratios. This is consistent with assuming that credit cycles occur at lower frequency and are longer than ordinary business cycles (Drehmann and Yetman, 2018). To assess the effect of private debt expansions on the correlation between new borrowing and the net accumulation of financial asset, we estimate the following version equation 3.3:

$$\frac{a_{it} - l_{it}}{Y_{it}} = \alpha_i + \theta_t + \beta \left(\frac{b_{it}}{Y_{it-1}}\right) + \beta_{LEV} \left[\left(\frac{b_{it}}{Y_{it-1}}\right) \times LEV_{it}\right] + \sum_{p=1}^{P} \delta_p \left(\frac{b_{it-p}}{Y_{it-p-1}}\right) + \sum_{p=1}^{P} \gamma_p \left(\frac{a_{it-p} - l_{it}}{Y_{it-p}}\right) + \varepsilon_{it}$$

where LEV_{it} is a dummy variable taking value 1 if the non-financial private sector in country i during quarter t is in a high leverage state, and 0 otherwise. Macroeconomic controls are not included in the estimation. Formally, LEV_{it} is built as follows:

$$LEV_{it} = \begin{cases} 1, & \text{if } \quad {}^{D_{it}}\!/_{Y_{it}} \geq \tau_{it} \\ 0, & \text{otherwise} \end{cases}$$

where ${}^{D_{it}}\!/_{Y_{it}}$ is the sum of household ($D^{HH,BIS}$) and non-financial corporate ($D^{F,BIS}$) debt, Y_{it} is nominal GDP, and τ_{it} is the trend of ${}^{D_{it}}\!/_{Y_{it}}$ extracted using the Hodrick–Prescott filter.

[21]Figure C.4 in Appendix C.5 shows that cash-like financial assets (currency, deposits and money market funds) account for almost 20% of total financial assets.

TABLE 3.4: NEW BORROWING LEADS TO A RISE IN THE ACQUISITION OF FINANCIAL ASSETS

Dependent variable:	*Net accumulation of financial assets*		
		$\frac{(a_{it}-l_{it})}{Y_{it}}$	
	(1)	(2)	(3)
b_{it}/Y_{it-1}	0.861***	0.819***	0.826***
	(0.04)	(0.04)	(0.04)
$LEV_{it} = 1$			-0.396
			(0.34)
$[(b_{it}/Y_{it-1}) \times LEV_{it}]$			0.069*
			(0.03)
(4) lags dependent variable	✓	✓	✓
(4) lags new borrowing	✓	✓	✓
Macroeconomic controls ($\mathbf{x}_{it}$)		✓	
Country fixed effects	✓	✓	✓
Quarter fixed effects	✓	✓	✓
within-R^2 (adj.)	0.626	0.625	0.627
Observations	1391	1357	1391
Debt data source	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficient β estimated from equation 3.3 where the dependent variable z is the net of accumulation of financial assets, or more specifically the accumulation of total financial assets, net of non-debt liabilities, and as share of GDP ($(a_{it}-l_{it})/Y_{it}$). All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table C.2 in Appendix C.3 report all coefficients estimated from equation 3.3.

ment characterized by historically low interest rates, non-financial corporations may expand long-term debt-liabilities and invest in liquid financial assets, like currency and money market funds. Indeed, there is a large amount of evidence that the rise of corporate saving led non-financial corporations to accumulate liquid financial assets (Dao and Maggi, 2018).

To rule out the influence of mechanical balance sheet adjustments and of cash hoarding, we estimate a version of equation 3.3 that distinguishes between cash-like and non-cash financial assets. We consider currency, deposits and money market funds as cash-like financial assets.[22] Instead, we define the residual financial assets as non-cash financial assets. Figure C.4 in Appendix C.5 shows that non-cash financial assets account for about 80% of total financial assets. This category groups together bonds, shares, financial derivatives, insurance premiums and other non-cash financial assets. Columns (1)-(2) in Table 3.5 show the estimated correlation between new borrowing-to-GDP and the net acquisition of cash-like financial assets as share of GDP. Overall, the correlation between new borrowing and the net accumulation of total financial assets seems to be only partially driven by rising holding of cash-like financial assets. A 1 percentage point increase in new borrowing-to-GDP leads to a rise in the net accumulation of cash-like financial assets as share of GDP by about 0.1 percentage points. Moreover, the estimated coefficient is only marginally significant. Actually, most of growth in total financial assets showed in the previous section is accounted for by rising non-cash financial assets. In fact, columns (3)-(4) in Table 3.5 show that net accumulation of non-cash financial assets is positively correlated with new borrowing and that this correlation is statistically significant.

Before proceeding to the next section, it is useful to linger over the sign of the coefficients associated with the macroeconomic controls. We do not report these estimates in Table 3.5 for space concerns. However, they are available in Table C.3 in Appendix C.3. In that table, we show that log real GDP growth is negatively correlated with the acquisition of cash-like financial assets and that this correlation is statistically significant. This finding suggests that the accumulation of cash and other liquid assets is counter-cyclical. Namely, recessions are periods during which non-financial corporations increase cash saving, perhaps driven by a precautionary motive for saving. An alternative interpretation would be that, lacking investment opportunity, firms may prefer to hoard cash and defer investment to future periods when demand will increase.[23]

[22] We follow the System of National Accounts 2008 in treating money market funds as close substitutes for deposits, given their liquidity and short-term maturity.

[23] At first sight, our finding of a negative coefficient associated with real GDP growth is in contrast with Covas and Den Haan (2011). They show that US firms accumulate financial assets, in addition to real assets, during periods of economic expansions and they interpret this correlation as reflecting the desire of firms to insure against future negative shocks. However, they find that total assets (financial and real assets) increase during booms while we focus directly on financial assets. Moreover, they do not distinguish between cash-like and non-cash financial assets. In addition, results hold in a cross-country panel that do not distinguish between large and small firms.

TABLE 3.5: NON-CASH FINANCIAL ASSETS DRIVE FINANCIAL ASSETS GROWTH

Dependent variable:	*Cash-like financial assets*		*Non-cash financial assets*	
	$\frac{(a_{it}^{Cash}-l_{it})}{Y_{it}}$		$\frac{(a_{it}^{Non-cash}-l_{it})}{Y_{it}}$	
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.083	0.106*	0.809***	0.805***
	(0.05)	(0.05)	(0.04)	(0.04)
(4) lags dependent variable	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓
Macroeconomic controls ($\mathbf{x}_{it}$)		✓		✓
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓
within-R^2 (adj.)	0.159	0.171	0.591	0.591
Observations	1391	1357	1391	1357
Debt data source	Transactions	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficient β estimated from equation 3.3 where the dependent variable z is the net accumulation of cash-like financial assets as share of GDP ($(a_{it}^{Cash}-l_{it})/Y_{it}$) in columns (1)-(2), and the net accumulation of non-cash financial assets as share of GDP ($(a_{it}^{Non-cash}-l_{it})/Y_{it}$) in columns (3)-(4). All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table C.3 in Appendix C.3 report all coefficients estimated from equation 3.3.

3.4.3 Is there a role for financial globalization?

We established that most of the rise in the accumulation of financial assets in response to changes in new borrowing is plausibly driven by rising non-cash financial assets. Non-cash financial assets is a broad category consisting of very heterogeneous financial instruments, like equity, investment fund shares, loans and debt securities, insurances, financial derivatives and other accounts receivable. On average, non-cash financial assets account for more than 80% of total financial assets in the balance sheet of the non-financial corporate sector, on average. Of these assets, equities and shares account for about 40% of total financial assets (see Figure C.4 in Appendix C.5). We estimate a version of equation 3.3 that distinguishes between equities and non-cash miscellaneous financial assets. Non-cash miscellaneous financial assets are obtain by subtracting equities from non-cash financial assets. In this exercise, we find that the correlation between new borrowing and the net acquisition of financial assets is plausibly driven by a rise in both purchases of equities and rising accumulation of non-cash miscellaneous financial assets. We do not report these results in the main text but they are available in Table C.4 in Appendix C.3.[24]

Having said that, the positive correlation between new borrowing and equity purchases opens the possibility for another interpretation of the weak relationship between non-financial

[24]We do not delve into discussing these results because, at this level of decomposition of financial assets, it is difficult to compare entries in the financial accounts across countries. Although it is possible to separate between the subcategories that compose non-cash miscellaneous financial assets at more granular levels (for example, by distinguishing between financial derivatives and debt securities), this would come at the cost of loosing many data points since some countries in the sample report only aggregate figures.

corporate debt and domestic economic activity. Expanding stock of equities on the asset side of the sector's balance sheet means that non-financial corporations are increasing their purchases of shares issued by both foreign and domestic entities. Therefore, if (part of) new borrowing leaks out of the domestic economy in form of investment abroad, then international financial integration, namely financial globalization, may be one of the factors that contribute to explain the puzzling weak correlations showed in Section 3.2.

Financial globalization and the rise in cross-border holdings of financial assets and liabilities induced profound changes in corporate finance. Under financial globalization, firms increasingly issue debt an equity in foreign markets while listing their stocks in prominent financial centers (Gozzi et al., 2015). This trend makes the non-financial corporate sector a leading contributor in cross-border financial flows (Avdjiev et al., 2014). In fact, Lane and Milesi-Ferretti (2008) argue that, before the Great Financial Crisis, financial globalization manifested in advanced economies as *(i)* a considerable decrease in the share of international trade of advanced economies and *(ii)* as a massive increase in the share of cross-border holdings of financial assets and liabilities for the same group of countries.

To assess the role of financial globalization, we use the model in equation 3.3 and regress a number of variables capturing the country-level acquisition of foreign assets on new borrowing by non-financial corporations. We collect data on transactions involving financial assets and liabilities with the rest of the world and for the economy as a whole.[25] We focus on foreign investment in equity only, as opposed to foreign investment in bonds. In other words, we assume that non-financial corporations are most likely to be involved in foreign investment by entering into the ownership of foreign businesses rather than by financing them through bonds. We use two indicators of investment abroad: net purchase of foreign equity in form of direct investment (or net direct equity investment, DI_{it}) and net purchase of foreign equity in form of portfolio investment (or net portfolio equity investment, PI_{it}). Direct equity investment involves some form of control and influence on the foreign entity while portfolio equity investment describes any other holding of foreign shares, generally motivated by speculative reasons.[26] Moreover, all quantities are normalized by country-level nominal GDP, Y_{it}. We consider only net positions, namely the purchase of foreign equities by residents net of purchases of domestic equities by non-residents. Hence, one can think of these quantities as similar to capital outflows net of capital inflows.

Table 3.6 suggests that financial globalization is likely to play a role in explaining the weak

[25] We use country-level data because the financial accounts of the non-financial corporate sector provide limited information on claims on foreign entities by domestic firms. For example, for many countries, we are not able to separate between shares issued by foreign entities and shares issued by domestic units among the financial assets held by the non-financial corporate sector.

[26] The Balance of Payment Statistics considers also other functional categories in addition to direct investment and portfolio investment. They are financial derivatives and employee stock options, other investments, and reserve assets. However, we neglect these categories because it is unlikely that non-financial corporations are significantly involved in these types of investment.

correlation between non-financial corporate debt and domestic economic activity. Columns (1)-(2) show that a rise in new borrowing by non-financial corporations is positively associated with residents obtaining more stakes in foreign businesses, net of disinvestment and of foreign direct investment in equity in the home economy. For a specification that includes macroeconomic controls, a 1 percentage point increase in new borrowing-to-GDP by non-financial corporations is associated with a 0.12 percentage points rise in economy-wide net direct equity investment as share of GDP (Column 2). We also find that periods of growth in the domestic stock market are associated with a reduction of capital outflows net of inflows (see Table C.5 in Appendix C.3). In contrast, we do not find any significant relationship between new borrowing by non-financial corporations and net portfolio equity investment abroad, a suggested in columns (3)-(4) in Table 3.6.

These findings are telling about the international dimension of non-financial corporations in advanced economies. They suggest that shocks that increase borrowing by non-financial corporations in one country may spill over to other countries through an international financial transmission channel. Indeed, as argued by Lane and Milesi-Ferretti (2017), the increasing net investment abroad of advanced economies is likely to depend on the increased complexity of multinational companies which extend their structure across border.

To sum up, the estimation of the model in equation 3.3 provided some insights into the relationship between new borrowing by non-financial corporations and financial assets growth on their balance sheets. A rise in new borrowing is associated with an increase in the net accumulation of financial assets. Although we observe a positive though small correlation between new borrowing and increasing holdings of cash-like (liquid) financial assets, the majority of the rise in total financial assets is likely to be driven by the growth of non-cash assets. Finally, we find that a rise in new borrowing is associated with an increase in net foreign direct equity investment.

3.5 Robustness checks

How robust is the relationship between new borrowing by non-financial corporations and the accumulation of financial assets? We conduct a series of robustness checks and report these results in Appendix C.4.

3.5.1 Robustness to using BIS data

Our main source of data for new borrowing are the financial accounts of the non-financial corporate sector. In the financial accounts, the total change in the stock of debt can be decomposed into three sub-elements: *(i)* transactions, *(ii)* changes in position other than transactions (or other changes) and *(iii)* revaluations occurred during the period. Our definition of new borrowing ensures that we measure the formation of debt-liabilities (loans and debt securities) by

TABLE 3.6: NEW BORROWING LEADS TO GROWING FOREIGN DIRECT EQUITY INVESTMENT

Dependent variable:	*Net direct equity investment*		*Net portfolio equity investment*	
	$\frac{DI_{it}}{Y_{it}}$		$\frac{PI_{it}}{Y_{it}}$	
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.101**	0.124**	0.015	0.005
	(0.05)	(0.04)	(0.02)	(0.02)
(4) lags dependent variable	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓
Macroeconomic controls ($\mathbf{x}_{it}$)		✓		✓
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓
within-R^2 (adj.)	0.137	0.154	0.161	0.171
Observations	1206	1172	1242	1208
Debt data source	Transactions	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficient β estimated from equation 3.3 where the dependent variable z is the net direct equity investment as share of GDP (DI_{it}/Y_{it}) in columns (1)-(2), and net portfolio equity investment as share of GDP (PI_{it}/Y_{it}) in columns (3)-(4). All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table C.5 in Appendix C.3 report all coefficients estimated from equation 3.3.

the non-financial corporate sector. Hence, new borrowing (b_{it}) reflects only volume changes and it excludes any other change induced by price fluctuations and reclassification.

An alternative strategy is to take the stock of non-financial corporate debt from the BIS dataset on private credit ($D_{it}^{F,BIS}$) and obtain new borrowing simply as first difference of the stock of debt, namely $b_{it}^{BIS} = D_{it}^{F,BIS} - D_{it-1}^{F,BIS}$. As robustness checks, we estimate all versions of equation 3.3 after replacing new borrowing (b_{it}) with the BIS-based measure of new borrowing (b_{it}^{BIS}). In Appendix C.4, we report the results for the relationship between the BIS-based measure of new borrowing and net growth of financial assets (Panel A in Table C.6), net growth in cash-like and non-cash financial assets (Panel A in Table C.7), and net direct and portfolio equity investment (Panel A in Table C.8). In all cases, we confirm the results from the previous section. This suggests that the estimated relationship between new borrowing and the accumulation of financial assets is not driven by some built-in correlation in the financial accounts. However, we find that, in most cases, using the BIS-based measure of new borrowing yields lower coefficients relative to those that have been estimated in the previous section. We interpret these differences as arising from the fact that the BIS-based measure of new borrowing is likely to reflect the effects of price fluctuations and of other changes, in addition to effective borrowing.[27]

[27]To fix ideas, let D_{it}^{F} be the stock of non-financial corporate debt. The total change in the level of debt can be decomposed as follows:

$$\underbrace{\Delta D_{it}^{F}}_{\text{total change}} = \underbrace{\underbrace{\underbrace{\Delta D_{it}^{F,T}}_{\text{transactions}}}_{b_{it}} + \underbrace{\Delta D_{it}^{F,O}}_{\text{other changes}} + \underbrace{\Delta D_{it}^{F,R}}_{\text{revaluations}}}_{b_{it}^{BIS}}$$

3.5.2 Robustness to post-1995 sample

In our unbalanced panel, there is an over-representation of US data. As a robustness check, we explore whether the estimated coefficients are sensitive to a sample consisting only of post-1995 observations. In fact, using only post-1995 observations, our panel is more balanced and the over-representation of US data is a less serious concern. In Appendix C.4, we report the results for the post-1995 relationship between the new borrowing and net growth of financial assets (Panel B in Table C.6), net growth in cash-like and non-cash financial assets (Panel B in Table C.7), and net direct and portfolio equity investment (Panel B in Table C.8). In all cases, we confirm the results from the previous section.

3.5.3 Identification-through-heteroskedasticity

So far, we showed that there is a significant correlation between new borrowing by non-financial corporations and an array of indicators for the accumulation of financial assets, after controlling for country and time fixed effects. However, the OLS estimates may be biased and inconsistent because new borrowing and disturbances to the outcome variables in equation 3.3 are likely to be correlated. Moreover, we cannot completely rule out omitted variable problems and measurement errors.

To tackle the identification problem, we employ the identification-through-heteroskedasticity strategy proposed by Lewbel (2012) and estimate the effects of new borrowing by non-financial corporations. This identification strategy exploits the presence of heteroskedasticity in the regression's residuals to construct *internal* instruments when traditional external instruments are not available (see Appendix C.4.1 for details on the identification strategy).

For each of the version of equation 3.3, we instrument new borrowing-to-GDP and report the results in Table 3.7. Instruments are generated by interacting the residuals from a first-stage regression with the (demeaned) controls used in the various versions of the baseline model. For each dependent variable, under Column (IV), we report the coefficient associated with new borrowing-to-GDP and estimated following Lewbel (2012). We also report, for comparison, the OLS estimates from the tables in the previous section. In general, the identification-through-heteroskedasticity approach confirms the results obtained in the previous section. In some cases, the identification-through-heteroskedasticity estimator yields slightly larger or smaller coefficients though the qualitative results are unchanged. The specification tests suggest that the coefficients are precisely estimated. The Hansen J test for over-identifying restrictions fails to reject the validity of the instruments while the Kleibergen-Paap rk LM test implies that we can comfortably reject the null that the model is under-identified.

Therefore, the BIS-based measure of new borrowing contains also other changes and changes induced by price fluctuations, in addition to transactions.

TABLE 3.7: THE EFFECTS OF NEW BORROWING: IDENTIFICATION-THROUGH-HETEROSKEDASTICITY

Dependent variable:	*Financial assets*		*Cash-like financial assets*		*Non-cash financial assets*		*Direct equity investment*		*Portfolio equity investment*	
	$\frac{a_{it}-l_{it}}{Y_{it}}$		$\frac{a^{Cash}_{it}-l_{it}}{Y_{it}}$		$\frac{a^{Non-cash}_{it}-l_{it}}{Y_{it}}$		$\frac{DI_{it}}{Y_{it}}$		$\frac{PI_{it}}{Y_{it}}$	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
b_{it}/Y_{it-1}	0.819***	0.860***	0.106*	0.060**	0.805***	0.815***	0.124**	0.095***	0.005	0.04***
	(0.04)	(0.02)	(0.05)	(0.03)	(0.04)	(0.02)	(0.04)	(0.01)	(0.02)	(0.01)
IV specification tests										
Under id-test		178.368		173.220		176.145		166.930		169.132
p-val		$p = 0.0015$		$p = 0.0034$		$p = 0.0021$		$p = 0.0086$		$p = 0.0145$
Weak id-test (F-stat)		16.153		73.731		13.358		79.221		11.022
Over id-test		131.412		102.242		130.376		131.928		119.279
p-val		$p = 0.3297$		$p = 0.9325$		$p = 0.3530$		$p = 0.3184$		$p = 0.6275$
(4) lags dependent variable	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Macroeconomic controls ($\mathbf{x}_{it}$)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1357	1357	1357	1357	1357	1357	1172	1172	1208	1208

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). For each dependent variable z, the table reports the coefficient β estimated from equation 3.3 with OLS and with the estimator by Lewbel (2012) ('IV' labeled columns). All regressions include lags of the dependent variable, lags of new borrowing-to-GDP and the usual macroeconomic controls (log real GDP growth, changes in stock prices and government bond yields). The IV model is estimated using the Stata command `ivreg2h` which allows to implement the Lewbel (2012) identification-through-heteroskedasticity. Because we instrument new borrowing using more than one variable, we invoke the instrumental variable generalized method of moments for obtaining classic specification tests.Under id-test (under identification) reports the Kleibergen and Paap (2006) rk LM statistics and p-value with rejection of the null implying identification; Weak in-test reports the Kleibergen and Paap (2006) rk Wald F statistics for weak identification; Over id-test reports Hansen J statistics and p-value with rejection implying that instruments may not be valid. For the IV model, we do not report estimates from the first-stage regression. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.6 Concluding remarks

A recent empirical literature has revealed that non-financial corporate debt expansions do not predict economically meaningful boom-and-bust cycles in economic activity. In contrast, household debt expansions are found to predict future contractions in economic activity, after short periods of economic growth. Until recently, the weak relationship between non-financial corporate debt expansions and economic activity has received little attention in the literature. If non-financial corporate debt does not predict future increases in the level of aggregate demand, what is the non-financial corporate sector borrowing for?

In this chapter, we showed that the weak correlation between non-financial corporate debt and aggregate demand can be explained by considering that corporate borrowing provides funds which can be given alternative uses. The financing of capital investment, which would be associated with higher domestic aggregate demand, is only one of these possible uses. Other alternative uses are the accumulation of a portfolio of financial assets and foreign direct investment. If non-financial corporations channels part of corporate debt toward these alternative uses, the relationship between debt expansions and aggregate demand may not br straightforward.

For a sample of advanced economies over the period 1970-2018, we showed that a rise in new borrowing (i.e. the flow of credit to firms) is strongly associated with growing holdings of financial assets on the balance sheets of the non-financial corporate sector. This result suggests that part of the growth of non-financial corporate debt-to-GDP ratios in advanced countries would have financed the acquisition of financial assets. Moreover, we showed that new borrowing is correlated with residents obtaining large-stake equity holdings in foreign entities. This result emphasizes that non-financial corporations are complex organizations operating in global financial and goods markets. In addition, the relationship between new borrowing and foreign direct investment opens new research paths on the role of financial globalization in explaining the weak correlation between non-financial corporate debt and domestic economic activity.

To conclude, although our findings provide a series of robust stylized facts on the real and financial implications of corporate debt, they are limited in the interpretation. To this respect, macroeconomic data, while providing useful information on aggregate trends in the non-financial corporate sector, are silent on whether the observed correlations between new borrowing and financial assets accumulation reflect a deliberate choice or whether they mirror the growing complexity of non-financial firms, or both. Moreover, reliance on aggregate flow of funds data may imply that our results are driven by the behavior of large non-financial corporations which drive most of the aggregate flows in the financial accounts (Covas and Den Haan, 2011; Ma, 2019). As a result, the relationship between new borrowing and financial assets growth may depend of the size of the firm as well as on the industry in which it operates, as showed by many firm-level studies (Davis, 2018). Addressing these limitations is left for future research.

Appendix C

C.1 Data Appendix

C.1.1 Non-financial firm and household debt

Data on the stock of sectoral debt are assembled from the Bank of International Settlements (BIS) "Long series of total credit to the nonfinancial sector". Data are expressed in local currency. More specifically:

- Non-financial firm debt ($D_{it}^{F,BIS}$) is 'Total credit to non-financial corporations' (stock),
- Household debt ($D_{it}^{H,BIS}$) is 'Total credit to households' (stock).

C.1.2 Other variables

Name	*Symbol*	*Data source*
Nominal GDP	Y_{it}	FRED database
Log real GDP	y_{it}	Monnet and Puy (2019)
Medium-long government bond yields	g_{it}	Monnet and Puy (2019)
Stock price index	p_{it}	Monnet and Puy (2019)
Net direct equity investment	$a_{it}^{DI,Net}$	Balance of Payment Statistics
Net portfolio equity investment	$a_{it}^{PI,Net}$	Balance of Payment Statistics

C.1.3 Non-financial firms' source and uses of funds

Variables' definition, source, and construction on non-financial firms' source and uses of funds are reported in the table below.

Additional information:

- Most of flow series (apart from the U.S. ones) are published as non-seasonally adjusted. However, they display substantial variables. Therefore, they have been seasonally adjusted using the X-13 ARIMA procedure before the estimation.
- Data for European Union countries and U.K. have been retrieved from the ECB Statistical Data Warehouse. In this data set, all series for Denmark start in 2012Q4 and therefore time series for Danish financial data have short length. To increase the length of Danish series we *back data* published by Statistics Denmark which start in 2005 and are compiled using the same methodology of current data. Moreover, Danish series about new equity include money market funds since they are jointly reported with unlisted shares.
- According to the System of National Accounts 2008 guidelines, equity is recorded jointly with money market and non-money market investment funds and shares in a category named 'Equity and investment fund shares'. However, these sub-categories are reported separately and therefore it is possible to distinguish between equity, money market funds, and non-money market investment funds shares. In this chapter, we consider money market funds as akin to currency and deposits. As Eurostat (2013) claims money market fund shares or units are often regarded as close substitutes for deposits because of their easy transferability. Instead, we treat non-money market investment fund shares

and units as part of non-cash non-equity financial assets. We pursue this choice since equity represents ownership in the companies, non-money market investment funds span participation in different entities.

- Currency and deposits are reported as separate category in the financial accounts by all countries in the sample. Money market funds and shares are reported for shorter periods as separate category. For example, Belgium reports money market fund shares from 2014Q1 on; Canada and United Kingdom do not have separate accounts; Denmark reports them jointly with unlisted shares; Netherlands reports them from 2006Q1 on. Since we consider jointly currency, deposits, and money market fund shares as a single cash-like financial assets category, when data on money market funds are not available, cash-like financial assets reflect only currency and deposits.

Name	*Symbol*	*Construction*	*Data source*	*Original identifier*
Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, United Kingdom				
Capital expenditure	k_{it}	Gross fixed capital formation + Changes in inventories and acquisition less disposals of valuables + Acquisition less disposals of non-produced assets	Quarterly Sector Accounts (sector S11)	P51G+P5M+NP
Gross fixed capital formation	I_{it}	Gross fixed capital formation	Quarterly Sector Accounts (sector S11)	P51G
Corporate saving	S_{it}	Saving, gross + Capital transfers, received - Capital transfers, paid	Quarterly Sector Accounts (sector S11)	B8G+D9R-D9P
Equity issuance	ΔEq_{it}	Corporate equity issued by resident non-financial corporations(transactions, liabilities)	Quarterly Sector Accounts (sector S11)	F51
New borrowing	b_{it}	Debt securities + Loans (transactions, liabilities)	Quarterly Sector Accounts (sector S11)	F3+F4
Financial assets	a_{it}	Transactions in financial assets (AF) (transactions, assets)	Quarterly Sector Accounts (sector S11)	F
Cash-like financial assets	a_{it}^{Cash}	Currency and deposits + MMF shares/units (transactions, assets)	Quarterly Sector Accounts (sector S11)	F2+F521
Non-cash financial assets	$a_{it}^{Non-cash}$	$a_{it} - a_{it}^{Cash}$ (transactions, assets)	Quarterly Sector Accounts (sector S11)	F-(F2+F521)
Equity purchases	e_{it}	Equity (transactions, assets)	Quarterly Sector Accounts (sector S11)	F51
Miscellaneous financial assets	a_{it}^{Misc}	$a_{it}^{Non-cash} - e_{it}$ (transactions, assets)	Quarterly Sector Accounts (sector S11)	F-(F2+F521)-F51
Liabilities	l_{it}^{Tot}	Transactions in financial liabilities (transactions, liabilities)	Quarterly Sector Accounts (sector S11)	F
Non-debt liabilities	l_{it}	$l_{it}^{Tot} - b_{it}$ (transactions, liabilities)	Quarterly Sector Accounts (sector S11)	F-(F3+F4)
Australia *(Australian National Accounts: Finance and Wealth; Private non-Financial Corporations)*				
Capital expenditure	k_{it}	Gross fixed capital formation + Changes in inventories + Acquisition less disposals of non-produced non-financial assets	Table 5238.7	A83822432K + A8338822542X + A83822412A
Gross fixed capital formation	I_{it}	Gross fixed capital formation	Table 5238.7	A83822432K
Corporate saving	S_{it}	Gross saving and net capital transfers	Table 5238.7	A838222240T
Equity issuance	ΔEq_{it}	Listed shares and other equity + Unlisted shares and other equity (transactions, liabilities)	Table 5238.7	A3554942K+A3554945T
New borrowing	b_{it}	Drawings of bills of exchange + One name paper issued in Australia and offshore + Bonds issued in Australia and offshore + Short and Long term loans (transactions, liabilities)	Table 5238.7	A3554898L+A3554908F+A3554911V+A3554920W+ A3554923C+A3554933J+A3554936R
Financial assets	a_{it}	Transactions in financial assets (transactions, assets)	Table 5238.7	A3554977K
Cash-like financial assets	a_{it}^{Cash}	Currency + Deposits + Money market financial investment funds (transactions, assets)	Table 5238.7	A3554878C+A3554882V+A3546661R
Non-cash financial assets	$a_{it}^{Non-cash}$	$a_{it} - a_{it}^{Cash}$ (transactions, assets)	Table 5238.7	A3554977K-(A3554878C+A3554882V+A3546661R)
Equity purchases	e_{it}	Shares and other equity (transactions, assets)	Table 5238.7	A3554937T
Miscellaneous financial assets	a_{it}^{Misc}	$a_{it}^{Non-cash} - e_{it}$ (transactions, assets)	Table 5238.7	A3554977K-(A3554878C+A3554882V+A3546661R)- A3554937T
Liabilities	l_{it}^{Tot}	Transactions in financial liabilities (transactions, liabilities)	Table 5238.7	A3554978L
Non-debt liabilities	l_{it}	$l_{it}^{Tot} - b_{it}$ (transactions, liabilities)	Table 5238.7	A3554978L- b_{it}
Canada *(Canadian System of National Accounts: Financial and Wealth Accounts; Non-financial private corporations)*				
Capital expenditure	k_{it}	Non-financial capital acquisition	Table 36-10-0578-01	
Gross fixed capital formation	I_{it}	New capital + existing capital	Table 36-10-0578-01	
Corporate saving	S_{it}	Gross saving less net capital transfers	Table 36-10-0578-01	v62690820
Equity issuance	ΔEq_{it}	Listed shares + Unlisted shares + Foreign investment (equity) (transactions, liabilities)	Table 36-10-0578-01	
New borrowing	b_{it}	Debt securities + Loans (transactions, liabilities)	Table 36-10-0578-01	
Financial assets	a_{it}	Net transaction in financial assets (transactions, assets)	Table 36-10-0578-01	
Cash-like financial assets	a_{it}^{Cash}	Total currency and deposits (transactions, assets)	Table 36-10-0578-01	
Non-cash financial assets	$a_{it}^{Non-cash}$	$a_{it} - a_{it}^{Cash}$ (transactions, assets)	Table 36-10-0578-01	
Equity purchases	e_{it}	Listed shares + Unlisted shares + Foreign investment (equity)	Table 36-10-0578-01	
Miscellaneous financial assets	a_{it}^{Misc}	$a_{it}^{Non-cash} - e_{it}$ (transactions, assets)	Table 36-10-0578-01	
Liabilities	l_{it}^{Tot}	Net transactions in financial liabilities (transactions, liabilities)	Table 36-10-0578-01	
Non-debt liabilities	l_{it}	$l_{it}^{Tot} - b_{it}$ (transactions, liabilities)	Table 36-10-0578-01	
United States *(Z1. Financial Accounts of the United States: Integrated Macroeconomic Accounts: Nonfinancial Corporate Business)*				
Capital expenditure	k_{it}	Capital expenditure	Table F.103	FA105050005
Gross fixed capital formation	I_{it}	Fixed investment	Table F.103	FA105019005
Corporate saving	S_{it}	Gross saving less net capital transfers	Table F.103	FA106000105
Equity issuance	ΔEq_{it}	Corporate equities + Foreign direct investment in the US (transactions, liabilities)	Table S.5	FA103164103+ FA103192005
New borrowing	b_{it}	Debt securities + Loans (transactions, liabilities)	Table S.5	FA104122005+FA104123005
Financial assets	a_{it}	Net acquisition of financial assets (transactions, assets)	Table S.5	FA104090005
Cash-like financial assets	a_{it}^{Cash}	Currency and deposits + Money market fund shares (transactions, assets)	Table S.5	FA104000005+FA103034000
Non-cash financial assets	$a_{it}^{Non-cash}$	$a_{it} - a_{it}^{Cash}$ (transactions, assets)	Table S.5	
Equity purchases	e_{it}	Corporate equities + US direct investment abroad + Investment in finance company subsidiaries+Equity in GSEs	Table S.5	FA103064103+FA103092005+FA103094105+FA103092405
Miscellaneous financial assets	a_{it}^{Misc}	$a_{it}^{Non-cash} - e_{it}$ (transactions, assets)	Table S.5	
Liabilities	l_{it}^{Tot}	Net incurrence of liabilities (transactions, liabilities)	Table S.5	FA104194005
Non-debt liabilities	l_{it}	$l_{it}^{Tot} - b_{it}$ (transactions, liabilities)	Table S.5	FA104194005-(FA104122005+FA104123005)

C.2 Non-financial corporate debt and aggregate demand: further evidence

In this Appendix, we provide further evidence and robustness checks to support the impulse response analysis in Section 3.2.

C.2.1 The role of global and country-specific time-varying shocks

In Figure C.1 we test whether the dynamic patterns on the real effects of non-financial corporate and household debt shocks are robust to alternative specifications with respect to time fixed effects. The (red) lines with markers in panel A and B in Figure C.1 are the impulse responses obtained from a version of equation 3.1 where we set the time fixed effect to zero. We also report the impulse responses from the baseline model with time fixed effects. We find that the response of log real GDP to an impulse to non-financial corporate debt is more negative when we do not allow global unobserved shocks to affect country-level GDP. For the case of corporate debt, omitting the time fixed effects produces results which are qualitative similar to those reported in the main text. In fact, the impulse response functions are almost overlapping. On the contrary, a shock to household debt-to-GDP predicts a significant boom-and-bust cycle in log real GDP when time fixed effects are omitted, consistently with the findings in Mian et al. (2017).

In contrast to Mian et al. (2017) that estimate specifications very similar to our own (see also Drehmann et al., 2018), we include time fixed effects in our main specification (see equation 3.1). The inclusion of time dummies is motivated by the fact that unobserved global shocks may be an important source of variation for country-level GDP and, although giving an economic interpretation of these shocks is not straightforward, we believe that they should be included. Moreover, we conduct a joint test on the null that all coefficients associated to time dummies are zero. The test strongly rejects the null that coefficients are jointly equal to zero. The fact that the impulse response function associated to a shock to household debt turns larger and statistically significant if time fixed effects are excluded casts doubts on previous results on the predictive power of household debt expansions. It suggests that excluding the influence of global unobserved factors may amount to an omitted variable bias.

C.2.2 Specification in first difference

Figure C.2 and Panel B in Figure C.3 report impulse responses estimated from the following local projection model:

$$\Delta_h z_{it+h} = \alpha_i^h + \theta_t^h + \sum_{p=1}^{P} \beta_{Fp}^h \Delta d_{it-p}^F + \sum_{p=1}^{P} \beta_{HHp}^h \Delta d_{it-p}^{HH} + \sum_{p=1}^{P} \gamma_p^h \Delta z_{it-jp} + \varepsilon_{it+h} \tag{C.1}$$

$$\Delta_h z_{it+h} = (z_{it+h} - z_{it-1})$$

where z_{it+h} is the logarithm of real GDP (y_{it+h}), or alternatively the business investment share ($^{I_{it+h}}/Y_{it+h}$), Δ stands for the quarterly change (or first difference) and $P = 8$ as the in baseline specification. The dependent variable is the cumulative change (business investment share) of cumulative changes in logarithms (log real GDP). We do not find any qualitative difference in the impulse responses.

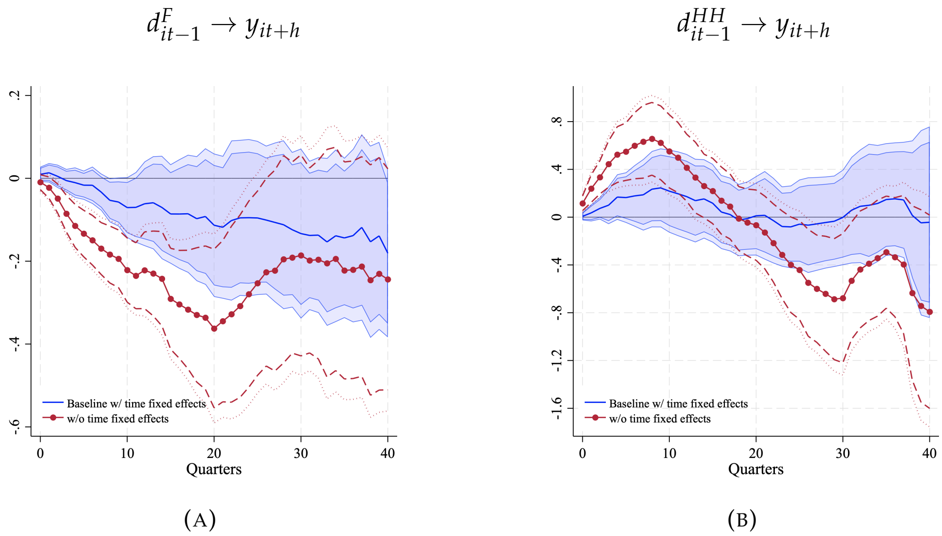
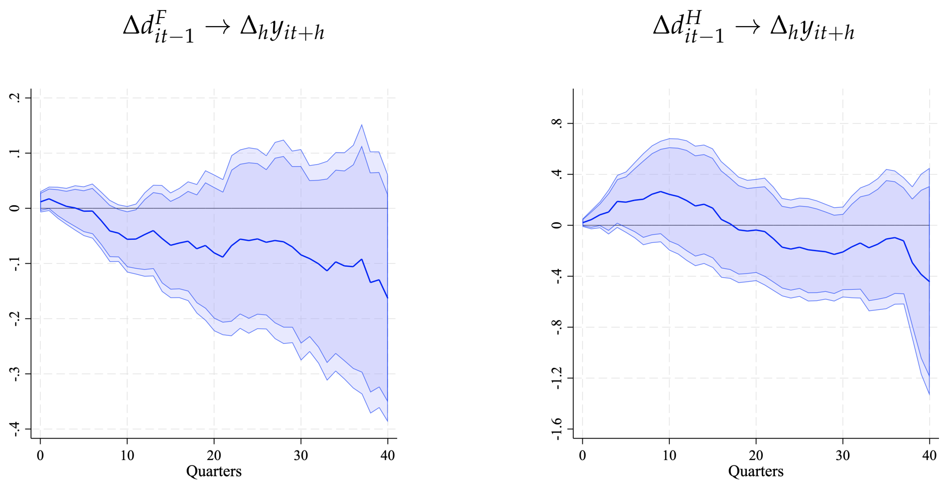


FIGURE C.1: LOCAL PROJECTIONS IMPULSE RESPONSES FROM EQUATION 3.1, W/ AND W/O TIME FIXED EFFECTS

Notes: this figure plots the responses of log real GDP to a one percentage point increase in non-financial corporate debt-to-GDP in $t-1$ (panel A) and in household debt-to-GDP in $t-1$ (panel B). The (blue) solid lines are the estimated coefficient for the baseline model with time fixed effects. Dark and light shaded regions are 90% and 95% confidence intervals constructed HAC standard errors clustered by country for the baseline model with time fixed effects. The (red) lines with markers are the estimated estimated coefficient for the model without time fixed effects. Dashed and dotted (red) lines are 90% and 95% confidence intervals constructed HAC standard errors clustered by country for the model without time fixed effects.

C.2.3 A different definition of business investment

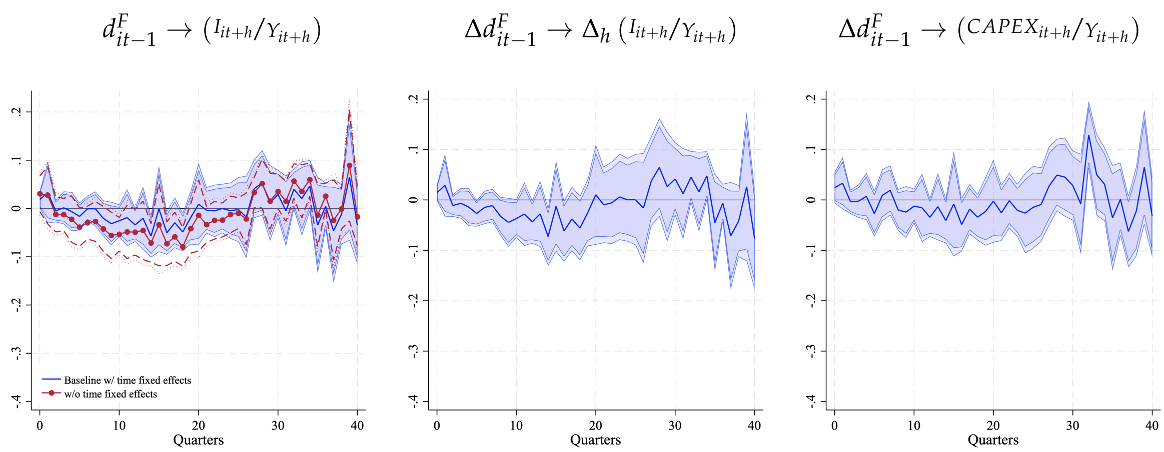
Panel C in Figure C.3 reports impulse responses from a specification in which we obtained business investment using capital expenditure (CAPEX) rather than gross fixed capital formation. In both cases, business investment is observed for the non-financial corporate sector only. There are no qualitative differences between using CAPEX and using gross fixed capital formation. This is not surprising since CAPEX includes gross fixed capital formation.



(A) (B)

FIGURE C.2: LOCAL PROJECTIONS IMPULSE RESPONSES FROM C.1

Notes: this figure plots the responses of the cumulative change log real GDP to a one percentage point increase in non-financial corporate debt-to-GDP in first difference $t-1$ (panel A) and in household debt-to-GDP in $t-1$ first difference (panel B), from equation C.1. The (blue) solid lines are the estimated coefficient for the baseline model with time fixed effects. Dark and light shaded regions are 90% and 95% confidence intervals constructed HAC standard errors clustered by country for the baseline model with time fixed effects.



(A) (B) (C)

FIGURE C.3: LOCAL PROJECTIONS IMPULSE RESPONSES: BUSINESS INVESTMENT SHARE

Notes: panel A plots the response of the business investment share of GDP to a one percentage point increase in non-financial corporate debt-to-GDP in $t-1$ with (blue solid line) and without (red line with markers) time fixed effects. Dark and light shaded regions are 90% and 95% confidence intervals constructed HAC standard errors clustered by country for the baseline model with time fixed effects. Dashed and dotted (red) lines are 90% and 95% confidence intervals constructed HAC standard errors clustered by country for the model without time fixed effects. Panel B plots the response of the cumulative change of the business investment share of GDP to a one percentage point increase in non-financial corporate debt-to-GDP in $t-1$ in first difference. Dark and light shaded regions are 90% and 95% confidence intervals constructed HAC standard errors clustered by country. Panel C plots the response of the business investment share (obtained using the capital expenditure) to a one percentage point increase in non-financial corporate debt-to-GDP in $t-1$. Dark and light shaded regions are 90% and 95% confidence intervals constructed HAC standard errors clustered by country.

C.3 Further results

TABLE C.1: PANEL UNIT ROOTS TESTS

		Statistics	
Variable	Symbol	Fisher-type test	Im-Pesaran-Shin test
Financial assets, net of non-debt liabilities, share of GDP	$(a_{it}-l_{it})/Y_{it}$	- 9.2133	-16.1790
		$p = 0.0000$	$p = 0.0000$
New borrowing-to-GDP (FA-based)	b_{it}/Y_{it-1}	-5.9085	-8.1436
		$p = 0.0000$	$p = 0.0000$
New borrowing-to-GDP (BIS-based)	b_{it}^{BIS}/Y_{it-1}	-8.0662	-12.1747
		$p = 0.0000$	$p = 0.0000$
Cash-like financial assets, net of non-debt liabilities, share of GDP	$(a_{it}^{Cash}-l_{it})/Y_{it}$	-8.7715	-18.1940
		$p = 0.0000$	$p = 0.0000$
Non-cash financial assets, net of non-debt liabilities, share of GDP	$(a_{it}^{Non-cash}-l_{it})/Y_{it}$	-9.7151	-17.8179
		$p = 0.0000$	$p = 0.0000$
Miscellaneous financial assets, net of non-debt liabilities, share of GDP	$(a_{it}^{Misc}-l_{it})/Y_{it}$	-10.2219	-21.3629
		$p = 0.0000$	$p = 0.0000$
Equity purchases, net of non-debt liabilities, share of GDP	$(e_{it}-l_{it})/Y_{it}$	-9.4030	-17.5736
		$p = 0.0000$	$p = 0.0000$
Net direct equity investment abroad, share of GDP	$(a_{it}^{DI,Net}-l_{it})/Y_{it}$	-8.3055	-16.9266
		$p = 0.0000$	$p = 0.0000$
Net portfolio equity investment abroad, share of GDP	$(a_{it}^{PI,Net}-l_{it})/Y_{it}$	-9.9827	-16.4797
		$p = 0.0000$	$p = 0.0000$

Fisher-type and Im-Pesaran-Shin (Im et al., 2003) tests are suitable for testing for the presence for unit roots in unbalanced panels. For both tests, the null hypothesis is that all panels contain a unit roots. Therefore, *low* p-values imply the rejection of the null. In building the Im-Pesaran-Shin, lags in the ADF regression are automatically selected by AIC criterion. Instead, two lags are included in the ADF regression used in the Fisher-type tests. For the Fisher-type test, we follow Choi (2001) and report the inverse normal Z statistic. Both tested are conducted on seasonally adjusted series (X-13 ARIMA is used to perform seasonal adjustments).

TABLE C.2: NEW BORROWING LEADS TO A RISE IN THE ACQUISITION OF FINANCIAL ASSETS: FULL TABLE

Dependent variable:	*Net accumulation of financial assets*		
		$\frac{(a_{it}-l_{it})}{Y_{it}}$	
	(1)	(2)	(3)
b_{it}/Y_{it-1}	0.861***	0.860***	0.819***
	(0.04)	(0.04)	(0.04)
$LEV_{it}=1$			-0.396
			(0.34)
$[(b_{it}/Y_{it-1}) \times LEV_{it}]$			0.069*
			(0.03)
b_{it-1}/Y_{it-2}	-0.077**	-0.086**	-0.098**
	(0.03)	(0.03)	(0.04)
b_{it-2}/Y_{it-3}	-0.098**	-0.078*	-0.097**
	(0.04)	(0.04)	(0.04)
b_{it-3}/Y_{it-4}	-0.140***	-0.145***	-0.140***
	(0.04)	(0.04)	(0.04)
b_{it-4}/Y_{it-5}	-0.009	-0.003	0.008
	(0.05)	(0.04)	(0.04)
$\frac{(a_{it-1}-l_{it-1})}{Y_{it-1}}$	0.036	0.043	0.035
	(0.03)	(0.03)	(0.03)
$\frac{(a_{it-2}-l_{it-2})}{Y_{it-2}}$	0.072	0.069	0.071
	(0.04)	(0.04)	(0.04)
$\frac{(a_{it-3}-l_{it-3})}{Y_{it-3}}$	0.130***	0.131***	0.131***
	(0.04)	(0.04)	(0.04)
$\frac{(a_{it-4}-l_{it-4})}{Y_{it-4}}$	-0.038	-0.044	-0.036
	(0.04)	(0.04)	(0.04)
Δy_{it}		-0.256	
		(0.29)	
Δp_{it}		0.015	
		(0.02)	
g_{it}		0.362***	
		(0.07)	
Country fixed effects	✓	✓	✓
Quarter fixed effects	✓	✓	✓
within-R^2 (adj.)	0.626	0.625	0.627
Observations	1391	1357	1391
Debt data source	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficients estimated from equation 3.3 where the dependent variable z is the net of accumulation of financial assets, or more specifically the accumulation of total financial assets, net of non-debt liabilities, and as share of GDP ($(a_{it}-l_{it})/Y_{it}$). All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C.3: NON-CASH FINANCIAL ASSETS DRIVE FINANCIAL ASSETS GROWTH: FULL TABLE

Dependent variable:	*Cash-like financial assets*		*Non-cash financial assets*	
	$\frac{(a_{it}^{Cash}-l_{it})}{Y_{it}}$		$\frac{(a_{it}^{Non-cash}-l_{it})}{Y_{it}}$	
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.083	0.106*	0.809***	0.805***
	(0.05)	(0.05)	(0.04)	(0.04)
b_{it-1}/Y_{it-2}	0.090	0.098	-0.116***	-0.129***
	(0.12)	(0.13)	(0.03)	(0.04)
b_{it-2}/Y_{it-3}	-0.062**	-0.083**	-0.082**	-0.049
	(0.02)	(0.03)	(0.04)	(0.04)
b_{it-3}/Y_{it-4}	-0.099	-0.070	-0.107***	-0.120***
	(0.07)	(0.06)	(0.03)	(0.03)
b_{it-4}/Y_{it-5}	0.064	0.046	-0.010	-0.023
	(0.06)	(0.06)	(0.04)	(0.04)
$\frac{(a_{it-1}^{Cash}-l_{it-1})}{Y_{it-1}}$	0.096	0.102		
	(0.07)	(0.06)		
$\frac{(a_{it-2}^{Cash}-l_{it-2})}{Y_{it-2}}$	0.146***	0.131***		
	(0.04)	(0.03)		
$\frac{(a_{it-3}^{Cash}-l_{it-3})}{Y_{it-3}}$	0.102**	0.107**		
	(0.04)	(0.05)		
$\frac{(a_{it-4}^{Cash}-l_{it-4})}{Y_{it-4}}$	-0.074*	-0.097**		
	(0.04)	(0.04)		
$\frac{(a_{it-1}^{Non-cash}-l_{it-1})}{Y_{it-1}}$			0.041	0.054*
			(0.02)	(0.03)
$\frac{(a_{it-2}^{Non-Cash}-l_{it-2})}{Y_{it-2}}$			0.085*	0.073
			(0.05)	(0.05)
$\frac{(a_{it-3}^{Non-Cash}-l_{it-3})}{Y_{it-3}}$			0.123***	0.131***
			(0.03)	(0.03)
$\frac{(a_{it-4}^{Non-Cash}-l_{it-4})}{Y_{it-4}}$			-0.025	-0.031
			(0.03)	(0.03)
Δy_{it}		-0.496*		-0.182
		(0.24)		(0.24)
Δp_{it}		0.020		0.012
		(0.04)		(0.03)
g_{it}		0.591***		0.368***
		(0.13)		(0.10)
(4) lags dependent variable	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓
Macroeconomic controls		✓		✓
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓
within-R^2 (adj.)	0.159	0.171	0.591	0.591
Observations	1391	1357	1391	1357
Debt data source	Transactions	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficients estimated from equation 3.3 where the dependent variable z is the net accumulation of cash-like financial assets as share of GDP ($(a_{it}^{Cash}-l_{it})/Y_{it}$) in columns (1)-(2), and the net accumulation of non-cash financial assets as share of GDP ($(a_{it}^{Non-cash}-l_{it})/Y_{it}$) in columns (3)-(4). All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C.4: DELVING DEEPER INTO NON-CASH FINANCIAL ASSETS

Dependent variable:	*Miscellaneous financial assets*		*Equity purchases*	
	$\frac{(a_{it}^{Misc}-l_{it})}{Y_{it}}$		$\frac{(e_{it}-l_{it})}{Y_{it}}$	
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.684^{***}	0.679^{***}	0.159	0.180^{*}
	(0.07)	(0.07)	(0.10)	(0.10)
(4) lags dependent variable	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓
Macroeconomic controls ($\mathbf{x}_{it}$)		✓		✓
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓
within-R^2 (adj.)	0.376	0.372	0.187	0.207
Observations	1391	1357	1391	1357
Debt data source	Transactions	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficient β estimated from equation 3.3 where the dependent variable z is the growth of non-cash miscellaneous financial assets, net of non-debt liabilities and as share of GDP ($(a_{it}^{Misc}-l_{it})/Y_{it}$) in columns (1)-(2), and equity purchases, net of non-debt liabilities and as share of GDP ($(e_{it}-l_{it})/Y_{it}$) in columns (3)-(4). Non-cash miscellaneous financial assets are non-cash financial assets minus equity purchases. All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: New borrowing leads to growing foreign direct equity investment: full table

Dependent variable:	*Net direct equity investment*		*Net portfolio equity investment*	
	$\frac{DI_{it}}{Y_{it}}$		$\frac{PI_{it}}{Y_{it}}$	
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.101**	0.124**	0.015	0.005
	(0.05)	(0.04)	(0.02)	(0.02)
b_{it-1}/Y_{it-2}	-0.081	-0.093	-0.003	0.013
	(0.07)	(0.08)	(0.02)	(0.02)
b_{it-2}/Y_{it-3}	0.124	0.120	0.012	0.016
	(0.07)	(0.08)	(0.04)	(0.04)
b_{it-3}/Y_{it-4}	0.074	0.095	0.013	0.005
	(0.07)	(0.08)	(0.01)	(0.02)
b_{it-4}/Y_{it-5}	-0.072	-0.090	0.004	0.006
	(0.05)	(0.06)	(0.03)	(0.03)
DI_{it-1}/Y_{it-1}	0.191**	0.185**		
	(0.08)	(0.09)		
DI_{it-2}/Y_{it-2}	0.022	0.021		
	(0.11)	(0.11)		
DI_{it-3}/Y_{it-3}	0.051	0.048		
	(0.04)	(0.04)		
DI_{it-4}/Y_{it-4}	-0.0003	0.005		
	(0.03)	(0.03)		
PI_{it-1}/Y_{it-1}			0.187**	0.182**
			(0.08)	(0.08)
PI_{it-2}/Y_{it-2}			0.156***	0.156***
			(0.04)	(0.03)
PI_{it-3}/Y_{it-3}			0.074	0.068
			(0.10)	(0.10)
PI_{it-4}/Y_{it-4}			-0.143***	-0.151***
			(0.04)	(0.04)
Δy_{it}		-0.235		-0.011
		(0.24)		(0.11)
Δp_{it}		-0.102*		-0.006
		(0.05)		(0.03)
g_{it}		-0.013		0.398***
		(0.20)		(0.10)
(4) lags dependent variable	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓
Macroeconomic controls		✓		✓
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓
within-R^2 (adj.)	0.137	0.154	0.161	0.171
Observations	1206	1172	1242	1208
Debt data source	Transactions	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficient β estimated from equation 3.3 where the dependent variable z is the net direct equity investment as share of GDP (DI_{it}/Y_{it}) in columns (1)-(2), and net portfolio equity investment as share of GDP (PI_{it}/Y_{it}) in columns (3)-(4). All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 Robustness

TABLE C.6: NEW BORROWING LEADS TO A RISE IN THE ACQUISITION OF FINANCIAL ASSETS: ROBUSTNESS

Panel A: Robustness to BIS-based new borrowing data			
	Net accumulation of financial assets		
	(1)	(2)	(3)
b_{it}/Y_{it-1}	0.516***	0.514***	0.496***
	(0.07)	(0.08)	(0.07)
$LEV_{it} = 1$			-0.465
			(0.35)
$[(b_{it}/Y_{it-1}) \times LEV_{it}]$			0.031
			(0.03)
(4) lags dependent variable	✓	✓	✓
(4) lags new borrowing	✓	✓	✓
Macroeconomic controls ($\mathbf{x}_{it}$)		✓	
Country fixed effects	✓	✓	✓
Quarter fixed effects	✓	✓	✓
within-R^2 (adj.)	0.393	0.401	0.394
Observations	1390	1356	1390
Debt data source	BIS	BIS	BIS
Panel B: Robustness to post-1995 sub-sample			
	Net accumulation of financial assets		
	(1)	(2)	(3)
b_{it}/Y_{it-1}	0.863***	0.862***	0.817***
	(0.04)	(0.04)	(0.04)
$LEV_{it} = 1$			-0.478
			(0.34)
$[(b_{it}/Y_{it-1}) \times LEV_{it}]$			0.074*
			(0.03)
(4) lags dependent variable	✓	✓	✓
(4) lags new borrowing	✓	✓	✓
Macroeconomic controls ($\mathbf{x}_{it}$)		✓	
Country fixed effects	✓	✓	✓
Quarter fixed effects	✓	✓	✓
within-R^2 (adj.)	0.625	0.623	0.626
Observations	1257	1223	1257
Debt data source	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficient β estimated from equation 3.3 where the dependent variable z is the net of accumulation of financial assets, or more specifically the accumulation of total financial assets, net of non-debt liabilities, and as share of GDP ($(a_{it}-l_{it})/Y_{it}$). All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C.7: NON-CASH FINANCIAL ASSETS DRIVE FINANCIAL ASSETS GROWTH: ROBUSTNESS

Panel A: Robustness to BIS-based new borrowing data				
	Cash-like financial assets		*Non-cash financial assets*	
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	-0.019	-0.024	0.493***	0.491***
	(0.07)	(0.08)	(0.07)	(0.07)
(4) lags dependent variable	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓
Macroeconomic controls ($\mathbf{x}_{it}$)		✓		✓
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓
within-R^2 (adj.)	0.148	0.159	0.381	0.391
Observations	1390	1356	1390	1356
Debt data source	BIS	BIS	BIS	BIS
Panel B: Robustness to post-1995 sub-sample				
	Non-cash financial assets		*Non-cash financial assets*	
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.082	0.106**	0.811***	0.807***
	(0.05)	(0.05)	(0.03)	(0.03)
(4) lags dependent variable	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓
Macroeconomic controls ($\mathbf{x}_{it}$)		✓		✓
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓
within-R^2 (adj.)	0.146	0.158	0.589	0.589
Observations	1257	1223	1257	1223
Debt data source	Transactions	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficient β estimated from equation 3.3 where the dependent variable z is the net accumulation of cash-like financial assets as share of GDP $((a_{it}^{Cash} - l_{it})/Y_{it})$ in columns (1)-(2), and the net accumulation of non-cash financial assets as share of GDP $((a_{it}^{Non-cash} - l_{it})/Y_{it})$ in columns (3)-(4). All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C.8: NEW BORROWING LEADS TO GROWING FOREIGN DIRECT EQUITY INVESTMENT: ROBUSTNESS CHECKS

	Net direct equity investment		Net portfolio equity investment	
Panel A: Robustness to BIS-based new borrowing data				
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.111***	0.116***	-0.026	-0.021
	(0.02)	(0.02)	(0.03)	(0.03)
(4) lags dependent variable	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓
Macroeconomic controls		✓		✓
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓
within-R^2 (adj.)	0.132	0.143	0.168	0.175
Observations	1271	1237	1343	1309
Debt data source	BIS	BIS	BIS	BIS
Panel B: Robustness to post-1995 sub-sample				
	Net direct equity investment		*Net portfolio equity investment*	
	(1)	(2)	(3)	(4)
b_{it}/Y_{it-1}	0.102**	0.124***	0.014	0.005
	(0.04)	(0.04)	(0.02)	(0.02)
(4) lags dependent variable	✓	✓	✓	✓
(4) lags new borrowing	✓	✓	✓	✓
Macroeconomic controls		✓		✓
Country fixed effects	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓
within-R^2 (adj.)	0.135	0.152	0.158	0.168
Observations	1088	1054	1108	1074
Debt data source	Transactions	Transactions	Transactions	Transactions

All series are seasonally adjusted using the X-13 ARIMA method (US series were already adjusted using the same method). The table reports the coefficient β estimated from equation 3.3 where the dependent variable z is the net direct equity investment as share of GDP (DI_{it}/Y_{it}) in columns (1)-(2), and net portfolio equity investment as share of GDP (PI_{it}/Y_{it}) in columns (3)-(4). All variables but the difference in stock prices are multiplied by 100. HAC robust standard errors (clustered by country) are in parentheses and stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4.1 Identification-through-heteroskedasticity explained

We begin by rewriting equation 3.3 here as:

$$
\begin{aligned}
z_{it} &= \alpha_i + \theta_t + \beta \left(\frac{b_{it}}{Y_{it-1}} \right) + \sum_{p=1}^{P} \delta_p \left(\frac{b_{it-p}}{Y_{it-p-1}} \right) + \sum_{p=1}^{P} \gamma_p z_{it-p} + \boldsymbol{\lambda}' \mathbf{x}_{it} + \varepsilon_{it} \\
&= \beta \left(\frac{b_{it}}{Y_{it-1}} \right) + \boldsymbol{\gamma}(L)' \mathbf{x}_{it} + \varepsilon_{it} \qquad \text{(C.2)}
\end{aligned}
$$

where the vector $\mathbf{x}_{it}$ collects all right-hand side variables in equation C.2 different from contemporaneous new borrowing-to-GDP. To see the Lewbel (2012) estimator at work, let's rewrite equation C.2 as embedded in a system of equations in which we can identify a first-stage (equation C.4) and a second-stage regression (equation C.3). We also rewrite the errors in each equation as being consisted by a common factor (U_{it}) and an idiosyncratic component (v_{1it} and v_{12t}, respectively). The system reads as:

$$
\text{second stage:} \quad z_{it} = \beta \left(\frac{b_{it}}{Y_{it-1}} \right) + \boldsymbol{\gamma}(L)' \mathbf{x}_{it} + \underbrace{cU_{it} + v_{1it}}_{\varepsilon_{it}} \qquad \text{(C.3)}
$$

$$
\text{first stage:} \quad \frac{b_{it}}{Y_{it-1}} = \boldsymbol{\delta}(L)' \mathbf{m}_{it} + \underbrace{U_{it} + v_{2it}}_{\eta_{it}} \qquad \text{(C.4)}
$$

The vector $\mathbf{z}_{it}$ contains a subset of variables included in $\mathbf{x}_{it}$ such that $\mathbf{m}_{it} \subseteq \mathbf{x}_{it}$. Moreover, η_{it} is the error term of the first-stage (auxiliary) regression, possibly correlated with ε_{it}. Both error terms η_{it} and ε_{it} are assumed to be zero-mean disturbances

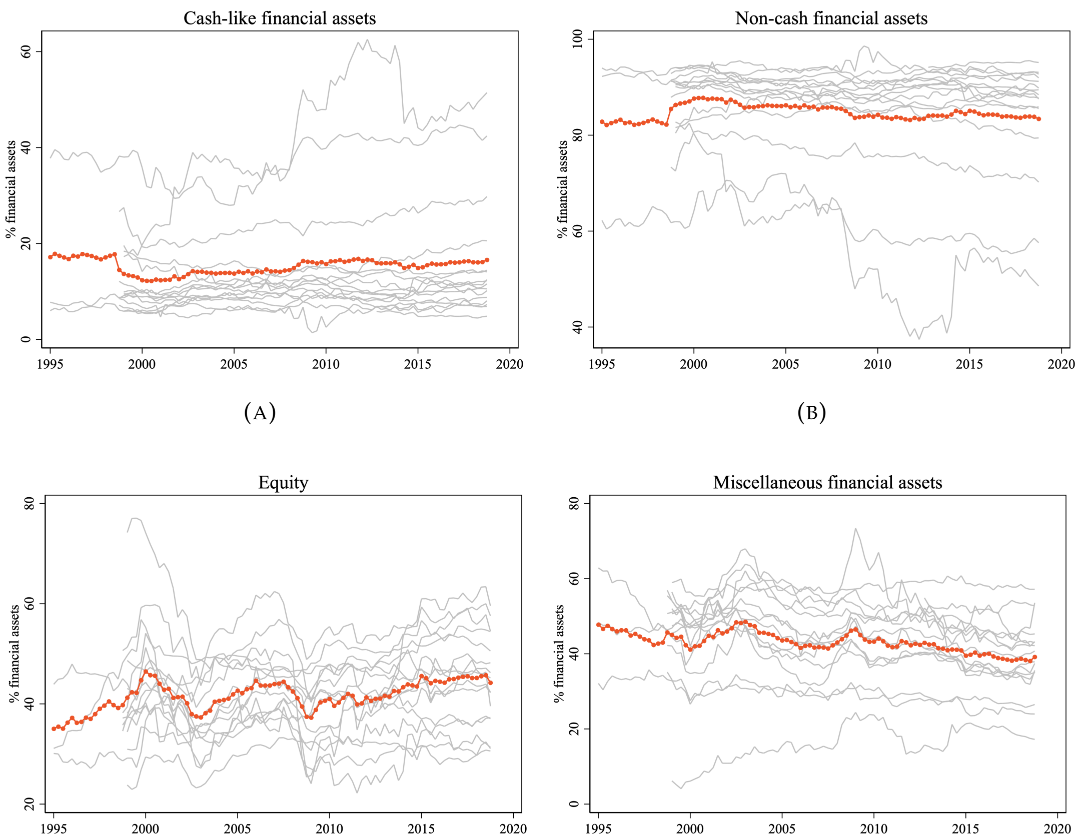
In addition to the standard assumption that $\mathbb{E}(\mathbf{x}\varepsilon) = \mathbb{E}(\mathbf{x}\eta) = 0$ (A1), Lewbel (2012) proves that identification amounts to select $\mathbf{m} \subseteq \mathbf{x}$ such that $\mathrm{Cov}(\mathbf{m}, \eta^2) \neq 0$ (A2) and $\mathrm{Cov}(\mathbf{m}, \varepsilon\eta) = 0$ (A3). A2 states that the first stage errors are heteroskedastic and that $\mathbf{m}\eta^2$ is correlated with ${}^{b_{it}}/{}_{Y_{it-1}}$ through η_{it}. While, A3 states that $\mathbf{m}\eta^2$ is not correlated with the covariance between η_{it} and ε_{it} and in turn is uncorrelated with ε_{it} in the second-stage regression. If A1, A2, A3 are satisfied, it is possible to construct valid instruments by interacting the first-stage residuals with the demeaned elements of $\mathbf{m}$, namely $\tilde{\mathbf{m}}_{it} = (\mathbf{m}_{it} - \bar{\mathbf{m}})\hat{\eta}_{it}$. These are valid instruments for new borrowing-to-GDP if assumptions A1, A2, A3 are satisfied. These instruments are valid as they are uncorrelated with residuals in the second stage regression while being correlated with new borrowing-to-GDP. The estimation algorithm proposed by Lewbel (2012) can be summarized in the following steps:

1. in the first stage, regress ${}^{b_{it}}/{}_{Y_{it-1}}$ on $\mathbf{m}_{it}'\delta$ and obtain the fitted residuals $\hat{\eta}_{it}$,
2. construct the instrument as $\tilde{\mathbf{m}}_{it} = (\mathbf{m}_{it} - \bar{\mathbf{m}})\hat{\eta}_{it}$ with $\mathbf{m}_{it} \subseteq \mathbf{x}_{it}$,
3. estimate the second-stage regression: $z_{it} = \tilde{\beta}\tilde{\mathbf{m}}_{it} + \mathbf{x}_t'\gamma + \varepsilon_{it}$.

The procedure is employed by implementing the Stata command `ivreg2h` proposed by Baum et al. (2012). Since we include more than one variable in $\mathbf{z}$, we invoke the instrumental variable generalized method of moments for obtaining classic specification tests.

According to Lewbel (2012), A2 and A3 are satisfied if the errors in both regressions C.3 and C.4 have a common factor structure. For example, the errors ε and η may be determined by a common unobserved (homoskedastic) component U_{it} in addition to the idiosyncratic errors v_{1it} and v_{2it}, with c being a scaling constant. Assuming a common factor structure for disturbances amounts to assuming that the source of endogeneity is an unobserved factor affecting both new borrowing and the outcome variable z. We believe that this treatment of endogeneity affecting new borrowing is plausible and potential candidates for the common factor may be unobserved changes in financial regulation, financial development or expectation variables driving both firms' financial policy.

C.5 Other figures

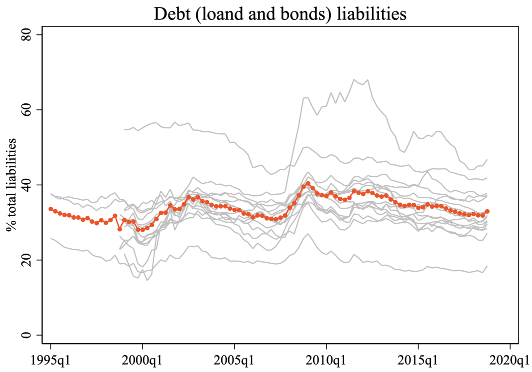


(A) (B)

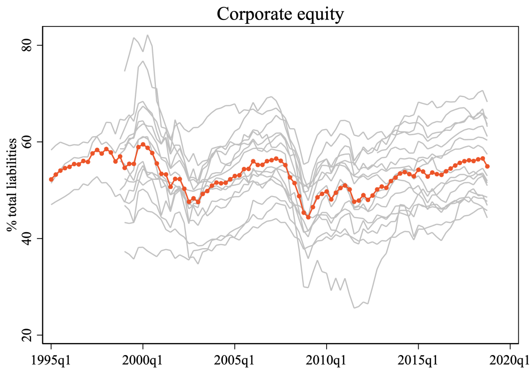
(C) (D)

FIGURE C.4: DECOMPOSITION OF FINANCIAL ASSETS

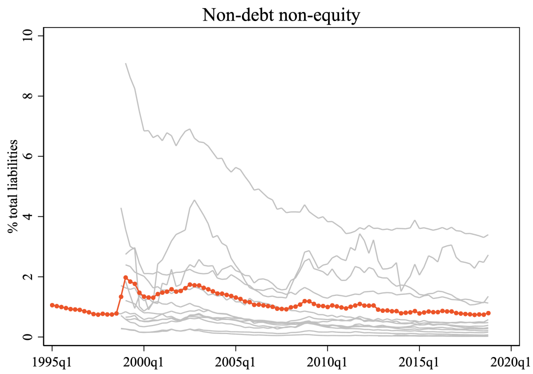
Notes: this figure plots the decomposition of the financial assets side of the balance sheet of the non-financial corporate sector. The red line with marker is the average share of cash-like financial assets (Panel A), non-cash financial assets (Panel B), equity (Panel C) and miscellaneous financial assets (Panel D) of total financial assets (stock). Grey lines in the background are country-level shares. Note that the sum of equity and miscellaneous financial assets equals non-cash financial assets.



(A)



(B)



(C)

FIGURE C.5: DECOMPOSITION OF LIABILITIES

Notes: this figure plots the decomposition of the liability side of the balance sheet of the non-financial corporate sector. The red line with marker is the average share of debt liabilities (Panel A), corporate equity (Panel B) and non-debt non-equity (Panel C) of total liabilities (stock). Grey lines in the background are country-level shares.

Bibliography

Adelino, M., Schoar, A., and Severino, F. (2016). Loan originations and defaults in the mortgage crisis: The role of the middle class. *The Review of Financial Studies*, 29(7):1635–1670. 15

Adelino, M., Schoar, A., and Severino, F. (2018). The role of housing and mortgage markets in the financial crisis. *Annual Review of Financial Economics*. Publisher: Annual Reviews. 33

Albuquerque, B. and Krustev, G. (2018). Debt overhang and deleveraging in the US household sector: gauging the impact on consumption. *Review of Income and Wealth*, 64(2):459–481. 13

Alpanda, S., Granziera, E., and Zubairy, S. (2019). *State dependence of monetary policy across business, credit and interest rate cycles*. Norges Bank. 35

Alpanda, S. and Zubairy, S. (2019). Household debt overhang and transmission of monetary policy. *Journal of Money, Credit and Banking*, 51(5):1265–1307. Publisher: Wiley Online Library. 17, 35

Alter, A., Feng, A. X., and Valckx, N. (2018). *Understanding the Macro-Financial Effects of Household Debt: A Global Perspective*. International Monetary Fund. 7

Amromin, G., Bhutta, N., and Keys, B. J. (2020). Refinancing, Monetary Policy, and the Credit Cycle. *Annual Review of Financial Economics*, 12:67–93. Publisher: Annual Reviews. 33

Andersen, A. L., Duus, C., and Jensen, T. L. (2016). Household debt and spending during the financial crisis: Evidence from Danish micro data. *European Economic Review*, 89:96–115. Publisher: Elsevier. 13, 15, 20

Angrist, J. D., Jordà, Ò., and Kuersteiner, G. M. (2018). Semiparametric estimates of monetary policy effects: string theory revisited. *Journal of Business & Economic Statistics*, 36(3):371–387. Publisher: Taylor & Francis. 47

Anundsen, A. K., Gerdrup, K., Hansen, F., and Kragh-Sørensen, K. (2016). Bubbles and crises: The role of house prices and credit. *Journal of Applied Econometrics*, 31(7):1291–1311. 7

Arcand, J. L., Berkes, E., and Panizza, U. (2015). Too much finance? *Journal of Economic Growth*, 20(2):105–148. Publisher: Springer. 2

Avdjiev, S., Chui, M. K., and Shin, H. S. (2014). Non-financial corporations from emerging market economies and capital flows. *BIS Quarterly Review December*. 127

Bachmann, R. and Rüth, S. K. (2020). Systematic Monetary Policy And The Macroeconomic Effects Of Shifts In Residential Loan-To-Value Ratios. *International Economic Review*, 61(2):503–530. Publisher: Wiley Online Library. 9, 16, 17, 18, 21, 29

Bagehot, W. (1873). *Lombard Street: A description of the money market*. Scribner, Armstrong & Company. iii

Bańbura, M., Giannone, D., and Reichlin, L. (2010). Large Bayesian vector auto regressions. *Journal of applied Econometrics*, 25(1):71–92. Publisher: Wiley Online Library. 40

Barakchian, S. M. and Crowe, C. (2013). Monetary policy matters: Evidence from new shocks data. *Journal of Monetary Economics*, 60(8):950–966. Publisher: Elsevier. 50

Barnichon, R. and Matthes, C. (2014). Measuring the non-linear effects of monetary policy. *Federal Reserve Bank of Richmond Manuscript*. 47

Bassett, W. F., Chosak, M. B., Driscoll, J. C., and Zakrajšek, E. (2014). Changes in bank lending standards and the macroeconomy. *Journal of Monetary Economics*, 62:23–40. Publisher: Elsevier. 17

Baum, C. F., Lewbel, A., Schaffer, M. E., and Talavera, O. (2012). Instrumental variables estimation using heteroskedasticity-based instruments. In *United Kingdom Stata User's Group Meetings*, volume 7. 148

Behringer, J. (2020). Factor shares and the rise in corporate net lending. Technical report, IMK Working Paper. 108, 115

Berkmen, S. P., Gelos, G., Rennhack, R., and Walsh, J. P. (2012). The global financial crisis: Explaining cross-country differences in the output impact. *Journal of International Money and Finance*, 31(1):42–59. 13

Bernanke, B. (2018). The real effects of the financial crisis. *Brookings Papers on Economic Activity*. 15

Bernanke, B. S. (1983). Nonmonetary Effects of the Financial Crisis in Propagation of the Great Depression. *American Economic Review*, 73(3):257–276. Publisher: American Economic Association. iv

Bernanke, B. S. (2007). Housing, housing finance, and monetary policy. Technical Report No. 311. 33, 61, 62, 63, 64, 65

Bernanke, B. S., Boivin, J., and Eliasz, P. (2005). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly journal of economics*, 120(1):387–422. Publisher: MIT Press. 57

Bernanke, B. S. and Gertler, M. (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic perspectives*, 9(4):27–48. 33

Bezemer, D. and Zhang, L. (2019). Credit composition and the severity of post-crisis recessions. *Journal of Financial Stability*, 42:52–66. Publisher: Elsevier. 13

Boivin, J., Kiley, M. T., and Mishkin, F. S. (2010). How has the monetary transmission mechanism evolved over time? In *Handbook of monetary economics*, volume 3, pages 369–422. Elsevier. 36, 50

Breitenlechner, M. and Scharler, J. (2020). Private Sector Debt, Financial Constraints, and the Effects of Monetary Policy: Evidence from the US. *Oxford Bulletin of Economics and Statistics*, 82(4):889–915. Publisher: Wiley Online Library. 35

Bridges, J., Jackson, C., and McGregor, D. (2017). Down in the slumps: the role of credit in five decades of recessions. 8, 20

Brooks, C. (2019). *Introductory econometrics for finance*. Cambridge university press. 3

Brüggemann, R., Jentsch, C., and Trenkler, C. (2016). Inference in VARs with conditional heteroskedasticity of unknown form. *Journal of econometrics*, 191(1):69–85. Publisher: Elsevier. 53, 54, 56, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 101, 102, 103, 104

Brunnermeier, M., Palia, D., Sastry, K. A., and Sims, C. A. (2019). Feedbacks: Financial Markets and Economic Activity. Technical report, Princeton University, Department of Economics. 9, 16, 17, 18, 22, 29, 49

Bunn, P. and Rostom, M. (2014). Household debt and spending. *Bank of England Quarterly Bulletin*, page Q3. 13, 15

Bunn, P. and Rostom, M. (2015). Household debt and spending in the United Kingdom. *Staff Working Paper No. 554*. 13, 15

Büyükkarabacak, B. and Valev, N. T. (2010). The role of household and business credit in banking crises. *Journal of Banking & Finance*, 34(6):1247–1256. Publisher: Elsevier. 7

Calza, A., Monacelli, T., and Stracca, L. (2013). Housing finance and monetary policy. *Journal of the European Economic Association*, 11(suppl_1):101–122. 17, 35, 47

Campbell, J. Y. (2012). Mortgage market design. *Review of finance*, 17(1):1–33. 35

Carriero, A., Clark, T. E., and Marcellino, M. (2015). Bayesian VARs: specification choices and forecast accuracy. *Journal of Applied Econometrics*, 30(1):46–73. Publisher: Wiley Online Library. 38, 44

Cecchetti, S. G., Mohanty, M. S., and Zampolli, F. (2011). The real effects of debt. 7

Cesaroni, T., De Bonis, R., and Infante, L. (2018). Firms' financial surpluses in advanced economies: the role of net foreign direct investments. *Economia Politica*, 35(3):1055–1080. Publisher: Springer. 108

Chan, J. C. and Strachan, R. W. (2020). Bayesian state space models in macroeconometrics. *Journal of Economic Surveys*. Publisher: Wiley Online Library. 40

Chan, J. C. C., Eisenstat, E., and Strachan, R. W. (2020). Reducing the state space dimension in a large TVP-VAR. *Journal of Econometrics*, 218(1):105–118. 40

Chen, P., Karabarbounis, L., and Neiman, B. (2017). The global rise of corporate saving. *Journal of Monetary Economics*, 89:1–19. Publisher: Elsevier. 108, 115

Choi, I. (2001). Unit root tests for panel data. *Journal of international money and Finance*, 20(2):249–272. Publisher: Elsevier. 140

Christiano, L. J., Eichenbaum, M., and Evans, C. (1996). The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds. *The Review of Economics and Statistics*, pages 16–34. Publisher: JSTOR. 38, 45

Christiano, L. J., Eichenbaum, M., and Evans, C. L. (1999). Monetary policy shocks: What have we learned and to what end? *Handbook of macroeconomics*, 1:65–148. Publisher: Elsevier. 46

Cloyne, J., Ferreira, C., and Surico, P. (2020). Monetary policy when households have debt: new evidence on the transmission mechanism. *The Review of Economic Studies*, 87(1):102–129. Publisher: Oxford University Press. 35, 36

Cogley, T. and Sargent, T. J. (2001). Evolving post-world war II US inflation dynamics. *NBER macroeconomics annual*, 16:331–373. Publisher: MIT press. 43

Cogley, T. and Sargent, T. J. (2005). Drifts and volatilities: monetary policies and outcomes in the post WWII US. *Review of Economic dynamics*, 8(2):262–302. 36, 37, 40, 43, 45

Covas, F. and Den Haan, W. J. (2011). The cyclical behavior of debt and equity finance. *American Economic Review*, 101(2):877–99. 125, 132

Cumming, F. and Hubert, P. (2020). The role of households' borrowing constraints in the transmission of monetary policy. Staff Working Paper No. 836, Bank of England. 35, 36

Cynamon, B. Z. and Fazzari, S. M. (2016). Inequality, the Great Recession and slow recovery. *Cambridge Journal of Economics*, 40(2):373–399. Publisher: Oxford University Press UK. 14

Dao, M. C. and Maggi, C. (2018). The Rise in Corporate Saving and Cash Holding in Advanced Economies: Aggregate and Firm Level Trends. 108, 115, 125

Davis, L. E. (2017). Financialization and investment: A survey of the empirical literature. *Journal of Economic Surveys*, 31(5):1332–1358. Publisher: Wiley Online Library. 108, 122

Davis, L. E. (2018). Financialization and the non-financial corporation: An investigation of firm-level investment behavior in the United States. *Metroeconomica*, 69(1):270–307. Publisher: Wiley Online Library. 108, 109, 115, 133

Demir, F. (2009). Financial liberalization, private investment and portfolio choice: Financialization of real sectors in emerging markets. *Journal of Development Economics*, 88(2):314–324. Publisher: Elsevier. 108

Den Haan, W. J. and Sterk, V. (2010). The myth of financial innovation and the great moderation. *The Economic Journal*, 121(553):707–739. 17, 36, 39, 47, 55

Di Maggio, M., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A., and Yao, V. (2017). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review*, 107(11):3550–88. 35

Doan, T., Litterman, R., and Sims, C. (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric reviews*, 3(1):1–100. Publisher: Taylor & Francis. 41

Drehmann, M., Juselius, M., and Korinek, A. (2018). Going with the flows: New borrowing, debt service and the transmission of credit booms. Technical report, National Bureau of Economic Research. 5, 6, 9, 16, 24, 27, 105, 106, 107, 109, 111, 122, 137

Drehmann, M. and Yetman, J. (2018). Why you should use the Hodrick-Prescott filter–at least to generate credit gaps. Publisher: BIS Working Paper. 123

Dynan, K. (2012). Is a household debt overhang holding back consumption? *Brookings Papers on Economic Activity*, pages 299–362. 9, 11, 12, 28

Epstein, G. A. (2005). *Financialization and the world economy*. Edward Elgar Publishing. 108

Eurostat (2013). *ESA2010*. Luxembourg: Publications Office of the European Union. 134

Finck, D., Schmidt, J., and Tillmann, P. (2018). Mortgage debt and time-varying monetary policy transmission. Technical report, MAGKS Joint Discussion Paper Series in Economics. 36, 47, 55, 61

Fisher, I. (1933). The debt-deflation theory of great depressions. *Econometrica: Journal of the Econometric Society*, pages 337–357. iv, v, 2, 12, 19, 24

Flodén, M., Kilström, M., Sigurdsson, J., and Vestman, R. (2019). Household debt and monetary policy: Revealing the cash-flow channel. *Riksbank Research Paper Series*, (166):18–4. 35

Frühwirth-Schnatter, S. (2006). *Finite mixture and Markov switching models*. Springer Science & Business Media. 42

Furlanetto, F., Ravazzolo, F., and Sarferaz, S. (2019). Identification of financial factors in economic fluctuations. *The Economic Journal*, 129(617):311–337. Publisher: Oxford University Press. 17

Gambetti, L. and Musso, A. (2017). Loan supply shocks and the business cycle. *Journal of Applied Econometrics*, 32(4):764–782. 17

Gertler, M. (1988). Financial Structure and Aggregate Economic Activity: An Overview. *Journal of Money, Credit and Banking*, 20(3):559–588. 2

Giannone, D., Lenza, M., and Primiceri, G. E. (2015). Prior selection for vector autoregressions. *Review of Economics and Statistics*, 97(2):436–451. Publisher: MIT Press. 44

Gilchrist, S., López-Salido, D., and Zakrajšek, E. (2015). Monetary policy and real borrowing costs at the zero lower bound. *American Economic Journal: Macroeconomics*, 7(1):77–109. 33

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1720. 17, 29

Giroud, X. and Mueller, H. M. (2017). Firm leverage, consumer demand, and employment losses during the Great Recession. *The Quarterly Journal of Economics*, 132(1):271–316. Publisher: Oxford University Press. 108

Glick, R. and Lansing, K. J. (2010). Global household leverage, house prices, and consumption. *FRBSF Economic Letter*, 1:1–5. 13

Goldsmith, R. W. (1969). *Financial structure and development*. Yale University Press, New Haven, CT. iii

Gourinchas, P.-O. and Obstfeld, M. (2012). Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics*, 4(1):226–65. 7

Gozzi, J. C., Levine, R., Peria, M. S. M., and Schmukler, S. L. (2015). How firms use corporate bond markets under financial globalization. *Journal of Banking & Finance*, 58:532–551. Publisher: Elsevier. 127

Green, R. K. and Wachter, S. M. (2005). The American mortgage in historical and international context. *Journal of Economic Perspectives*, 19(4):93–114. 63, 64

Gruber, J. W. and Kamin, S. B. (2016). The corporate saving glut and falloff of investment spending in OECD economies. *IMF Economic Review*, 64(4):777–799. Publisher: Springer. 108, 115, 121

Guerini, M., Moneta, A., Napoletano, M., and Roventini, A. (2018). The janus-faced nature of debt: Results from a data-driven cointegrated svar approach. *Macroeconomic Dynamics*, pages 1–31. 9, 16, 17, 29

Gurley, J. G. and Shaw, E. S. (1955). Financial aspects of economic development. *The American Economic Review*, 45(4):515–538. Publisher: JSTOR. iii

Hamilton, J. D. (1994). *Time series analysis*. Princeton university press. 47

Hart, A. G. (1938). *Debts and Recovery 1929 to 1937. Twentieth Century Fund*. Inc. iv

Hofmann, B. and Peersman, G. (2017a). Is there a debt service channel of monetary transmission? *BIS Quarterly Review, December*. 17, 35

Hofmann, B. and Peersman, G. (2017b). Monetary policy transmission and trade-offs in the United States: old and new. 17, 36, 40, 47, 50, 55, 61, 65

Im, K. S., Pesaran, M. H., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of econometrics*, 115(1):53–74. Publisher: Elsevier. 140

Jappelli, T. and Scognamiglio, A. (2018). Interest rate changes, mortgages, and consumption: evidence from Italy. *Economic Policy*, 33(94):183–224. Publisher: Oxford University Press. 35

Jazwinski, A. H. (1970). *Stochastic processes and filtering theory*. Number 64 in Mathematics in science and engineering. 45

Jordà, O. (2005). Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182. 5, 109, 110

Jordà, Ò., Kornejew, M., Schularick, M., and Taylor, A. M. (2020). Zombies at large? Corporate debt overhang and the macroeconomy. Technical report, National Bureau of Economic Research. 24, 107, 108, 109

Jordà, Ò., Schularick, M., and Taylor, A. M. (2015). Betting the house. *Journal of International Economics*, 96:S2–S18. 122

Jordà, Ò., Schularick, M., and Taylor, A. M. (2016). The great mortgaging: housing finance, crises and business cycles. *Economic Policy*, 31(85):107–152. 5, 6, 7, 9, 22, 27, 33, 107, 109

Jordà, Ò., Schularick, M., and Taylor, A. M. (2017). Macrofinancial history and the new business cycle facts. *NBER macroeconomics annual*, 31(1):213–263. iii, 2, 3

Kalemli-Özcan, S., Laeven, L., and Moreno, D. (2019). Debt overhang, rollover risk, and corporate investment: Evidence from the european crisis. Technical report, National Bureau of Economic Research. 108

Känzig, D. R. (2021). The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements. *American Economic Review*, (forthcoming). 53

Kapetanios, G., Marcellino, M., and Venditti, F. (2019). Large time-varying parameter VARs: A nonparametric approach. *Journal of Applied Econometrics*, 34(7):1027–1049. Publisher: Wiley Online Library. 40

Kaplan, G., Mitman, K., and Violante, G. L. (2020). Non-durable consumption and housing net worth in the great recession: Evidence from easily accessible data. *Journal of Public Economics*, 189:104176. Publisher: Elsevier. 12

Kilian, L. and Lütkepohl, H. (2017). *Structural vector autoregressive analysis*. Cambridge University Press. 47, 53

Kim, C.-J. and Nelson, C. R. (1999). State-space models with regime switching: classical and Gibbs-sampling approaches with applications. *MIT Press Books*, 1. Publisher: The MIT press. 37, 42

Kim, Y. K. (2020). Household debt accumulation and the Great Recession of the United States: a comparative perspective. *Review of Radical Political Economics*, 52(1):26–49. Publisher: SAGE Publications Sage CA: Los Angeles, CA. 14

Kindleberger, C. P. (1978). *Manias, Panics, and crashes; a history of financial crises*. Basic Books, New York. iv, v, viii, 2, 4, 7, 19, 24, 122

Kindleberger, C. P. and Aliber, R. Z. (2011). *Manias, panics and crashes: a history of financial crises*. Palgrave Macmillan. iii, iv

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of econometrics*, 133(1):97–126. Publisher: Elsevier. 131

Koop, G. and Korobilis, D. (2013). Large time-varying parameter VARs. *Journal of Econometrics*, 177(2):185–198. 34, 38, 40, 41, 42, 44, 45, 66, 75

Koop, G. and Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, 71:101–116. 34, 38, 40, 41, 42, 43, 44, 45, 59, 66, 75

Koop, G. and Potter, S. M. (2011). Time varying VARs with inequality restrictions. *Journal of Economic Dynamics and Control*, 35(7):1126–1138. Publisher: Elsevier. 43

Krishnamurthy, A. and Muir, T. (2017). How credit cycles across a financial crisis. Technical report, National Bureau of Economic Research. 27

Krishnamurthy, A. and Vissing-Jorgensen, A. (2011). The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy. *Brookings Papers on Economic Activity*, page 215. Publisher: Brookings Institution. 38

Lamont, O. (1995). Corporate-debt overhang and macroeconomic expectations. *The American Economic Review*, pages 1106–1117. Publisher: JSTOR. 108

Lane, P. R. and Milesi-Ferretti, G. M. (2008). The drivers of financial globalization. *American Economic Review*, 98(2):327–32. 127

Lane, P. R. and Milesi-Ferretti, G. M. (2011). The cross-country incidence of the global crisis. *IMF Economic Review*, 59(1):77–110. 13

Lane, P. R. and Milesi-Ferretti, G. M. (2017). International Financial Integration in the Aftermath of the Global Financial Crisis. Technical report, International Monetary Fund. 128

Leamer, E. E. (2007). Housing is the business cycle. Technical report, National Bureau of Economic Research. 33, 48

Levine, R. (2005). Finance and growth: theory and evidence. *Handbook of economic growth*, 1:865–934. Publisher: Elsevier. 2

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, 30(1):67–80. Publisher: Taylor & Francis Group. 130, 131, 148

Lombardi, M. J., Mohanty, M. S., and Shim, I. (2017). The real effects of household debt in the short and long run. 7

López-Salido, D., Stein, J. C., and Zakrajšek, E. (2017). Credit-market sentiment and the business cycle. *The Quarterly Journal of Economics*, 132(3):1373–1426. Publisher: Oxford University Press. 17, 122

Ma, Y. (2019). Nonfinancial Firms as Cross-Market Arbitrageurs. *The Journal of Finance*, 74(6):3041–3087. Publisher: Wiley Online Library. 121, 132

Mason, J. W. (2015). Disgorge the cash: The disconnect between corporate borrowing and investment. *Roosevelt Institute*, 25. 109

Mason, J. W. and Jayadev, A. (2014). " Fisher Dynamics" in US Household Debt, 1929-2011. *American Economic Journal: Macroeconomics*, 6(3):214–34. 14

McCarthy, J. and Peach, R. W. (2002). Monetary policy transmission to residential investment. *Economic policy review*, 8(1). 17, 33, 36, 47, 50, 61, 62, 63, 65

Mertens, K. (2008). Deposit rate ceilings and monetary transmission in the US. *Journal of Monetary Economics*, 55(7):1290–1302. Publisher: Elsevier. 63

Mian, A., Rao, K., and Sufi, A. (2013). Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics*, 128(4):1687–1726. 9, 11, 12, 28

Mian, A. and Sufi, A. (2009). The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis. *The Quarterly Journal of Economics*, 124(4):1449–1496. 33

Mian, A. and Sufi, A. (2010). Household Leverage and the Recession of 2007–09. *IMF Economic Review*, 58(1):74–117. 9, 11, 12, 20, 28, 33

Mian, A. and Sufi, A. (2011). House prices, home equity-based borrowing, and the US household leverage crisis. *American Economic Review*, 101(5):2132–56. 14

Mian, A. and Sufi, A. (2014). What explains the 2007–2009 drop in employment? *Econometrica*, 82(6):2197–2223. 8

Mian, A. and Sufi, A. (2015). *House of debt: How they (and you) caused the Great Recession, and how we can prevent it from happening again*. University of Chicago Press. iii, 10, 13

Mian, A. and Sufi, A. (2017). Household debt and defaults from 2000 to 2010: The credit supply view. *Evidence and Innovation in Housing Law and Policy*, pages 257–288. 13, 15

Mian, A. and Sufi, A. (2018). Finance and business cycles: the credit-driven household demand channel. *Journal of Economic Perspectives*, 32(3):31–58. 4, 7, 17

Mian, A., Sufi, A., and Verner, E. (2017). Household debt and business cycles worldwide. *The Quarterly Journal of Economics*, 132(4):1755–1817. 1, 5, 6, 7, 8, 9, 21, 22, 24, 27, 30, 31, 33, 105, 106, 107, 109, 111, 137

Mian, A., Sufi, A., and Verner, E. (2020). How does credit supply expansion affect the real economy? The productive capacity and household demand channels. *The Journal of Finance*, 75(2):949–994. Publisher: Wiley Online Library. 7, 8

Minsky, H. P. (1986). *Stabilizing an Unstable Economy*. Yale University Press, New Heaven and London. iv, v, viii, 2, 4, 7, 19, 24, 63, 122

Miranda-Agrippino, S. and Ricco, G. (2018). The transmission of monetary policy shocks. Publisher: Cepr discussion paper no. dp13396. 59

Mishkin, F. S. (1978). The household balance sheet and the Great Depression. *The Journal of Economic History*, 38(4):918–937. iv, 19

Mishkin, F. S. (2007). Housing and the monetary transmission mechanism. In *Proceedings-Economic Policy Symposium-Jackson Hole*, pages 359–413. Federal Reserve Bank of Kansas City. 33, 35

Mishkin, F. S., Gordon, R. J., and Hymans, S. H. (1977). What depressed the consumer? The household balance sheet and the 1973-75 recession. *Brookings papers on economic activity*, 1977(1):123–174. 19

Modigliani, F. and Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American economic review*, 48(3):261–297. Publisher: JSTOR. 106

Monnet, E. and Puy, D. (2019). One Ring to Rule Them All? New Evidence on World Cycles. International Monetary Funds(working Paper n° 19/202). 105, 109, 113, 121, 134

Montiel, J. L. O. and Plagborg-Møller, M. (2020). Local Projection Inference is Simpler and More Robust Than You Think. *arXiv e-prints*, pages arXiv–2007. 110

Müller, K. and Verner, E. (2020). Credit Allocation and Macroeconomic Fluctuations. 5, 6, 8, 9, 22, 27

Musso, A., Neri, S., and Stracca, L. (2011). Housing, consumption and monetary policy: How different are the US and the euro area? *Journal of Banking & Finance*, 35(11):3019–3041. Publisher: Elsevier. 35, 47

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of financial economics*, 5(2):147–175. Publisher: Elsevier. 108

Myers, S. C. (2001). Capital structure. *Journal of Economic perspectives*, 15(2):81–102. 106, 110, 116

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, 13(2):187–221. Publisher: Elsevier. viii, 106

Nakamura, E. and Steinsson, J. (2018). Identification in macroeconomics. *Journal of Economic Perspectives*, 32(3):59–86. 46, 47

Orhangazi, Ö. (2008). Financialisation and capital accumulation in the non-financial corporate sector: A theoretical and empirical investigation on the US economy: 1973–2003. *Cambridge journal of economics*, 32(6):863–886. Publisher: Oxford University Press. 108

Paul, P. (2020). The time-varying effect of monetary policy on asset prices. *Review of Economics and Statistics*, 102(4):690–704. 38, 53, 55

Peersman, G. (2011). Bank Lending Shocks and the Euro Area Business Cycle. Technical report, Ghent University, Faculty of Economics and Business Administration. 17

Peersman, G. and Wagner, W. (2015). Shocks to Bank Lending, Risk-Taking, Securitization, and their Role for US Business Cycle Fluctuations. CEPR Discussion Paper 10547. 9, 16, 17, 29

Persons, C. E. (1930). Credit expansion, 1920 to 1929, and its lessons. *The Quarterly Journal of Economics*, 45(1):94–130. iv

Petach, L. (2020). Local financialization, household debt, and the great recession. *Papers in Regional Science*, 99(3):807–839. Publisher: Wiley Online Library. 13

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, 72(3):821–852. vi, 34, 36, 40, 43, 47, 48, 59, 66

Raftery, A. E., Kárnỳ, M., and Ettler, P. (2010). Online prediction under model uncertainty via dynamic model averaging: Application to a cold rolling mill. *Technometrics*, 52(1):52–66. Publisher: Taylor & Francis. 45

Rajan, R. and Zingales, L. (1998). Financial Dependence and Growth. *American Economic Review*, 88(3):559–86. Publisher: American Economic Association. 2

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. In *Handbook of macroeconomics*, volume 2, pages 71–162. Elsevier. 57, 109

Rauch, H. E., Tung, F., and Striebel, C. T. (1965). Maximum likelihood estimates of linear dynamic systems. *AIAA journal*, 3(8):1445–1450. 41, 74

Robinson, J. (1952). The Generalization of the General Theory. In *The Rate of Interest and Other Essays*. Macmillan. iii

Romer, C. D. and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, 94(4):1055–1084. 48, 59, 62, 67

Ryding, J. (1990). Housing finance and the transmission of monetary policy. *Federal Reserve Bank of New York Quarterly Review*, 15(2):42–55. 61

Schumpeter, J. A. (1911). *Theorie der Wirtschaftlichen Entwicklung (The theory of economic development: an inquiry into profits, capital, credit, interest and the business cycle)*. Harvard University Press, Cambridge, MA (Dunker und Humblot, Jena. English ed., 1934). iii

Shiller, R. J. (2015). *Irrational exuberance: Revised and expanded third edition*. Princeton university press. 38, 39, 68

Sims, C. A. (1992). Interpreting the macroeconomic time series facts: The effects of monetary policy. *European economic review*, 36(5):975–1000. Publisher: Elsevier. 38

Sims, C. A. (1998). Comment on Glenn Rudebusch's" Do measures of monetary policy in a VAR make sense?". *International Economic Review*, 39(4):933–941. Publisher: JSTOR. 59

Sims, C. A. (2001). Comment on Sargent and Cogley's 'Evolving US Postwar Inflation Dynamics'. *NBER Macroeconomics Annual*, 16:373–379. 43, 45

Sims, C. A. and Zha, T. (2006a). Does Monetary Policy Generate Recessions? *Macroeconomic Dynamics*, 10(02):231–272. Publisher: Cambridge University Press. 57, 59

Sims, C. A. and Zha, T. (2006b). Were there regime switches in US monetary policy? *American Economic Review*, 96(1):54–81. 48

Slacalek, J., Tristani, O., and Violante, G. L. (2020). Household balance sheet channels of monetary policy: A back of the envelope calculation for the Euro Area. *Journal of Economic Dynamics and Control*, page 103879. Publisher: Elsevier. 35

Stock, J. H. and Watson, M. (2009). Forecasting in dynamic factor models subject to structural instability. *The Methodology and Practice of Econometrics. A Festschrift in Honour of David F. Hendry*, 173:205. 39, 71

Svensson, L. E. (2019). Housing Prices, Household Debt, and Macroeconomic Risk: Problems of Macroprudential Policy I. *Stockholm School of Economics, mimeo, February*. 15, 20

Tori, D. and Onaran, Ö. (2018). The effects of financialization on investment: evidence from firm-level data for the UK. *Cambridge Journal of Economics*, 42(5):1393–1416. Publisher: Oxford University Press UK. 108

Verner, E. and Gyöngyösi, G. (2020). Household debt revaluation and the real economy: Evidence from a foreign currency debt crisis. *American Economic Review*, 110(9):2667–2702. 13

Villani, D. (2021). The rise of corporate net lending among G7 countries: a firm-level analysis. *Review of Political Economy*, pages 1–24. Publisher: Taylor & Francis. 108

Walentin, K. (2014). Business cycle implications of mortgage spreads. *Journal of Monetary Economics*, 67:62–77. Publisher: Elsevier. 17

Wojnilower, A. M. (1980). The central role of credit crunches in recent financial history. *Brookings Papers on Economic Activity*, 1980(2):277–339. Publisher: JSTOR. 63

Wu, J. C. and Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291. Publisher: Wiley Online Library. 59