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Doctoral Thesis

Essays in Monetary Economics

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Preface

The papers included in this dissertation were composed during a period of considerable turmoil in many respects. But, it is always darkest before the dawn. Thus, for academic research, such periods open new venues and enable a reassessment of existing findings.

The event that has by far the greatest influence on the essays submitted here is the Global Financial Crisis. In particular, the crucial role of credit, the use and effectiveness of prudential measures in order to regulate credit developments, as well as the domestic and foreign (side-)effects of U.S. unconventional monetary policy, which the Fed employed with particular intensity in order to address the severe economic challenges posed by the financial crisis.

In response to the global economic downturn, central banks across the globe have taken swift and decisive action to lower their key interest rates. However, once the zero lower bound was reached, this sword became blunt, necessitating the implementation of unconventional measures. This strategy proved effective, resulting in a discernible economic recovery, i.a. by reviving labor markets. Concurrently, the central banks' asset-purchasing programs precipitated a notable surge in stock markets and asset prices. In turn, it is perceived that only a relatively limited proportion of the population has benefited from this appreciation, giving rise to heightened discourse surrounding the nexus between income inequality and the impact of (ultra-loose) monetary policy.

In the first paper, *Moving closer or drifting apart: Distributional effects of monetary policy*, which is joint work with Lucas Hafemann and Jörg Schmidt, we examine said nexus between unconventional monetary policy and inequality in six advanced economies. Furthermore, we analyse the two major transmission channels at work. The examined countries vary in their extent of governmental redistribution, allowing for an evaluation of whether governmental interventions affect the impact of unconventional monetary policy on income equality. To this end, we incorporate Gini coefficients in an otherwise standard vector autoregressive macro model, where we identify monetary policy shocks by means of sign restrictions.

Our findings show that, on the one hand, expansionary monetary policy shocks are associated with an increase in the Gini coefficients of gross incomes across all countries. On the other hand, only countries with relatively limited redistribution show a significant response of net income inequality as well.

In order to gain a deeper understanding of the underlying mechanism at play, we examine the two most relevant transmission channels: the employment channel and the income composition channel. We find that employment, captured by the total number of employed people, increases due to loose monetary policy in all countries. Once more, the reaction is observed to be weaker and less pronounced in countries with a high degree of redistribution (i.e. with a presumably more active state with potentially stricter regulations and, in turn, less flexible labor markets). In order to examine the income composition channel, we disaggregate the composition of net national income into its two major parts, labor-related income and capital-related income. This allows for an evaluation of the extent to which each category benefits disproportionately. Our results show that while both components are, in general, affected in a positive manner, the ratio of these components indicates that in the U.S., Canada, and South Korea, those who own capital benefit disproportionately. As the rise in employment is insufficient to offset the surge in net income inequality, it can be concluded that the composition of income has a greater impact than the positive effects of the labor market. Lastly, the capital-to-wage ratio indicates that in countries with a considerable degree of redistribution, both income sources appear to be affected in a similar manner.

In summary, this paper contributes two findings to the existing literature. Firstly, the disproportional surge in capital income is the driving force behind the increase in net income inequality and secondly, redistribution is capable of mitigating the effects of unconventional monetary policy on income dispersion.

In a globally interconnected world, the unintended and intended consequences of (unconventional) monetary policy extend beyond the confines of national borders. The existing literature clearly shows that the Federal Reserve's conventional monetary policy measures extend beyond the United States to both advanced and developing countries. Following the Global Financial Crisis, the Fed's policy was constrained by the zero lower bound on interest rates, such that she was forced to employ unconventional measures. One such measure is forward guidance, which is utilized to manage expectations regarding future Fed policies.

Nevertheless, while the spillover effects of conventional monetary policy measures have been extensively researched, there is a lack of literature concerning the spillover effects of unconventional monetary policy. The second submitted essay aims at filling this gap. *News shocks spillovers: How the euro area responds to expected Fed policy*, which is a joint effort with Peter Tillmann, is devoted to examining the cross-border effects of U.S. unconventional monetary policy on expectations and sentiment in the euro area.

To this end, we identify monetary news shocks, i.e. new information about the Fed's future monetary policy becoming available today, based on a vector autoregression (VAR) approach and estimate the responses of euro area variables to an anticipated Fed tightening.

We find that a U.S. news shock improves sentiment and business cycle expectations in the euro area. More precisely, asset prices, expectations about future economic activity, and sentiment indicators in the euro area appreciate in light of an anticipated Fed policy tightening. The findings are in line with the notion that an announcement issued today about a future tightening reveals private information the Fed might have about the state of the U.S. economy. This favorable news trigger an upward revision of sentiment indicators in the euro area. We underline this interpretation by showing that the news shocks, although raising expected future interest rates, also raise equity prices in the U.S. and, at the same time, lower equity market volatility. Hence, it is the new information about a stronger than expected economic expansion that spills over to the euro area.

A crucial driving factor for the Global Financial Crisis were the credit developments in the preceding years. The empirical literature demonstrates that boom-bust phases observed in the past four decades go back to credit supply expansions. Furthermore, unhinged credit developments can lead to vicious boom-bust cycles. That is, the initial stimulation of economic activity subsequently results in financial and banking crises, culminating in severe recessions.

Notwithstanding their dominant role in economic activity in the short and medium term, the existing literature has been largely confined to examining the effects of disturbances in credit supply in a linear world. In my third essay, *Do credit supply shocks have asymmetric effects?*, which is joint work with David Finck, we tackle this shortcoming by assessing whether positive and negative credit supply shocks cause analogous patterns in the U.S. economy.

This endeavor is relevant for two reasons. First, the theoretical literature on the responses to financial distortions is extensive and hints at potential asymmetries (and nonlinearities). Second, if potential asymmetries are disregarded, the true effects will be underestimated, as originally differently operating shocks eventually level out in a symmetric setup.

We test whether and to what extent asymmetries are present by identifying credit supply shocks via sign restrictions in a structural VAR and separating them into positive and negative. Using local projections, we find that positive credit supply shocks leave notably different patterns in private debt, mortgage debt, and debt:GDP, as opposed to negative credit supply shocks. However, even though this paper does not aim at tracing down the specific causes of asymmetries, we find that house prices, and thus the household-driven demand channel, are key for the persistence in the responses of mortgage debt and debt:GDP to credit supply shocks.

Furthermore, our results underpin the narrative of the boom-bust cycle in the presence of financial distortions which, again, is more pronounced in the presence of positive credit supply shocks. For example, after an initial increase in economic activity, that lasts for five to ten quarters, the economy transits into a bust phase with a notable slowdown in economic activity. In contrast, negative credit supply shocks cause notably stronger deflationary pressure.

The concluding paper of this doctoral thesis also addresses the impact of credit supply shocks. However, it concentrates specifically on the role of prudential regulation. This has become an invaluable tool for steering credit growth and thus, enhancing the stability of financial systems. Accordingly, this toolbox is being used more and more frequently.

However, in order to assess the use and effectiveness of prudential measures, the existing literature focuses on the direct effects of systematic or unsystematic prudential policies on economic outcomes such as credit growth or economic activity. In *Loan supply shocks, prudential regulation, and the business cycle*, I adopt a novel approach to examining the role of prudential regulation and analyze the extent to which the regulatory environment itself shapes the business cycle effects of loan supply shocks.

To this end, first, I derive regulatory cycles from a cumulative prudential policy index that tracks the evolution of the regulatory stance in the euro area. Using sign restrictions in a state-dependent local projections framework, I then identify loan supply shocks and analyse their business cycle effects conditional on whether the regulatory regime is tight or loose. The results suggest that in tight regimes, expansionary shocks trigger a noticeable boom-bust cycle. That is, key economic variables turn into a bust phase after an initial expansion, which lasts for about four quarters. These results hold regardless of the frequency of the chosen regulatory cycle. In the loose regime, results appear inconclusive due to the sensitivity of the outcomes to the underlying regulatory cycle frequency.

Moreover, a comparison of the business cycles effects revels asymmetric responses to loan supply shocks across regimes. Especially loan growth, which is of particular interest for prudential regulation, shows notably differing results. In the tight regime, expansionary loan supply shocks do not sustainably increase credit growth. In contrast, in the loose regime, lending follows a sustained growth path as a result of the shock. As noted, the responses found in a loose regulatory regime are not as robust. A key reason for this is that it is difficult to clearly identify loose regimes, as prudential measures have so far mainly taken only one form: tighter.

However, even if this paper cannot provide a definite conclusion, the tendencies for asymmetric effects should not be completely ignored in light of the importance of credit development for prudential regulation.

Acknowledgements

The phrase *on the shoulders of giants* is actually pretty worn out and hackneyed. And yet it couldn't be more true in my case. On this long journey, I always had companions at my side, on whose shoulders I could either stand or lean on.

First of all, I would like to mention my highly esteemed supervisor Peter Tillmann. He not only paved a path for me that I would never have thought of myself, but also accompanied me along the way with his expertise and always positive manner. On his shoulders, new disciplinary horizons opened up for me. But even more important than that was his tremendous patience. Without it, I would not have been able to take the path I did. I will always be grateful to him for that. I'd also love to thank my second supervisor, Jürgen Meckl, for being so patient. I'm sure at times he thought that the 1. FC Nürnberg would rather be promoted to 1. Bundesliga than have this dissertation in his hands.

During my time at the chair of Monetary Economics, I had the privilege of working with incredibly talented doctoral students: Annette Meinusch, Lucas Hafemann, Jörg Schmidt, Immaculate Machasio, and David Finck made what was already an exciting time a real pleasure. Today I can proudly call them my friends. And what makes it even better is the fact that some of them are still my colleagues today. In this way, the *VWL-Funf* spirit lives on at Deutsche Bundesbank. This fantastic spirit is of course also thanks to our brilliant assistants Sinem Kandemir, Anisa Tiza Mimun, Moritz Grebe, Niklas B(r)enner, Salah Hassani, Justin Berndt and Omar Omari. Many of them have also taken the path of a doctoral student. And of course our good soul Cornelia Strack should not go unmentioned.

I will be forever grateful to my family that I didn't end up as Oknos in Tartarus. They always believed in me and had my back. They selflessly took on hardships so that I could complete this heartfelt project.

To
my wife and son,
my parents, sister and nephews,
and the everlasting memory of my grandparents.

Thank you so much! You mean everything to me!

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Essay I:

Moving Closer or Drifting Apart: Distributional Effects of Monetary Policy

This paper has been published as:

Hafemann, Lucas, Paul Rudel, and Jörg Schmidt, "Moving closer or drifting apart: Distributional effects of monetary policy," *The Manchester School*, 2018, *86*, 110–136.

This paper was presented at the following workshops and international conferences:

i. Western Economic Association International (WEAI):
93rd Annual Conference, Vancouver, Canada.
Date: June 2018.
Presenter: Lucas Hafemann.

ii. Center for European Studies (CEUS):
14th Workshop: European Economics, Vallendar, Germany.
Date: May 2018.
Presenter: Lucas Hafemann.

iii. Money, Macro and Finance Research Group (MMF):
49th Annual Conference, London, United Kingdom.
Date: September 2017
Presenter: Paul Rudel.

Acknowledgement

We are grateful to two anonymous referees and participants at the 49th Money, Macro, and Finance Research Group Conference for fruitful comments. In this regard, we would also like to extend our gratitude to Peter Tillmann.

This essay is a revised edition of the published version.

Moving Closer or Drifting Apart: Distributional Effects of Monetary Policy

Lucas Hafemann† Paul Rudel‡ Jörg Schmidt§

Abstract

The heating debate about increasing income inequality forces monetary policymakers and academia to (re-)assess the nexus between (unconventional) monetary policy and inequality. We use a VAR framework to unveil the distributional effects of monetary policy and the role of redistribution in six advanced economies. While all of them experience an increase in Gini coefficients of gross income due to an expansionary monetary policy shock, only countries with relatively little redistribution display a significant response of net income inequality as well. To examine the underlying transmission channels we take a closer look at the sources of income, i.e. labor and capital income. Our findings suggest that the disproportional surge in capital income is the driving force behind the increase in net income inequality.

Keywords: Income inequality, factor income distribution, monetary policy, redistribution

JEL classification: E24, E25, E52, E64

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1 Introduction

"All economic policy-makers have some distributional impact as a result of the measures they introduce - yet until relatively recently, such consequences have been largely ignored in the theory and practice of monetary policy." Yves Mersch (ECB), 2014.

The financial crisis has set the limit of conventional monetary policy measures for the majority of the advanced economies. To stabilize financial markets and stimulate the economy major central banks around the world steadily lowered their policy rates up to the zero lower bound (ZLB). As this lowering was often not sufficient to fulfill their mandate, the central banks imposed unconventional measures including i.a. large-scale asset purchase programs (LSAP) and forward guidance on policy rates. As a consequence, equity and housing prices increased, while, at the same time, interest rates and returns on savings remained at an all-time low. In public, this constellation strengthened the perception of rising inequality arguing that such measures benefit already wealthy capital owners disproportionately. The public arousal forces policymakers and academia to discuss the distributional consequences of monetary policy.

However, no central bank pursues equality per mandate.[1] Nonetheless, economic key indicators that are within the scope of central banks, like inflation and growth, have distributional effects themselves. For example, Doepke and Schneider (2006), Albanesi (2007), and Adam and Zhu (2016) find that unexpected inflation coincides with higher levels of inequality. The analysis by Romer and Romer (1998) indicates a positive relationship between inequality and both, average inflation and volatility of nominal GDP growth. Thus, every policy measure that addresses one or both of the key indicators will have inevitably distributive effects.

Still, policymakers might have an intrinsic interest in moderate levels of inequality: Areosa and Areosa (2016) and Auclert (2019) ascertain that higher levels of inequality coincide with less stimulating power of monetary policy.

There are several mechanisms through which monetary policy may affect the distribution of income and wealth. Since we are interested in the nexus between monetary policy and income inequality, we limit our analyses to the following channels:

The *employment channel*: Labor income is the major earnings source for the vast majority of households. However, high-skilled and low-skilled households respond differently to monetary policy induced fluctuations on the labor market. If low-skilled households are more likely to be affected by unemployment in an economic downturn, monetary stimulus

[1] Also because it is troublesome to measure a (socially accepted) "natural level of inequality". Still, some attempts were made. See for example Rodriguez et al. (2002) or Heer and Maussner (2009). Mankiw (2015) describes anecdotally, why some inequality is necessary for prosperity.

benefits those households disproportionately and alleviates an increase in income inequality.

The *income composition channel*: Households differ in terms of their primary incomes. If monetary policy benefits capital income more than labor income, e.g. through boosting dividends or stock returns, as it can be observed since the introduction of Quantitative Easing (QE), income inequality will increase because capital income receivers are primary high-income households.

Neither is the transmission of monetary policy to inequality unambiguous, nor the findings in the literature. Mumtaz and Theophilopoulou (2017) and Coibion et al. (2017) find that contractionary monetary policy shocks increase inequality in earnings, income, and consumption. In their analysis for the U.S., Coibion et al. (2017) draw a number of conclusions. Following a monetary policy shock, wage earnings for those in upper percentiles of the wage distribution recover notably faster than for those at the bottom of the distribution. The total income effect is smaller because low-income households disproportionately rely on transfers which, in turn, react counter-cyclically. Lansing and Markiewicz (2018) and Coibion et al. (2017) state that the distributional effects of monetary policy were mitigated by governmental redistribution in the United States.[2] In contrast, Davtyan (2016) finds evidence for the U.S. that contractionary monetary policy shocks are associated with lower income dispersion in the long-run.

Primarily unconventional monetary policy measures are suspected to be one of the main drivers of increasing inequality in recent years. The argument is that ultra-loose monetary policy disproportionately benefits asset holders because the returns of a broad variety of assets surged due to LSAPs and low long-term yields. The stimulating effect elevated corporate profits faster than employment. Overall, the contribution of unconventional monetary policy measures to increasing inequality is not clear cut and respective research is limited.

Mumtaz and Theophilopoulou (2017) gauge an additional effect on inequality from unconventional measures taken by the Bank of England in the aftermath of the Global Financial Crisis. Adam and Tzamourani (2016) find that the ECB's 2012 announced Outright Monetary Transactions program influenced market prices such that the top 5% wealth group benefited disproportionately. Domanski et al. (2016) find that wealth inequality in advanced economies has risen since the financial crisis. They identify surging equity prices as the key driver.

Our contribution to the outlined controversy is twofold. First, cross-country analyses unveil the role of redistribution in the nexus between (gross and net) income inequality and monetary policy. Second, data on factor income from national accounts uncover the

[2] In addition, Ostry et al. (2014) show that redistribution can be beneficial for growth due to positive effects of lower levels of inequality.

underlying transmission mechanisms.

We focus on two transmission channels of monetary policy on income inequality, namely the *income composition channel* and the *employment channel*. The procedure outlined in Bernanke and Gertler (1995) is used to analyze the potential mechanisms that drive the Gini measures after an expansionary 25 basis points monetary policy shock. Moreover, this work shall expose the role of redistribution. For this task, we choose countries that a) have an independent and autonomous central bank, and b) differ in their scope of redistribution. Thus, our analysis relies on the U.S., Canada, South Korea, Sweden, the Czech Republic, and Hungary. To incorporate redistributive effects, we examine the impulse responses of both, Gini of gross income (pre-tax, pre-transfers, *Gini gross* hereafter) and Gini of disposable income (post-tax, post-transfers, *Gini net* hereafter).

Figure 1 provides an overview of the Ginis for gross (red solid) and net (dotted) income as well as the policy rates (green solid) for the chosen countries. All countries but Sweden show an upward trend in Gini gross. The U.S., Sweden, and Hungary show the highest levels of gross income dispersion. Concerning net income dispersion, Sweden, the Czech Republic, and Hungary kept their levels in the considered periods while the U.S., Canada, and South Korea show an increase in the Gini net. Furthermore, the interest rates dropped in all countries.

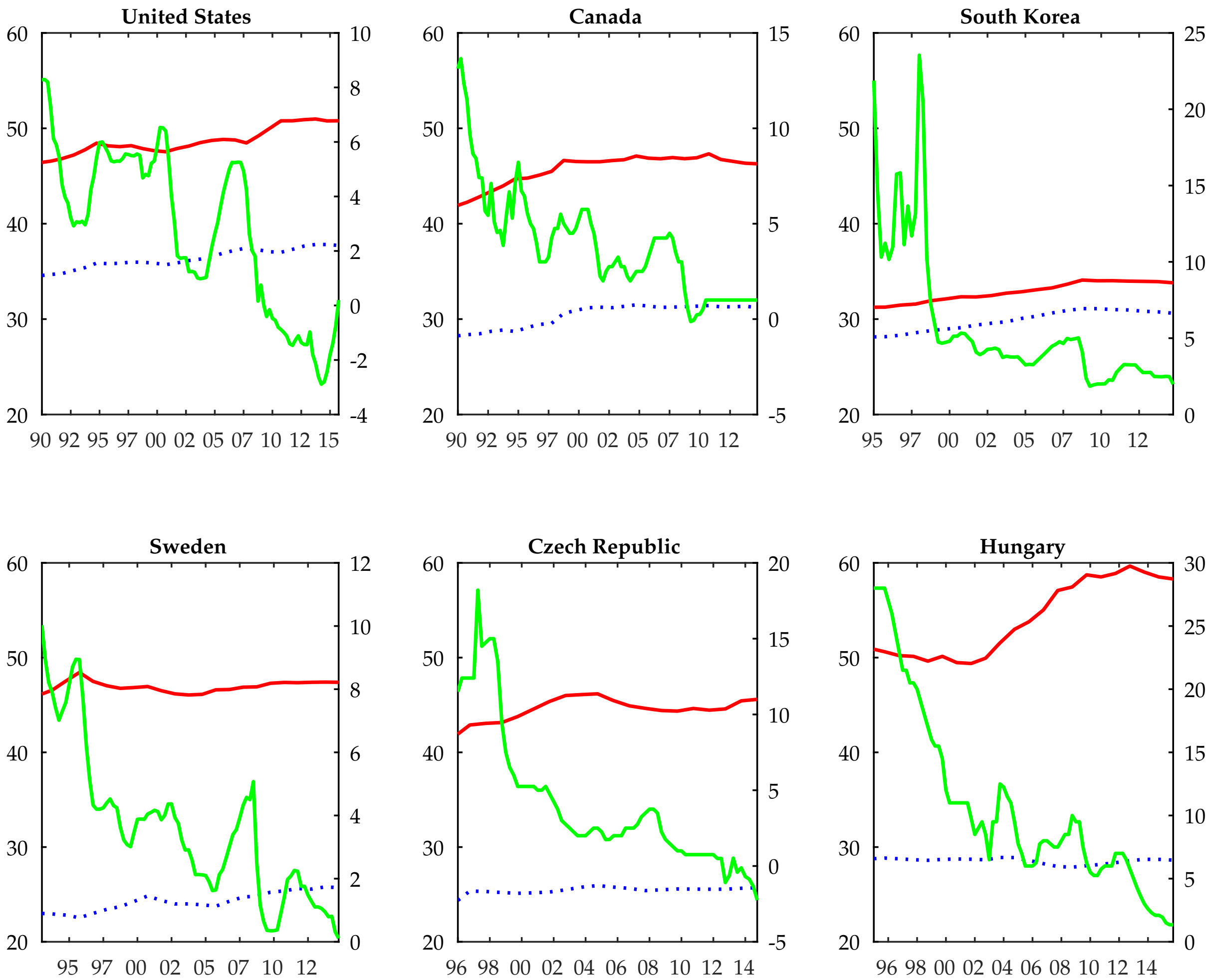
In a nutshell, the major findings of our paper are threefold: Firstly, we observe an increase in inequality of Gini gross for all countries included in this paper when facing expansionary monetary policy. Secondly, we find that the effect on the Gini net remains positive for countries with minor redistribution. In contrast to this, countries with high relative redistribution do not face the same positive reaction in their net income inequality. Thirdly, we show that monetary policy is transmitted via overall employment, labor income, and capital income. Moreover, the disproportional surge in capital income is the driving force behind the increase in net income inequality.

The remainder of the paper is organized as follows. First, we introduce our data and the methodology. Section 3 covers the analysis of the nexus between monetary policy shocks and income inequality. In Section 4 we take a closer look at the underlying transmission mechanisms. The conclusion follows after a robustness section.

2 Data and Methodology

Before we proceed to our analysis of the nexus between monetary policy and its impact on the distribution of income as well as the underlying channels of transmission, we want to take a closer look at the data and methodology.

Figure 1: Income Inequality and Policy Rates



Notes: Red solid (blue dotted) lines depict Gini gross (net), in percent, left y-axis. Green solid lines present key policy rates, in percent, right y-axis.

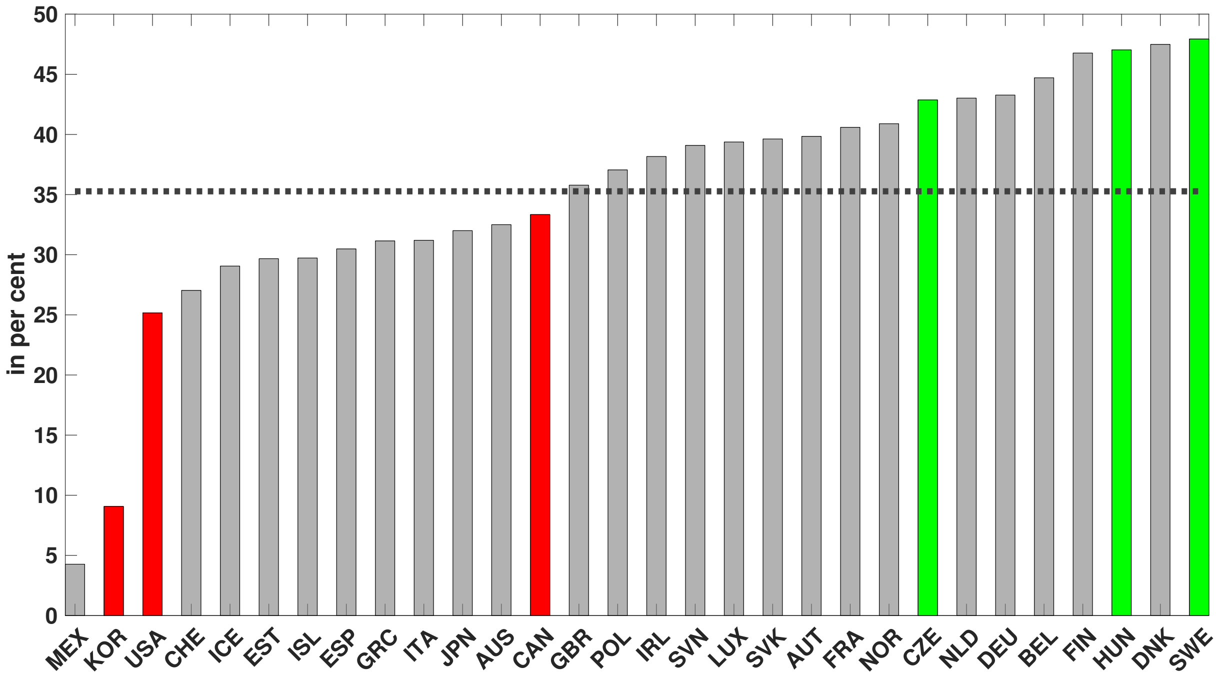
A. *Data*

The main objective of this paper is to examine the transmission mechanisms through which gross and net income distribution respond to monetary policy surprises and thus, obliquely, the role of governmental redistribution.

On the subject of redistribution, we select among OECD members regarding their relative redistribution.[3] Figure 2 depicts the average relative redistribution from 1995 to 2015, taken from the Standardized World Income Inequality Database (SWIID). Redistribution among OECD countries varies remarkably. At the upper end, Sweden, Denmark, and Hungary almost halve gross income inequality through redistribution, i.a. through taxes and transfers. In contrast, the U.S., South Korea, and lastly Mexico are the

[3]The relative redistribution is computed as the difference between gross and net income Gini divided by the gross income Gini and multiplied by 100.

Figure 2: Relative Redistribution Among OECD Members



Notes: Relative redistribution is computed as $100 \times (\textit{Gini gross} - \textit{Gini net}) \times \textit{Gini gross}^{-1}$. Dotted line depicts cross-country mean.

countries with the lowest relative redistribution.[4] It stands out that predominately European countries show the highest levels of redistribution among OECD members. For example, out of the countries with relatively much redistribution, Canada is the non-European country with the highest relative redistribution: they lower gross income inequality by 33% through governmental intervention.

To examine the reciprocation of (various measures of) inequality to monetary policy shocks in a meaningful manner, we exclude all countries that are either part of a monetary policy union (i.e. the euro area) or directly peg their currency to others for a substantial period, in other words, have no independent monetary policy.

That said, we are left with Sweden, Hungary, and the Czech Republic as surrogates for highly redistributing countries on the one hand and Canada, the U.S., and South Korea on the other hand.[5]

In the first step, we capture the reaction of Gini coefficients of gross incomes to monetary policy. We then evaluate in how far monetary policy shocks propagate to the dispersion of households' net income. For both exercises, we use the corresponding mean estimators

[4] Note that little redistribution does not necessarily correspond with a high level of inequality. South Korea, for example, already has a low level of inequality such that there is less need for redistribution to reach some sort of income equality. At the end, it remains a social decision how much redistribution a society desires.

[5] Mexico is a valid candidate, too. In Section 4, however, we compare the responses of labor-related income and capital income to a monetary policy shock where we ground our analysis on OECD data which are, unfortunately, not available for Mexico.

from the SWIID data set, compiled by Solt (2016), for all countries included in this paper. Since we use a VAR model with quarterly data, we linearly interpolate all Gini variables.[6]

Finally, we take a look at the transmission channels. Following the idea of Bernanke and Gertler (1995), we substitute the Gini coefficients with variables that are affiliated to the transmission mechanisms discussed above. In this respect, we analyze how the total number of employed persons as well as capital and labor income reacts to a monetary policy shock. The data for the channel variables stem mainly from the OECD.[7]

We conduct baseline vector autoregressions that (separately) include the inequality measures (i.e. the Gini coefficient or the channel variable) for each of the six countries in our sample, additional to the standard macroeconomic variables real GDP, consumer prices, a short-term interest rate, and the trade-weighted real effective exchange rate (REER). All non-stationary variables enter our model in log-levels. This assures that we take possible (long-run) cointegration relations between the variables into account. For example, Davtyan (2016) shows that there is a long-run relationship between monetary policy and inequality. The REER is incorporated because five of the six analyzed countries are small open economies where the exchange rate channel appears to be a relevant monetary transmission mechanism. Data on real GDP and CPI are taken from Datastream. Exchange rates stem from the Bank of International Settlements.[8]

Since we do not exclude periods of financial stress, we control for market uncertainty by including the CBOE Volatility Index (VIX). The VIX enters as an endogenous variable into the U.S. model and as an exogenous variable into the VAR model of the remaining countries.

Our applied short-term interest rates deserve some special attention. We generally prefer the use of money market rates because monetary policymakers aim at the short-term inter-bank refinancing conditions as their intermediate objective. However, for Hungary and the Czech Republic, money market data is not available for the considered period. Therefore, we have to use the key policy rate in these two countries.

Furthermore, the ZLB becomes an issue in the U.S., Canada, and the Czech Republic.[9] For the U.S., the interest rate variable is the Wu and Xia (2016) shadow rate, available since 2003, and the effective federal funds rate for previous periods. For Canada, we use a shadow

[6]One might argue that the variables could be sensitive to altering interpolation methods. We believe that the interpolation method does not alter the results in a notable manner due to the inherent inertia of the variables. Nonetheless, we provide estimates with yearly data in robustness Section 5 and get similar results.

[7]A more detailed description of the respective data is provided in Section 4.

[8]For the sake of comparability, we include the exchange rate in the U.S. model, although it is not a small open economy.

[9]In fact, in Hungary and South Korea the short-term interest rate remains above 1% throughout the entire time considered. In Sweden, the short-term interest rate is 0.5 from 2009Q3 to 2010Q2 and from 2014Q3. However, due to the quick recovery in 2010 and the small number of periods where the ZLB might have been binding, we restrain from the incorporation of a shadow rate.

interest rate estimated by MacDonald and Popiel (2020).[10]

Unfortunately, shadow interest rates are not available for the Czech Republic. Hence, we use the euro area shadow rate from 2012Q4 onward because the short-term interest rate dropped to 0.05% at this point in time. In 2013, the Koruna-Euro exchange rate reached its upper limit set by the Czech National Bank. Euro area shadow short-term rates are therefore an eligible alternative.

The start of our sample is restricted by data availability. For the U.S. and Canada, our samples start in 1990 because this marks the starting point of the VIX. For the four remaining countries, the OECD data set is the limiting factor, such that 1993 (1995) marks the beginning of the sample for Sweden (South Korea, the Czech Republic, and Hungary). Moreover, by 1995, the Czech Republic and Hungary had already undertaken major transformations after the dissolution of the Soviet Union. Our sample ends with the last observation available in the SWIID 6.0 database, i.e. in 2014 for Korea, Sweden, and the Czech Republic and in 2015 for the U.S., Canada, and Hungary.

B. *Methodology*

With the described variables at hand, we estimate the following reduced-form VAR model with external variables and lag length P, i.e. a VARX(P) model:

$$\mathbf{Y_t} = \mathbf{C} + \mathbf{A_p(L)Y_{t-p}} + \mathbf{\Gamma_q(L)X_{t-q}} + \varepsilon_t \ . \tag{2.1}$$

$\mathbf{A_p(L)}$ and $\mathbf{\Gamma_q(L)}$ are lag-polynomial matrices of order p and q in the lag-operator L, where $p = 1, \ldots, P$ and $q = 0, \ldots, P$. The deterministic components (i.e. included constants) are captured by $\mathbf{C}$ and $\varepsilon_\mathbf{t}$ is a column vector of reduced-form white noise error terms and variance-covariance matrix Σ_ϵ. $\mathbf{X}$ captures exogenous variables (i.e. the VIX for all non-U.S. models). The lag-length P is determined by the Akaike information criteria.[11]

Identification of our underlying, unknown structural model of the form

$$\mathbf{B_0Y_t} = \mathbf{D} + \mathbf{B_p(L)Y_{t-p}} + \mathbf{\Theta_q(L)X_{t-q}} + \mathbf{u_t} \ , \tag{2.2}$$

and the respective shocks linked to it is conducted via sign restrictions. This requires a priori assumptions about the specific relations between the variables included in the VAR model. These assumptions can root in theoretical considerations as well as in empirically robust common wisdom.[12]

[10] We want to thank the authors for data provision.

[11] The information criteria suggests a VAR(1)-model for the United States, Sweden, Czech Republic, and Hungary, a VAR(2)-model for Canada, and a VAR(3)-model for South Korea.

[12] A detailed description of the idea and methodology can be found in Uhlig (2005).

As we are interested in the interpretation of the effects of monetary policy shocks in a sensible manner, we only focus on the identification of the monetary policy shock and ignore other structural innovations to the model. Table 1 shows the imposed restriction scheme.

Table 1: Sign Restrictions for an Expansionary Monetary Policy Shock

Shock	Gini	real GDP	Prices	Interest Rate	REER
Monetary Policy	unrestricted	+	+	-	+

Notes: Gini is a surrogate for all inequality measures and variables related to the factor income that are considered in this paper. The VIX is unrestricted in the U.S. model. Imposed restrictions hold for four periods, but the results are not very sensitive to shorter durations.

We justify these assumptions as follows: Expansionary monetary policy lowers overall market interest rates, either via policy rate cuts or monetary base expansion. This results in a stimulus of overall demand or at least does not cause demand to fall simultaneously. Overall prices should also adjust due to excess demand, or at least cannot be expected to decrease. The real exchange rate reaction is assumed to be negative because of capital outflows caused by overall lower yields in the economy. To capture the research question of this paper and pick up the controversy outlined in the discussed literature we leave the variables related to income inequality unrestricted. All restrictions are theory-implied and also confirmed in many empirical applications. We think that identification via sign restrictions is appropriate because we use fast-reacting financial markets variables as well as sticky variables such as the GDP or prices and thus do not want to restrict contemporaneous relations between the variables via e.g. an assumed ordering.

3 Monetary Policy and Income Inequality

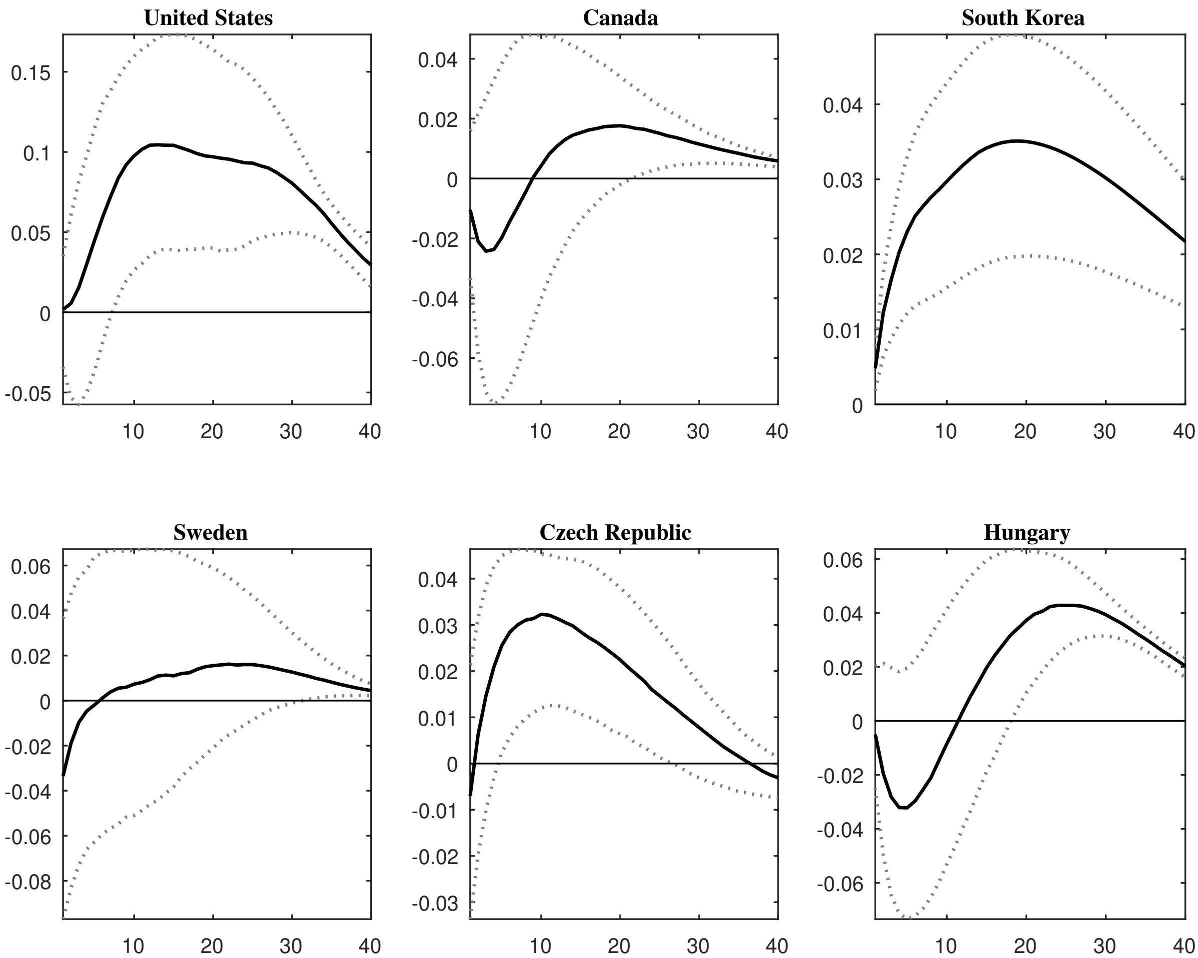
The ultimate goal of this paper is a) to examine the nexus between income inequality and monetary policy, b) emphasize the role of redistribution, and c) trace the channels of transmission. By usage of the aforementioned restrictions, we can pursue this goal.

To examine the linkage between monetary policy and income inequality as well as the role of governmental redistribution, we distinguish between the Gini of gross income and net income. Thus, we can scrutinize the respective responses to monetary policy shocks. Since the discrepancy of gross and net incomes stems from paid and received (income-)taxes and transfers, we are thus able to tackle the question concerning the role of governmental redistribution.

A. *Response of Gross Income Inequality*

First, we evaluate the effect of expansionary monetary policy on the distribution of gross income.[13] Figure 3 depicts the responses of Gini gross to an expansionary 25 basis points monetary policy shock.

Figure 3: Response of Gini Gross



Notes: Impulse responses of Gini gross to a 25 basis points expansionary monetary shock. The solid line depicts the median response. The dotted lines are the 16% and 84% percentiles.

Two findings stand out. First, inequality increases in all countries. The effect is most pronounced for the U.S., given a peak median response of 0.1 percentage points after 12 quarters (solid line), followed by Hungary. For the remaining countries, the peak response of the Gini index is above 0.015 percentage points.

Second, the effect comes with some delay. It takes between eight and 30 quarters until the probability bands surpass the zero line. This finding comes at no surprise since the Gini

[13] For the sake of greater clarity, we only depict the responses of the Gini indexes. Since we use sign restrictions, the fundamentals react as intended. Nevertheless, the complete set of impulse responses is available upon request.

index itself is rather sticky. Accordingly, the effect seems to be persistent since it seldom dies out after 40 quarters. The only exception is South Korea.

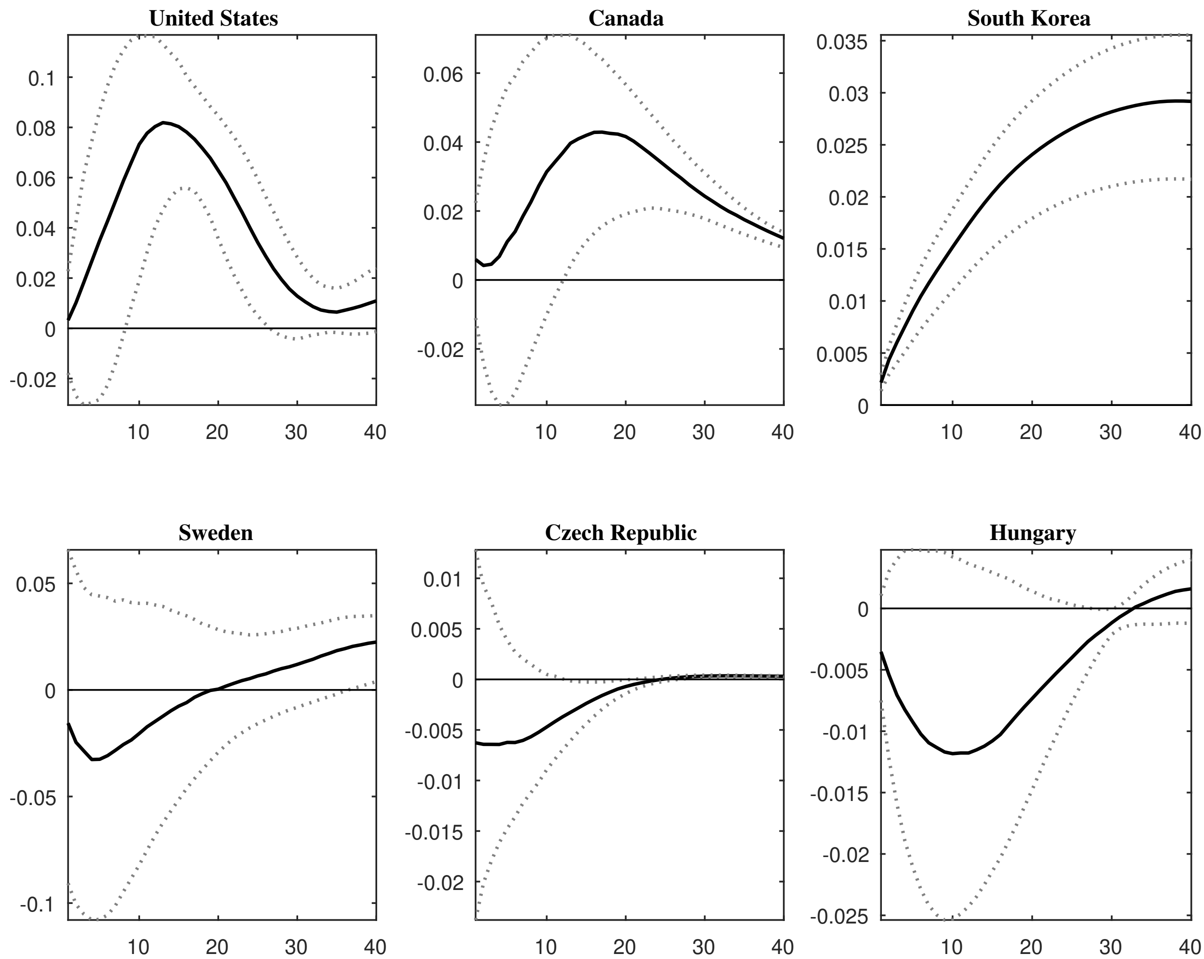
B. *Response of Net Income Inequality*

Focusing on net income Gini coefficients brings several advantages. First, the general debate about equitable income distribution is predominantly based on net values, such that potential dampening effects through governmental redistribution are incorporated. Furthermore, wealth is largely accumulated by savings that stem from the remaining share of income. Thus, a steady increase in income inequality might embrace an accelerating effect: low-income households are barely able to save and thus cannot accumulate wealth while, at the same time, high-income households amass wealth progressively, which in turn might increase inequality furthermore. Hence, monetary policy actions that benefit the latter disproportionately might even expedite this process. However, ultra-loose monetary policy as well as unconventional monetary policy measures are under suspicion to be such policy actions. In this respect, Montecino and Epstein (2015), Mumtaz and Theophilopoulou (2017), and Saiki and Frost (2014) find a positive relation between unconventional monetary policy and inequality hikes for the U.S., UK, and Japan, respectively. As their analysis excludes top-income households or ends before the introduction of unconventional measures, these papers might even underestimate the unveiled effects.

Figure 4 outlines the results of our baseline model including the Gini of net income as our measure of inequality. It stands out that the effect of an expansionary shock is mostly tempered, compared to the response of Gini gross in Figure 3. For the U.S., we find a positive reaction in the short-term that is notably smaller, namely 0.08 percentage points at its peak, than the rigid increase in Gini gross with its maximum at 0.1 percentage points. The difference between Gini gross and Gini net is most pronounced in Sweden, the Czech Republic, and Hungary – the countries with the highest relative redistribution in our sample. Here, the tendency for an increase in inequality is immensely mitigated. Finally, we find no notable difference in the response of the Gini net in Canada as against the response of Gini gross.

In summary, we find that governmental redistribution can dampen the effect of expansionary monetary policy on income inequality. Furthermore, it seems that the extent of redistribution matters more than the initial level of inequality. Sweden, the Czech Republic, as well as Hungary – countries with the highest relative redistribution in our sample – experience the strongest dampening effect. South Korea, that has low levels of income inequality combined with low levels of redistribution, faces similar effects as the U.S. and Canada.

Figure 4: Response of Gini Net



Notes: Impulse responses of Gini net to a 25 basis points expansionary monetary shock. The solid line depicts the median response. The dotted lines are the 16% and 84% percentiles.

Our findings are in line with Saiki and Frost (2014), Montecino and Epstein (2015), and Mumtaz and Theophilopoulou (2017), but contrast the much-noticed work by Coibion et al. (2017). The discrepancies in the findings are likely linked to the following issues: Firstly, our Gini measures differ. Coibion et al. (2017) derive their Gini measures from household survey data that do not cover the top 1% of the income distribution. This is troublesome given the dominant role of top income households among the income distribution, as emphasized by Atkinson et al. (2011). For example, in 2007 the top 1% accounts for about 23% of the total received income in the United States. Therefore, we rely on the mean estimator from the SWIID which incorporates the complete income distribution. Another merit of this database is that it enables cross-country comparability.

Secondly, the debate about increasing income inequality gained momentum especially since the Global Financial Crisis and the associated conduct of monetary policy. We take this extraordinary period into account. Lastly, we apply a substantially different estimation approach.

4 Transmission of Monetary Policy on Inequality

In this section, we want to elaborate what channel-related variables are involved in the transmission of monetary impulses to overall income dispersion. As outlined above, we focus on the *employment channel* and the *income composition channel*. We pick up the ideas of Bernanke and Gertler (1995) who disentangle overall transmission of monetary policy shocks to the real economy by taking a closer look at variables assumed to be involved in the transmission. With this approach, they shed light on major driving forces and related channels of monetary transmission linked to them. Similarly, we use variables related to the channels outlined previously to account for the variety of possible mechanisms that drive the observed movement in the overall Gini coefficients presented in Section 3. These variables replace our Gini coefficient in the baseline VAR model while identification assumptions remain unchanged. We proceed as follows:

First, we examine in how far the *employment channel* is involved in the transmission of monetary policy. Second, we separately include both components of the *income composition channel* in our VAR model. Third, we relate them to each other to figure out in how far their ratio is affected by monetary policy, or, in other words: Does the reaction of one income component dominate the reaction of the other? Thus, we need variables that can be assigned to the channels in order to assess the importance and overall role each channel plays in the six countries. We describe them in the following in more detail.

A. *Employment Channel*

Data

To take a closer look at the *employment channel*, we assess in how far employment reacts to monetary policy shocks. In contrast to most literature, we do not use unemployment rates, but overall employment instead because the officially reported rates are often biased as not every unemployed person registers. Additionally, changes in the labor force participation might distort unemployment rates although overall employment remains less affected or even unchanged. Accordingly, our measure more accurately reflects the actual utilization of the factor labor in our samples. To have a common data source, we rely on total employment provided by the OECD.[14]

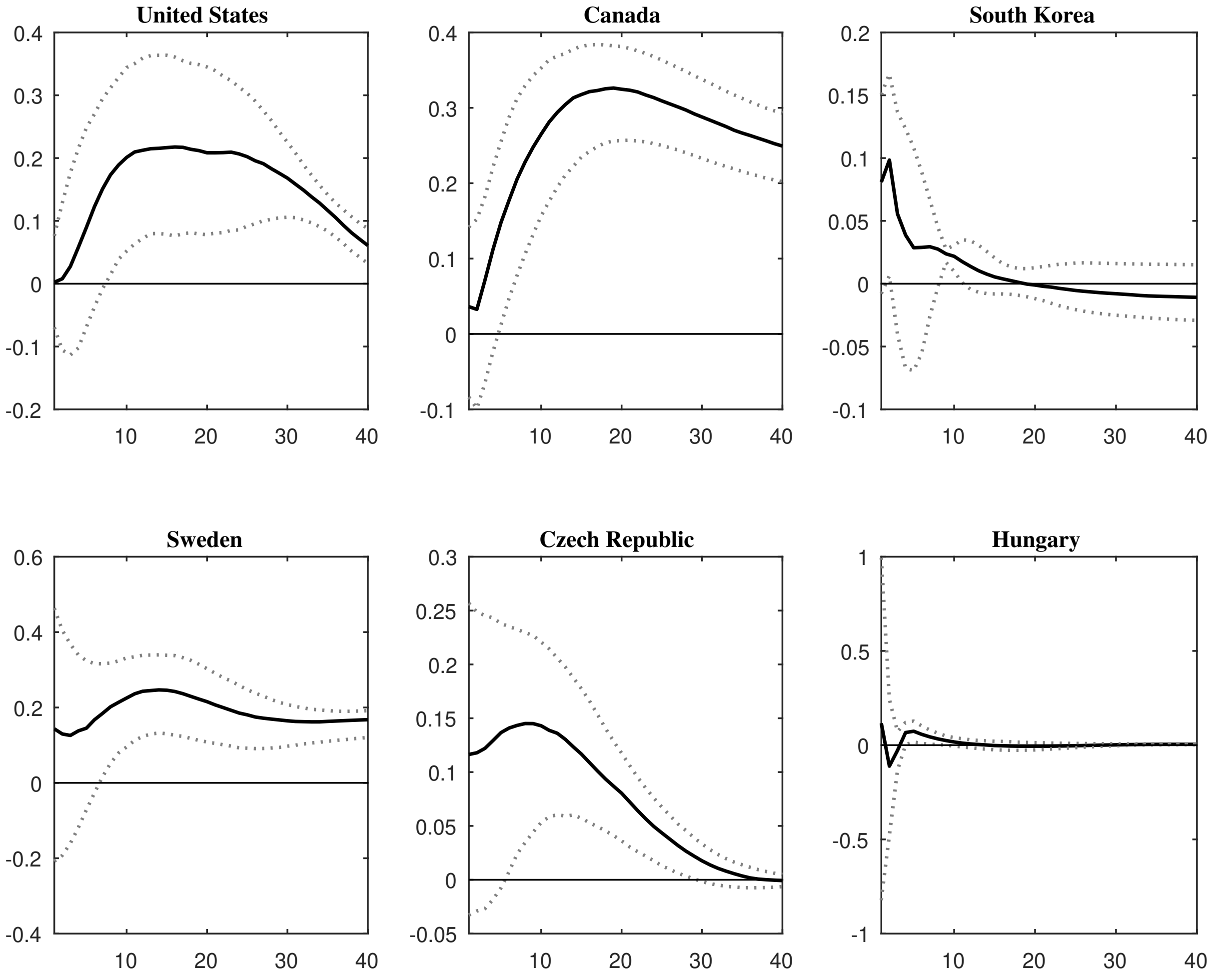
[14] Due to data issues for the U.S., we proxy the total number of employed persons by the employed workers according to the non-farm payroll statistics.

Results

According to the *employment channel*, an expansionary monetary policy shock lowers income inequality via its stimulating effect on the labor market. Typically low-skilled low-income households benefit from this channel. To evaluate the relevance of this channel, we substitute the Gini variable with the log of total employment in the respective country.

Figure 5 shows the impulse responses of employment to an expansionary monetary policy shock. Such shocks have a notable stimulating impact on employment in all countries. The reaction in employment is in general weaker in the countries with high redistribution. This can probably be linked to their more regulated labor markets, e.g. higher degrees of dismissal protections.

Figure 5: Monetary Policy Shocks and Employment



Notes: Impulse responses of employment to a 25 basis points expansionary monetary policy shock. The solid line reflects the median response, the dotted lines show the 16% and 84% percentiles.

The contrasting responses of the Gini net on the one hand and employment on the other hand indicate that the *employment channel* is dominated by other driving forces. Hence, we take a more detailed look at the primary factor income sources of households: labor and capital.

B. *Income Composition Channel*

Data

The *income composition channel* distinguishes between major sources of households' overall earnings: labor-related income and capital pay-offs. Thus, we include these different sources into our analysis. As we are primarily interested in net effects, we focus on disposable income. National accounts and income statistics provide detailed data to construct different variables based on the subcomponents related to the production factors capital and labor. More precisely, in our analysis capital income consists of net interest income, dividends after taxes, and net rental income. It is computed as the sum of net operating surplus, which is gross operating surplus (GOS) less consumption of fixed capital for the corporate sector, and net mixed income (NOS+NMI). Labor income incorporates solely (net) compensation of employees, i.e. wages, salaries, and employers' social contributions.[15] Again, we rely on data from the OECD to overcome possible problems of cross-country comparability.[16]

For South Korea, all income data are only available on a yearly frequency. Thus, we need to interpolate capital- and labor-related income. For the Czech Republic, the net operating surplus and the mixed income is only available from 1999. Since gross operating surplus and mixed income (GOS+MI) is accessible from 1995, we construct NOS+NMI from 1995 to 1998 by assuming the share of NOS+NMI in GOS+NMI in this time is identical to the share in 1999.[17] For Hungary, the OECD provides quarterly data for labor-related income and GOS+NMI, but only yearly data for NOS+NMI. This time we first construct each quarters' share in the yearly values of GOS+NMI. We then assume that the share for NOS+MI is identical.

Response of Labor-Related Income

We replace the Gini variable in the baseline model by the log of labor-related income. Since labor income and employment are strongly correlated, their outcomes are expected to be similar, too.

The results are represented in Figure 6. In all countries, labor-related income increases after an expansionary shock. The peak median responses vary between about 1.1 percentage

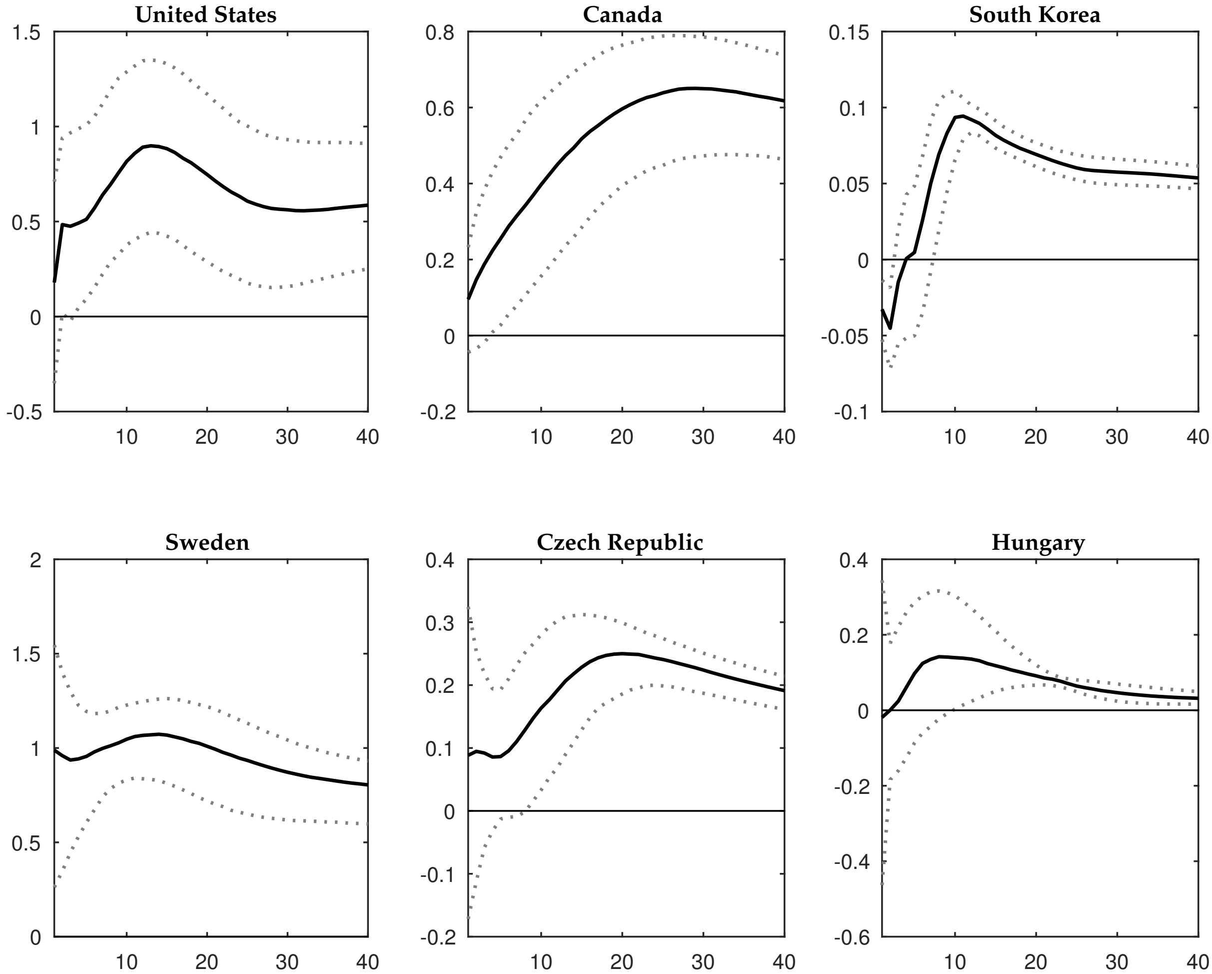
[15] Including transfers, for some households the dominant income source, would have been an option if all countries collect and process data on a similar approach and provide them for sufficiently long periods. Unfortunately, for the sake of cross-country comparability, we cannot include them in a meaningful manner.

[16] All data are seasonally adjusted and denoted in constant prices.

[17] The share of NOS+NMI in GOS+NMI varies between 55% and 62% from 1999 to 2014.

points (Sweden) and about 0.1 percentage points (South Korea).

Figure 6: Monetary Policy and Labor Income



Notes: Impulse responses of labor-related income to a 25 basis points expansionary monetary policy shock. The solid line reflects the median response, the dotted lines show the 16% and 84% percentiles.

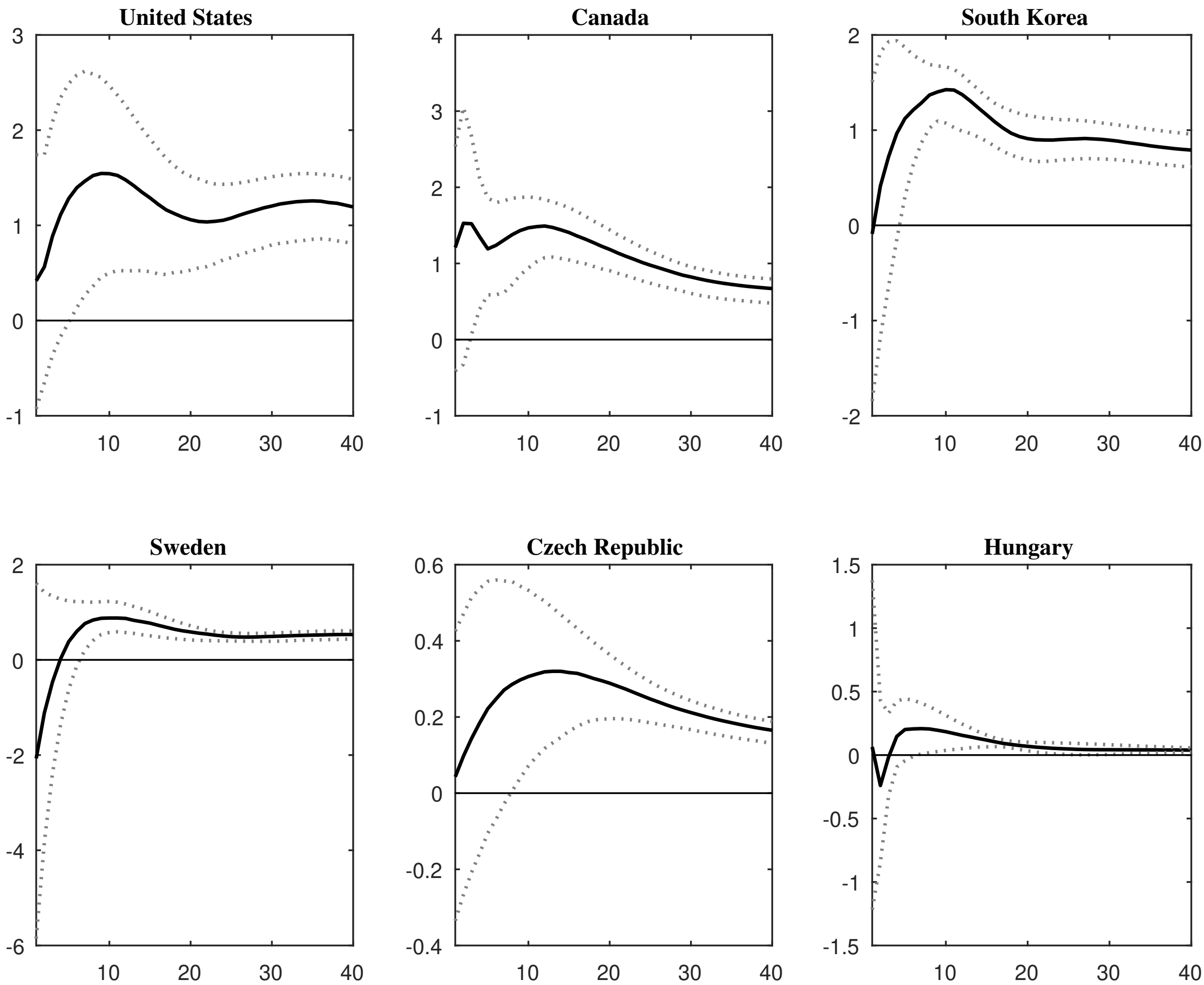
Unfortunately, we cannot draw conclusions about the distribution of labor income across households. Nevertheless, wages are the primary income source for the vast majority of households. In combination with the findings we draw from the *employment channel*, the results on labor-related income indicate that employees benefit from an expansionary monetary policy shock.

Response of Capital Income

To obtain aggregate net capital income, we sum up net operating surplus and net mixed income. Following Atkinson et al. (2011), we assume that high-income households are the main receivers of capital income. Thus, an increase in capital income suggests that these households benefit disproportionately, as opposed to low- and middle-income households.

Figure 7 indicates a similar pattern of net capital income to labor income. There is a notable increase in capital income in all countries. Besides the boost in asset prices, the stimulus of real activity leads, e.g to increasing corporate profits or rents and thus higher capital earnings for shareholders or real estate owners. We find the most pronounced

Figure 7: Monetary Policy and Capital Income



Notes: Impulse responses of capital-related income to a 25 basis points expansionary monetary policy shock. The solid line reflects the median response, the dotted lines show the 16% and 84% percentiles.

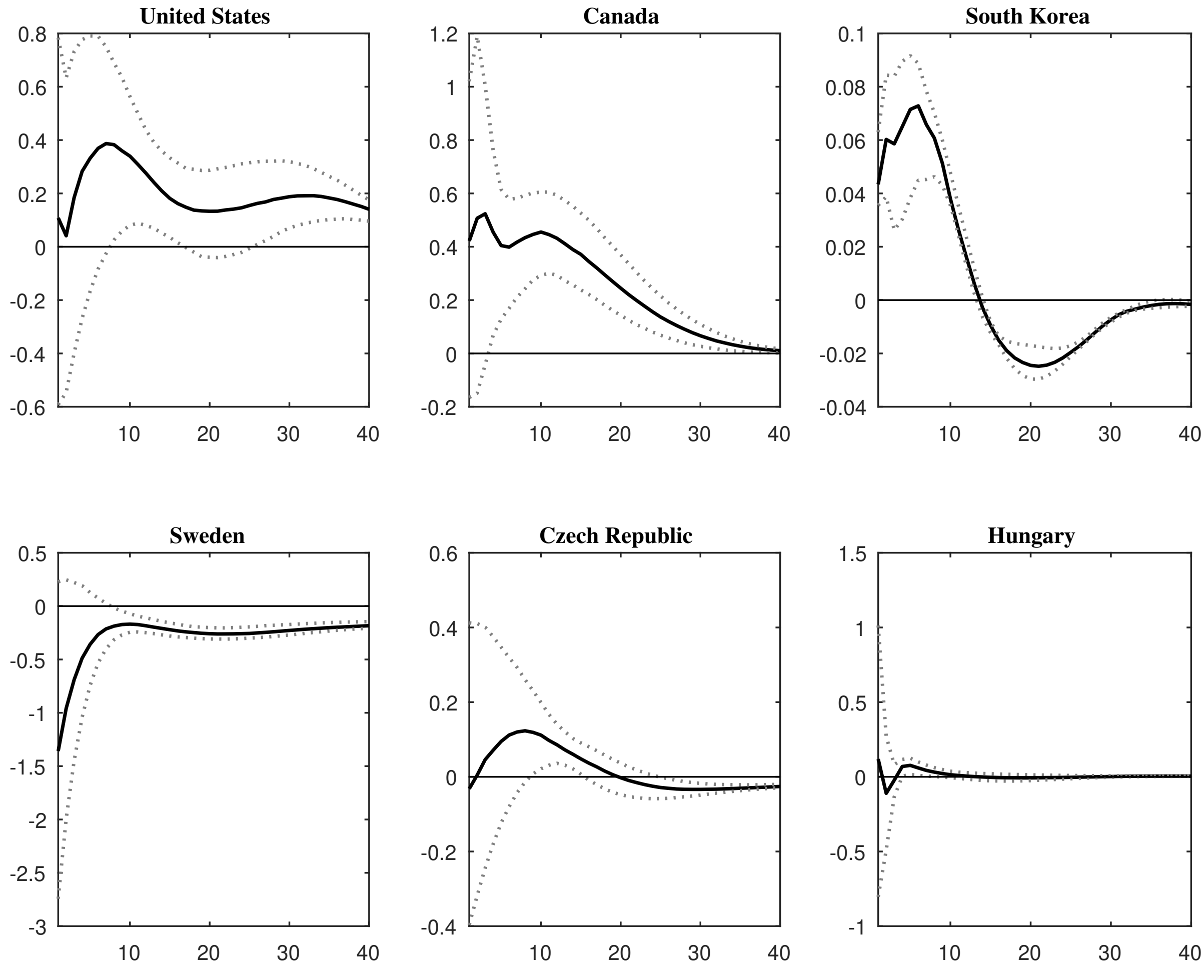
responses for countries with relative little redistribution, i.e. peak responses greater than one. While the size of the responses of the Czech Republic and Hungary are quite small, the impulse response of Sweden is similar to those of less redistributing countries.

Response of the Capital-Wage-Ratio

As has been shown above, expansionary monetary policy shocks increase both, capital income and labor-related income. Depending on the composition of income among households, this leads to either a rise or a fall in inequality. The *income composition channel* states that income inequality grows if capital income receivers benefit disproportionately, and vice versa. Hence, we finally evaluate the relevance of the *income composition channel* via the response of the capital-wage-ratio after such a monetary policy surprise. Since labor-related income also represents changes in employment, the capital-wage-ratio is not only suited for the evaluation of the *income composition channel*. It also indicates whether the *income composition channel* is dominating the *employment channel*.

The respective impulse responses are presented in Figure 8. Out of the countries with relatively little redistribution, the U.S. and Canada exhibit a clear increase in the capital-wage-ratio. In contrast, the responses of the extensively redistributing countries show either no clear response (Czech Republic and Hungary) or even a negative reaction (Sweden). South Korea stands out as a special case here. While capital owners benefit disproportionately in the short-term in South Korea, this effect is reversed after roughly 15 quarters.

Figure 8: Monetary Policy and the Capital-Wage-Ratio



Notes: Impulse responses of the capital-wage-ratio to a 25 basis points expansionary monetary policy shock. The solid line reflects the median response, the dotted lines show the 16% and 84% percentiles.

How does monetary policy impact inequality? We find evidence that the primary mechanism is the composition of income. The increase in Gini cannot be explained by the *employment channel* because we expect that particularly low-income households benefit from a stimulated labor market. Additionally, the labor market reacts stronger in less redistributing countries. The increase in the Gini net is in contrast to that finding. At the same time, we find that capital income increases more than labor income. Taken together, it is likely that the *income composition channel* explains the nexus between monetary policy and income inequality. This is true for both, much redistributing and less redistributing countries. Nevertheless, since the first-mentioned do not show an increase in net income inequality after expansionary monetary policy shocks and no increase in the capital-wage-ratio, both types of net factor income benefit more equally from expansionary monetary policy shocks in these countries. Thus, we conclude that income composition plays the primary role in the transmission of monetary policy shocks to income inequality.

5 Robustness

In this section we asses whether the results hold under different model specifications. One major concern about the methodology applied above is relates to the use of interpolated data. We test whether our results hold if we incorporate yearly data instead. Furthermore, we follow Coibion et al. (2017) and present evidence that uses local projections as additional robustness. Finally, we check the sensitivity of our results to various samples.

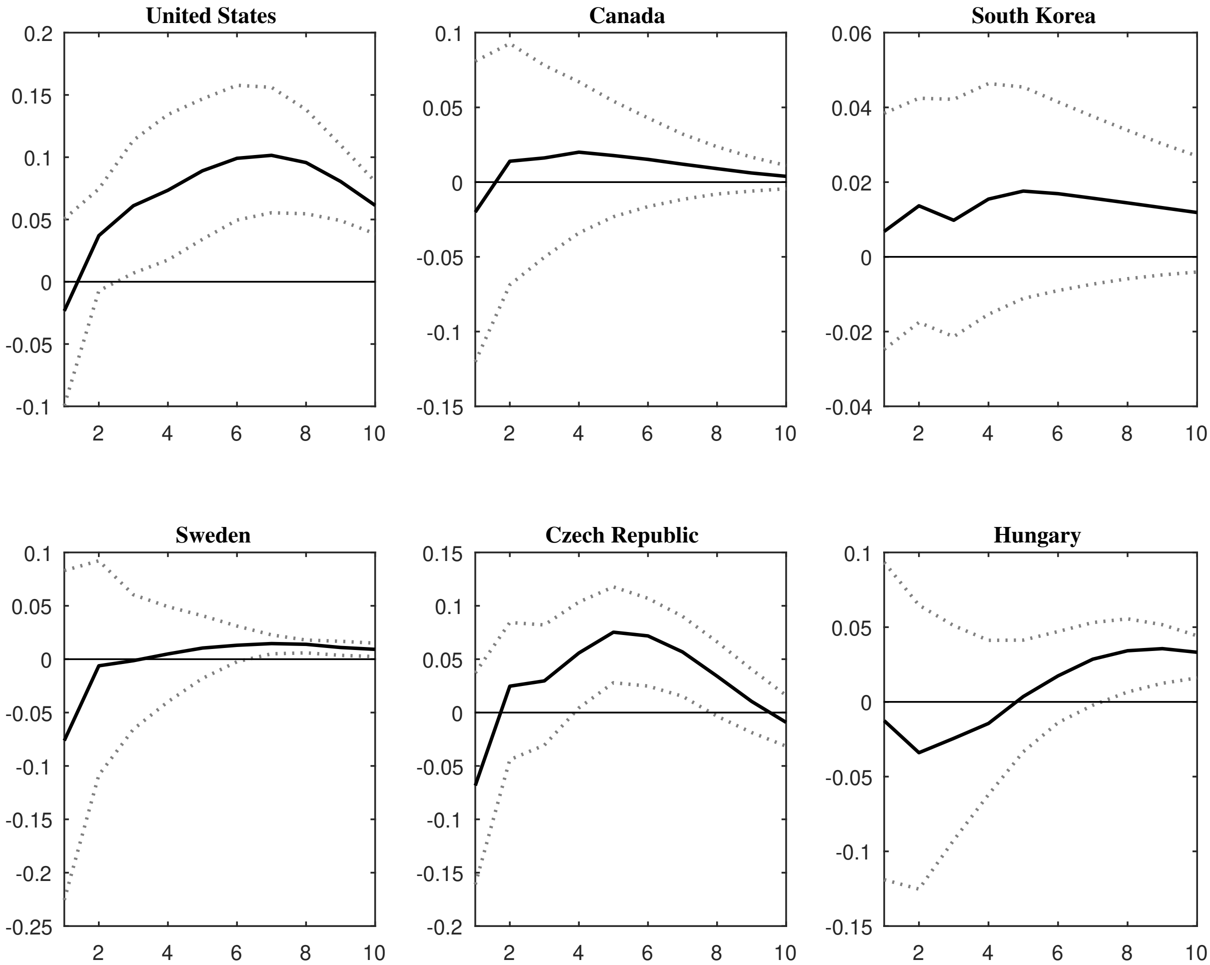
A. *VAR Model With Yearly Data*

The results found above rely on the assumption that the quarterly data we receive from linear interpolation of the Gini coefficients are similar to the true but unknown quarterly Gini coefficients. Thus, we test the outcome of our model by applying a VAR model with yearly data. If the results of the yearly and the quarterly VAR model are similar, we are confident that linear interpolation does not substantially affect the estimates. With the resulting shorter sample size we now incorporate only one lag and reduce our restriction duration to one period as well. Nevertheless, the short sample boosts uncertainty in the estimation and thus the resulting percentiles of the presented model should be treated with caution. Despite that, the major outcomes remain unchanged.

We again start by showing impulse responses of Gini gross, depicted in Figure 9. In line with the findings from Section 3, there is a tendency for increasing inequality after an expansionary monetary policy shock in five out of six countries. Only Canada shows no clear pattern.

The impact of expansionary monetary policy shocks on the Gini net, Figure 10, is again quite heterogeneous across countries. In economies characterized by a high degree of

Figure 9: Monetary Policy and Gini Gross, Yearly Model



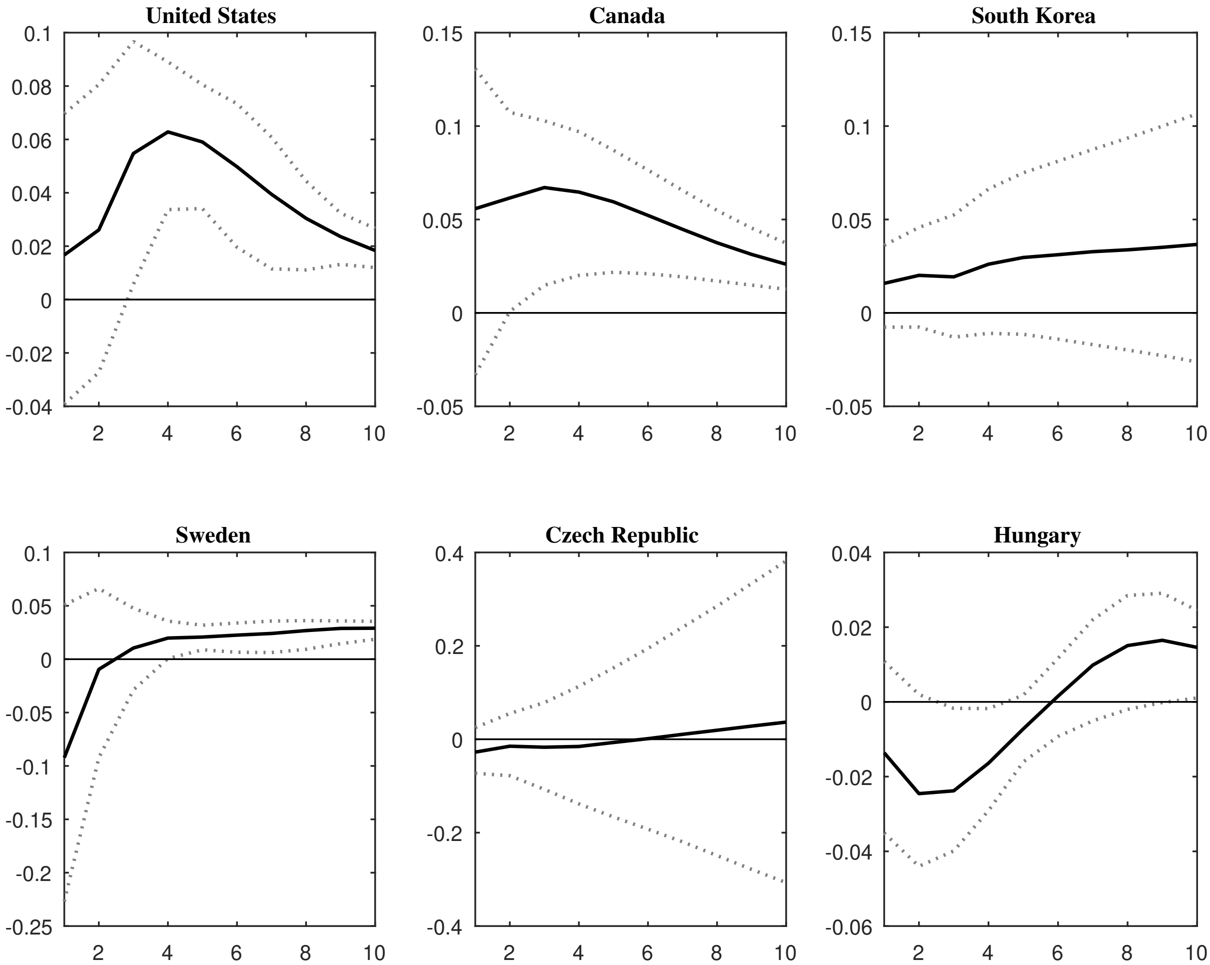
Notes: Impulse responses of Gini net to an expansionary monetary policy shock. Estimates with yearly data. The solid lines reflect the median responses, the dotted lines are the 16% and 84% percentiles.

redistribution, we can observe a lower sensitivity to a shock. In contrast, countries with little governmental intervention show no or, as is the case for the United States, a positive reaction. The findings thus lend support to the notion that governmental interventions have a mitigating effect.

B. *Local Projections*

Thus far, we have solely considered VAR models. We now follow Coibion et al. (2017) and assess the role of monetary policy shocks for income distributions via impulse responses from local projections, as suggested by Jordà (2005). This methodology describes the response of an endogenous variable (i.e. Gini coefficient) to a monetary policy shock that enters as an (strictly) exogenous variable into the model. Therefore, additional scrutiny is warranted regarding the selection of the incorporated exogenous shock.

Figure 10: MONETARY POLICY AND GINI NET, YEARLY MODEL



Notes: Impulse responses of Gini net to an expansionary monetary policy shock. Estimates with yearly data. The solid lines reflect the median responses, the dotted lines are the 16% and 84% percentiles.

Coibion et al. (2017) use Romer and Romer (2004) shocks for this purpose. This approach does not suite our specific data set for two reasons. First, Romer and Romer (2004) shocks are only available up to the point where short-term interest rates hit the ZLB. We explicitly want to account for periods characterized by unconventional monetary policy. Second, as Romer and Romer (2004) shocks are only available for the United States, our analysis would lose its cross-country dimension. Thus, we derive our exogenous quarterly monetary policy shock for each country from a standard three variable VAR model consisting of real GDP, consumer prices, and key policy rates. We identify the monetary policy shock via recursive ordering, where we assume that monetary policy reacts contemporaneously to output and prices, but not vice versa.[18]

With these exogenous shocks at hand, we estimate local projections. Following Jordà

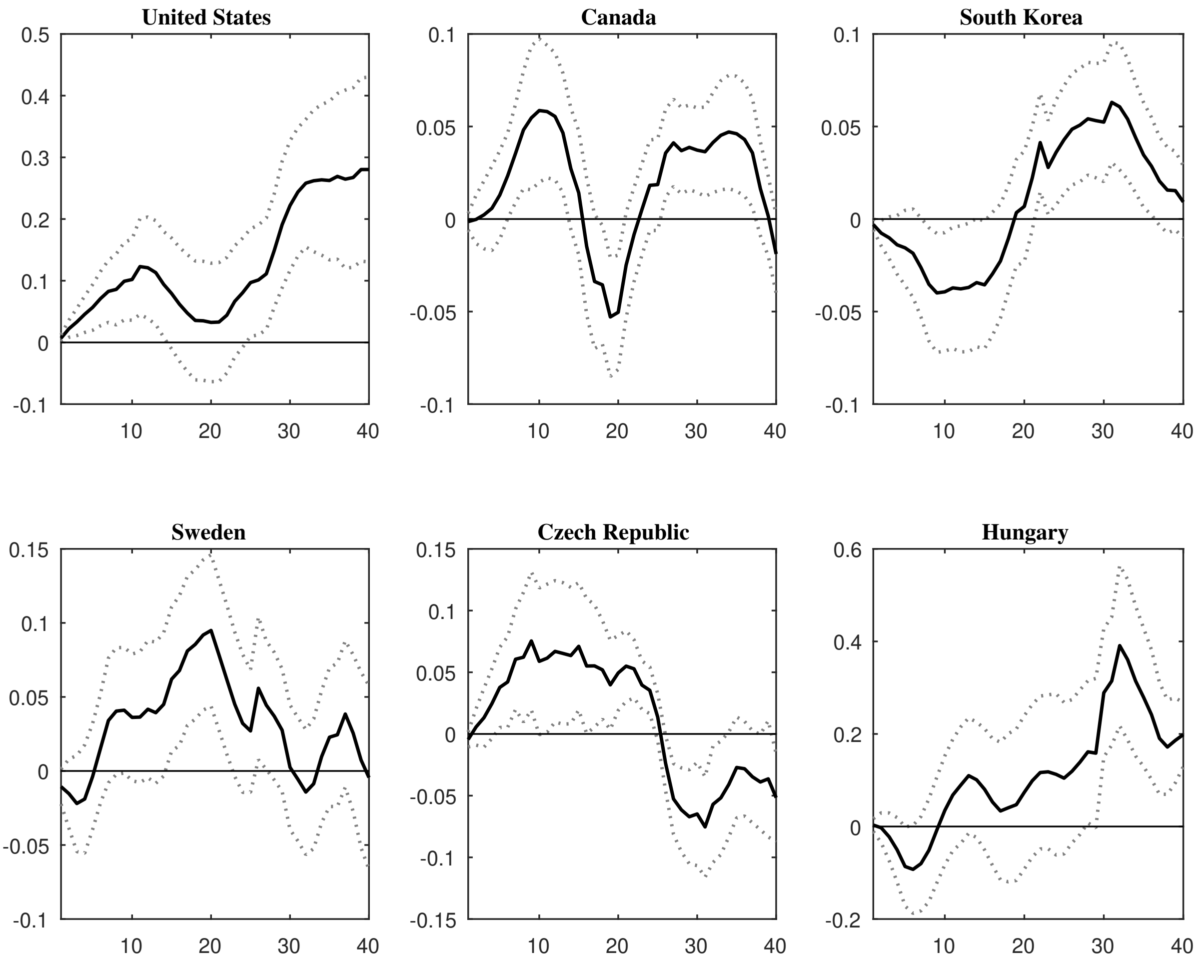
[18] The correlation between the resulting shock series (for the U.S. economy) and the quarterly aggregated Romer and Romer (2004) shocks is about 0.6 for the available period (1990 to 2007).

(2005), our model is given by

$$y_{t+h} = c + \beta_h \hat{u}_t^{MP} + \gamma_h' \sum_{s=1}^{q} y_{t-s} + \varepsilon_{t+h}\,. \tag{5.1}$$

Hereby, y_t is the inequality measure and $\hat{u}_t^{MP}$ the policy shock that stems from the VAR model described above. We set $q = 4$ so that the four latest inequality measures that appeared before the shock are incorporated as control variables.[19] By plotting β_h as a function of h along with error bands we get impulse responses. To circumvent serial correlation among the residuals, we apply Newey-West standard error correction. The resulting impulse responses are depicted in Figures 11 and 12.

Figure 11: Local Projections for Gini Gross

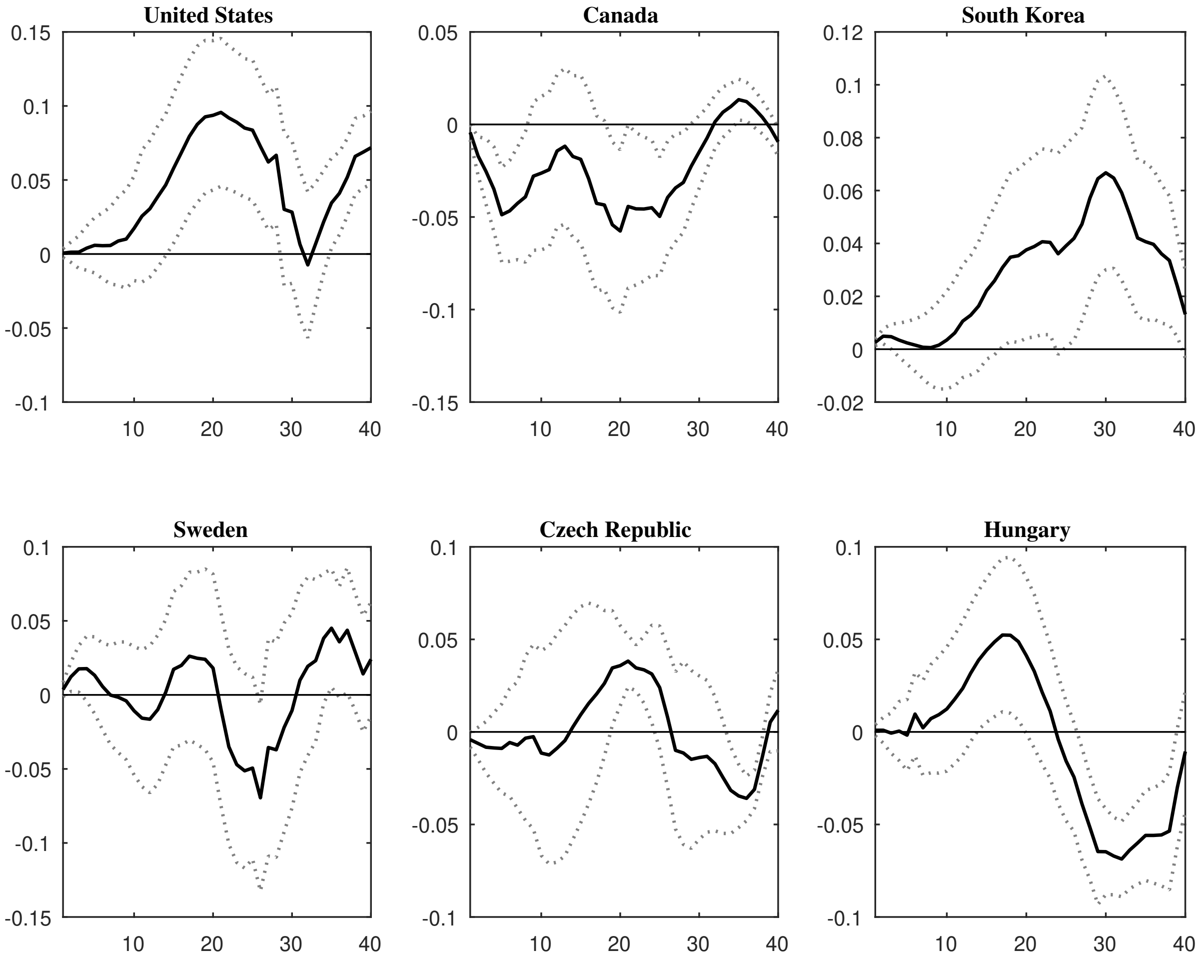


Notes: Local projections for β_h (solid line) and the respective one standard error bands (dotted lines). Shock measured in standard deviation units and inverted to reflect expansionary shocks.

In line with our VAR findings, we observe in four out of six countries a clear increase in the Gini gross after an expansionary monetary policy shock. South Korea and the Czech

[19] Altering q does not yield substantially different results.

Figure 12: Local Projections for Gini Net



Notes: Local projections for β_h (solid line) and the respective one standard error bands (dotted lines). Shock measured in standard deviation units and inverted to reflect expansionary shocks.

Republic display an increase in at least some periods.

Regarding the Gini net, local projections confirm our previously presented results as well. Countries with a high degree of redistribution show no clear pattern. This indicates that governmental intervention is able to dampen the effect of monetary policy shocks on gross income dispersion.

It is worth noting that despite the use of a similar methodology as Coibion et al. (2017) we obtain diverging results. Hence, we next test whether the differences stem from different samples.

C. *Sample Size*

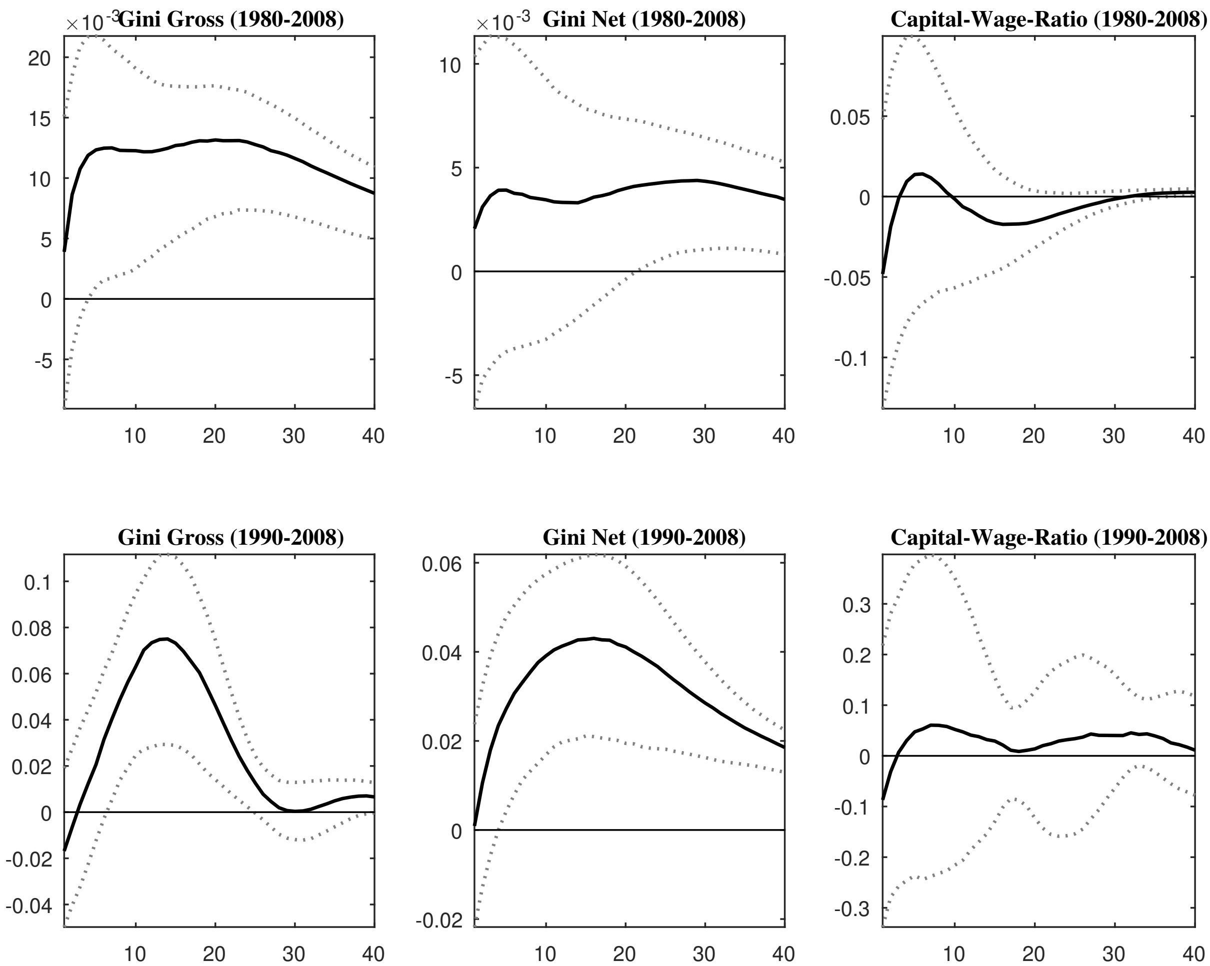
Thus far, data availability limited the analyzed estimation horizon from the beginning of the 1990s to 2014 or 2015, respectively. To ensure the comparability with Coibion et al. (2017) we perform two further robustness exercises: we firstly estimate a U.S. model akin

Coibion et al. (2017) before we incorporate the Global Financial Crisis to examine its effect on the nexus between monetary policy shocks and income inequality.

One discussed driving force for the nexus between income inequality and expansionary monetary policy are the unconventional monetary policy measures following the financial crisis.

Figure 13 presents model outcomes for 1980Q1/1990Q1 – 2008Q4. The results do not differ notably from our results so far, no matter whether we estimate a model with or without the VIX (1990Q1 vs. 1980Q1).

Figure 13: US: Excluding Financial Crisis

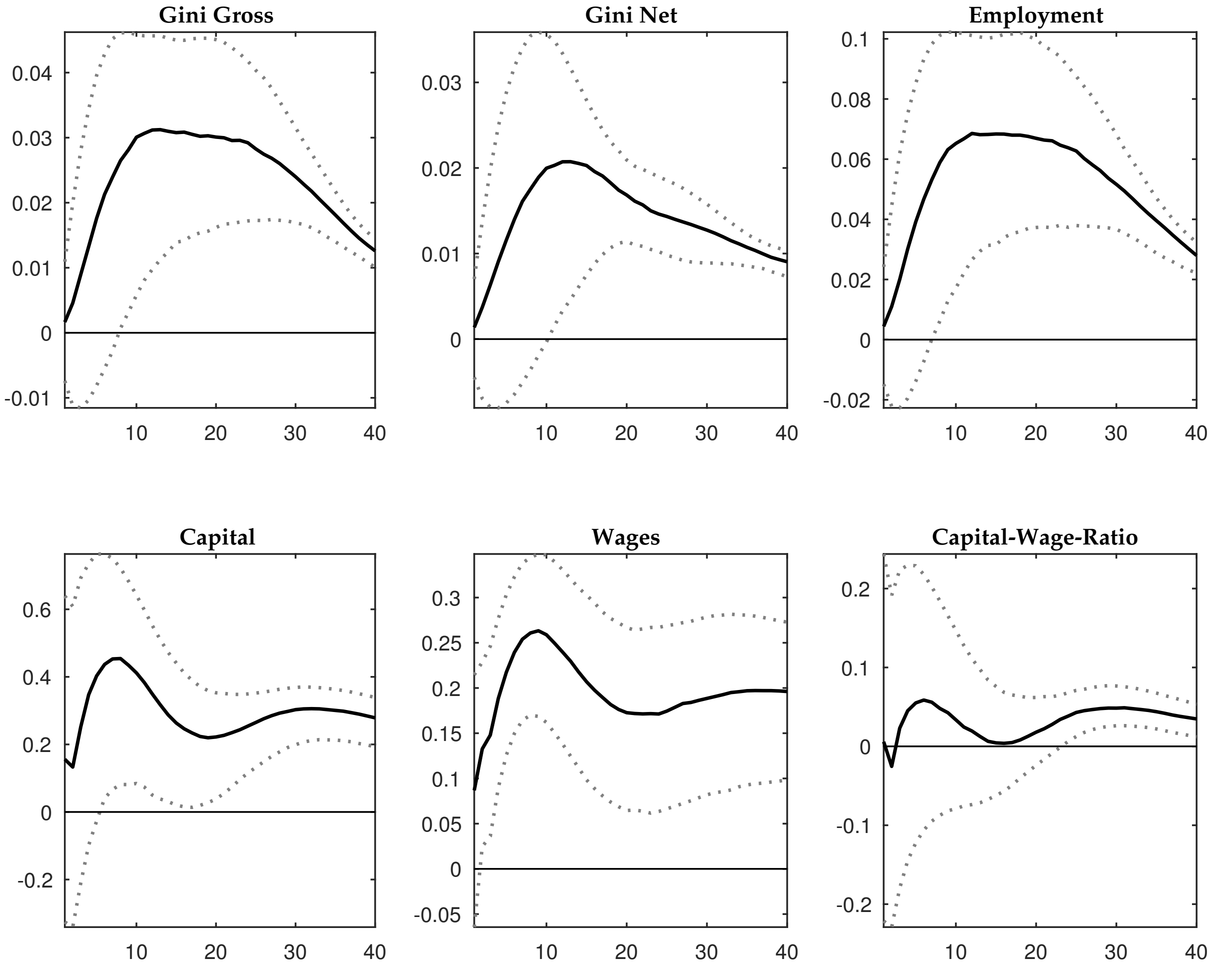


Notes: Impulse responses of net Gini to an expansionary monetary policy shock. The solid lines reflect the median responses, the dotted lines are the 16% and 84% percentiles. VIX excluded in sample 1980–2008 (top row) and included in sample 1990–2008 (bottom row).

If we include the financial crisis into our sample, the magnitude of the response of inequality to a monetary policy shock increases, as seen in Figure 14. As pointed out by Montecino and Epstein (2015), unconventional monetary policy measures have indeed raised income inequality in the United States. Our analysis supports their findings.

In brief, our results are qualitatively robust to a variety of methodological as well as sample

Figure 14: US: Long Sample 1980 - 2014



Notes: Impulse responses of net Gini to an expansionary monetary policy shock. The solid lines reflect the median responses, the dotted lines are the 16% and 84% percentiles.

selection aspects. Expansionary monetary policy shocks increase income inequality.

6 Conclusion

In the recent decade, the issue of rising income inequality gained more and more attention in the public perception as well as in the political debate. The nowadays observable historically high levels of income dispersion are accompanied by an environment of very expansionary monetary policy. In this respect, we add new empirical evidence to the current controversy. To assess the effects of monetary policy shocks, we incorporate Gini coefficients in a standard macroeconomic VAR model consisting of GDP, consumer prices, a monetary policy variable, and the corresponding real exchange rate. Gini coefficients of gross incomes increase in all countries, namely the U.S., Canada, South Korea, Sweden, the Czech Republic, and Hungary, when facing expansionary monetary policy shocks. In contrast, the reaction of net income dispersion varies between the countries under consideration. Countries with a relatively low degree of redistribution, i.e. the U.S., Canada, and South Korea, show notable positive reactions of Gini net in the presence of expansionary monetary policy shocks. On the contrary, this measure does not increase in countries with a high degree of redistribution.

Furthermore, we take a more detailed look at the importance of two major transmission channels, the *employment channel* and the *income composition channel*. The reaction in employment, captured by the total number of employed people, shows the expected positive sign in all countries. Again, the reaction is weaker and less pronounced in countries with a high degree of redistribution. By splitting the composition of net national income into its major parts, labor-related income and capital-related income, we can evaluate which income category benefits disproportionately. While both components are, in general, affected positively, their ratio indicates that in the U.S., Canada, and South Korea capital owners benefit disproportionately. As the increase in employment cannot offset the surge in net income inequality we conclude that the composition of income outweighs the positive labor market effects. The capital-wage-ratio indicates that in countries with a high degree of redistribution both income sources seem to profit similarly. Lastly, we show that the distributional effects of monetary policy (on disposable income) can be addressed by the degree of governmental intervention.

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Essay II:

News Shock Spillovers: How the Euro Area Responds to Expected Fed Policy

This paper has been published as:

> Rudel, Paul and Peter Tillmann, “News shock spillovers: How the euro area responds to expected Fed policy," *MAGKS Joint Discussion Paper Series in Economics*, 2024, No. 13-2024.
>
> Rudel, Paul and Peter Tillmann, “News shock spillovers: How the euro area responds to expected Fed policy," *MAGKS Joint Discussion Paper Series in Economics*, 2018, No. 32-2018.

This paper was presented at the following international conferences:

i. Computing in Economic and Science (CEF):
   24^{th} International Conference, Milan, Italy.
   Date: June 2018.
   Presenter: Paul Rudel.

ii. Western Economic Association International (WEAI):
   93^{rd} Annual Conference, Vancouver, Canada.
   Date: June 2018.
   Presenter: Paul Rudel.

Acknowledgement

We thank seminar participants at the CEF conference (Milan, 2018), the Western Economic Association International (Vancouver, 2018), and the University of Giessen for helpful comments on an earlier draft.

News Shock Spillovers: How the Euro Area Responds to Expected Fed Policy

Paul Rudel[†] Peter Tillmann[‡]

Abstract

Monetary policy increasingly relies on steering market expectations about future policy. This paper identifies a monetary policy news shock based on a VAR model. A monetary news shock is equivalent to new information about the Fed's future monetary policy becoming available today. One example of a monetary news shock is a forward guidance announcement, where the Fed unveils its prospectively (binding) monetary policy, today. In this paper, we study the spillover effects of news shocks. We estimate the response of the euro area to an expected future policy tightening of the Fed. The U.S. news shock improves sentiment and business cycle expectations in the euro area, which is consistent with the notion of the Fed revealing favorable news by a tightening announcement. We also distinguish the news shock from a conventional U.S. policy surprise and find that they lead to diverging responses in the euro area.

Keywords: News shocks, spillovers, forward guidance, monetary policy, interest rates, expectations, central bank information effects

JEL classification: E43, E58, F42

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1 Introduction

Central banks increasingly aim at steering financial market expectations. Releasing information about the monetary policy stance prevailing in the future, the argument goes, allows market participants to anticipate interest rate changes and thus stabilizes markets. The case for steering market expectations became even stronger when several advanced economies hit the zero lower bound on nominal interest rates.

When changes to the short-term interest rate were no longer feasible, central banks engaged in forward guidance, that is providing guidance on future monetary conditions. A surprise change to forward guidance, e.g. surprisingly lower interest rates in the future are communicated after a meeting of the Federal Open Market Committee (FOMC), is one example of a monetary news shock. In this case, a news shock reflects information becoming available today about a future policy step. In the case of effective forward guidance, the Fed maintains a low level of the federal funds rate in the future even though the economy improves. Hence, the forward guidance announcement issued today pertains to policy actions in the future.

While a surprise change to forward guidance is one obvious example of a news shock, there are others. Think of a central bank announcing a path for future asset purchases. The monetary policy action, i.e. the actual purchases, often happens in the future. Yet, the news themselves enter the market today. Importantly, a news shock needs to be distinguished from a standard monetary policy surprise, which pertains to an unexpected change in the contemporary monetary conditions.

A large body of literature documents that standard policy surprises have cross-border effects. A contemporaneous policy tightening of the Fed spills over to advanced as well as emerging market economies, leading to a depreciation of domestic currencies and a tightening of local real and monetary conditions, as reported in i.a. Iacoviello and Navarro (2019), Dedola et al. (2017), and Georgiadis (2016). The contribution of this paper is to study the effects of U.S. monetary news shocks on expectations in the euro area.

Our identification of the news shock is closely related to Ben Zeev et al. (2020). In particular, we estimate a standard Taylor rule for the Fed, whose residuals reflect unexpected changes in the (shadow) federal funds rate. These residuals are included in a vector autoregression (VAR) along with other endogenous variables such as interest rates, forecasts, bonds, or other assets. We identify a news shock as the shock which is orthogonal to a contemporaneous, exogenous change in the Taylor rule residual, which at the same time is explaining the largest share of (shadow) federal funds rate changes. This identification follows the work of Barsky and Sims (2011) and Kurmann and Otrok (2013).

In the second step, we extend the analysis and augment the VAR with euro area variables such as asset prices, uncertainty indicators, and expectations. Importantly, the additional variables do not interfere with the identification of the news shock. The resulting impulse response functions show how euro area variables adjust to such shocks.

We find that a positive monetary news shock, i.e. an announcement of a future interest rate hike, leads to a contemporaneous increase in long-term interest rates in the United States. This is consistent with the expectations hypothesis whereupon long rates incorporate information about the expected future short rate interest path. At the same time, the shock boosts U.S. equity prices and leads to a decrease in uncertainty. In the euro area, sentiment indicators improve after the shock. The reaction of uncertainty is ambiguous. While inflation and unemployment uncertainty tend to fall, growth uncertainty about the future rises.

At first sight, these results appear to contradict the expected effects of an U.S. tightening. However, we rationalize the findings based on the notion that by announcing a future policy tightening, the Fed reveals private information about its assessment of the current state of the economy. In this regard, Cieslak and Schrimpf (2019) report that market participants predominantly react to news concerning economic growth during central bank press conferences and other communication events. If markets are uncertain about the true state of the business cycle, such a policy move should be expansionary today, which is in line with what we find. We also assess the response of stock prices in order to separate the negative effect of the expected tightening from the positive effect of revealing new information. If the latter dominates, we should observe an increase in stock prices. This argument is similar to Lakdawala and Schaffer (2019) and the seminal work of Jarociński and Karadi (2020), who study the role of information shocks originating on FOMC meeting days. We show that the euro area responds consistently: new information about the Fed's assessment of the cyclical position of the U.S. economy is good news for markets and the private sector in the euro area.

Our contribution adds to three strands of the literature. The first is the literature on anticipated monetary policy shocks and their identification. D'Amico and King (2023) use a combination of sign and zero restrictions in a VAR model, an approach different from Barsky and Sims (2011), to identify an anticipated monetary policy shock. The authors refer to the shock as a "shock to expectations", which has even stronger effects on inflation and real economic activity than a conventionally identified monetary policy surprise. The paper closest to this one is Ben Zeev et al. (2020). We follow their identification of U.S. monetary news shocks. While Ben Zeev et al. (2020) study the domestic (real) effects of news shocks only, this paper extends the analysis and quantifies international news shock spillovers.

The second strand is the growing body of literature concerning spillover effects of central bank information. In advanced and emerging markets economies, Fed information shocks increase risk appetite (Pinchetti and Szczepaniak, 2023, Georgiadis and Jarociński, 2023), fuel asset prices (Gai and Tong, 2022, Georgiadis and Jarociński, 2023, Pinchetti and Szczepaniak, 2023), and stimulate economic activity (Gai and Tong, 2022, Georgiadis and Jarociński, 2023, Pinchetti and Szczepaniak, 2023). Regarding spillovers to the euro area, Jarociński (2022) finds similar expansionary effects on stock prices, financing conditions, and economic activity within his VAR.[1] Our paper adds a further layer to the spillover effects of Fed information by analyzing how such news affect expectations and economic sentiment in the euro area.

The third line of research relevant for this paper addresses the Fed's possible information advantage reflected in monetary policy decisions. Nakamura and Steinsson (2018) employ a high-frequency identification of monetary policy shocks based on intra-day meeting data to separate the policy surprise from the revelation of new information. They find upward revisions in growth expectations following a policy tightening, which is consistent with superior information available to the Fed about the current state of the economy, e.g. as famously reported in Romer and Romer (2000). Miranda-Agrippino and Ricco (2021) and Jarociński and Karadi (2020) use structural VAR models to separate the information inherent in policy decisions. As mentioned before, the latter paper uses the response of stock prices to differentiate between a detrimental surprise tightening and a revelation of favorable information. Jarociński (2024) uses the non-Gaussian properties of the reactions of financial market variables to FOMC announcements within a high-frequency window in order to disentangle the variations in the range of effects of the Fed's policy toolkit.

The remainder of this paper is organized as follows. Section 2 introduces the empirical model and outlines the identification of U.S. monetary news shocks. Section 3 extends the analysis to spillover effects on the euro area. Section 4 provides evidence for the favorable nature of news emerging from an anticipated Fed tightening. Section 5 presents results from alternative model specifications before Section 6 concludes.

2 Identifying U.S. News Shocks

In this chapter, we present the scheme to identify U.S. monetary news shocks. To verify the consequent shocks, we analyze the impulse responses of a group of financial variables that proxy expectations about future Fed policy.

[1] Another paper worth mentioning is Miranda-Agrippino and Nenova (2022). Following Swanson (2021), they extract the three most important factors, namely *target*-, *path*-, and *QE*-factor, that explain variations in the entire term structure of interest rates. Their results show notable spillover effects from both, contractionary shocks to the *path*-factor as well as to the *QE*-factor, which lead to a slowdown in economic activity as well as an increase in risk aversion. Their results are in contrast to Jarociński (2022), as the authors restrict in such way that they must lead to falling stock prices "in line with economic intuition".

A. *Fed Policy: Expectations, Surprises, and News*

Assume the Fed's policy rule can be described as

$$i_t = E_{t-1}\{i_t\} + \epsilon_t \,. \tag{2.1}$$

That is, the nominal interest rate i_t is a combination of the expected interest rate $E_{t-1}\{i_t\}$ and an unanticipated shock ϵ_t. The aforementioned are formed based on a set of available information at time $t-1$.

Shocks comprise both, surprises and news shocks. Formally,

$$\epsilon_t = v_t + \eta_{t-j} \,, \tag{2.2}$$

where v_t denotes the monetary policy surprise at time t and η_{t-j} is the news shock received j periods earlier. Given her mandate and interest rate smoothing behavior, expectations about future monetary policy of the U.S. Federal Reserve are formed via a Taylor rule that contains past realizations of the interest rate, inflation, and the unemployment rate. Thus, we estimate the expected interest rate in the form of

$$E_{t-1}\{i_t\} = \mu + \rho i_{t-1} + \phi_\pi (\pi_{t-1} - 2) + \phi_y \left(u_{t-1}^{NAIRU} - u_{t-1}\right) \,, \tag{2.3}$$

where we take into account an inflation gap $(\pi_{t-1} - 2)$ — we allege a two percent inflation target by the Fed — and the deviation of the unemployment rate from the NAIRU $\left(u_{t-1}^{NAIRU} - u_{t-1}\right)$.[2] The constant μ captures the real interest rate as well as the inflation target. Unexpected movements in the Fed's policy rate, the monetary policy residual, are then computed as

$$mpr_t = i_t - E_{t-1}\{i_t\} \,. \tag{2.4}$$

Equation (2.4) implies that expectations are formed solely based on the information from the previous period.[3] The monetary policy residual in turn can be partitioned into

$$mpr_t = v_t + \eta_{t-j} \,. \tag{2.5}$$

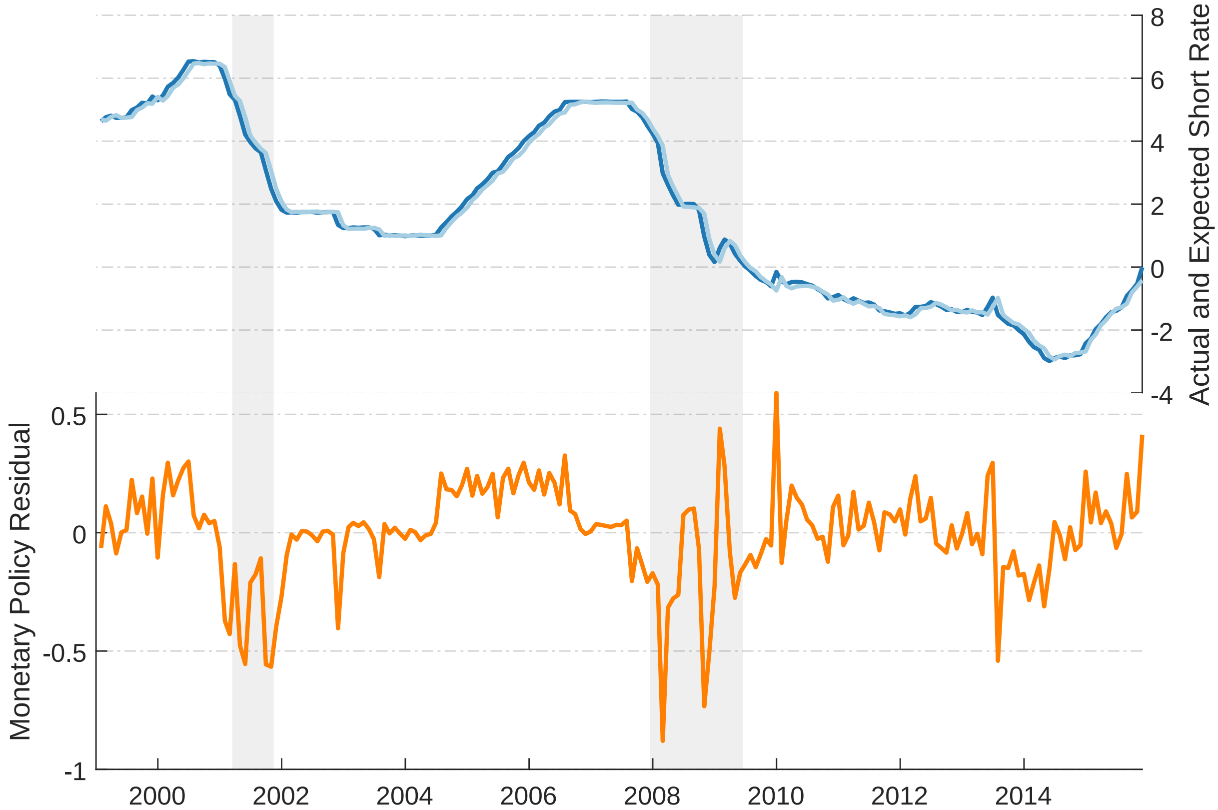
Figure 1 plots the short-term (shadow) interest rate, its expected value, as estimated in equation (2.3), as well as the monetary policy residual *mpr*. One can see that the jutting

[2] We estimate the Taylor rule using OLS with Newey-West HAC standard errors. The NAIRU, the Non-Accelerating Inflation Rate of Unemployment, is a long-term estimation drawn from the Federal Reserve Bank of St. Louis database. This is also our source for inflation and unemployment data.

[3] In the robustness Section 5, we use interest rate rules with higher lag orders. As will be seen, our results do not hinge on the initial assumption.

phases are the Dot-Com bubble burst in the early 2000', the "too-low for too-long" phase between 2004 and 2006, as well as the outburst of the financial crisis and the associated beginning of the Great Recession around 2008.

Figure 1: MONETARY POLICY RESIDUAL



Notes: In the upper panel, the bark blue solid line depicts the actual, while the light blue line shows the expected (shadow) short rate. The resulting monetary policy residual is depicted in the bottom panel. Grey bars mark NBER recession dates.

The exogenous movements of the monetary policy residual build the foundation for the upcoming identification of news shocks. As described by equation (2.5), we assume that these fluctuations are determined by both, contemporaneous surprises as well as news shocks.

B. *The VAR Model*

We build on the the total factor productivity (TFP) news shock identification procedure by Barsky and Sims (2011) who combine a VAR model with a set of restrictions in order to identify TFP news shocks. The basic idea is to extract the single shock that explains most of the forecast error variance (FEV) in TFP, yet has no contemporaneous effect on said variable. As we are interested in monetary policy news shocks, we seek to identify the shock that explains most of the movements of the monetary policy residual introduced in the previous section, while leaving the monetary policy residual unaffected on impact. Such a constraint would be consistent with an unexpected forward guidance announcement: the Fed's future policy steps will drive the monetary policy residual in the future, but not at the time of the announcement.

In what follows, we lay the foundation for the subsequent identification of our news shock. The starting point is an unrestricted VAR model that can be written as

$$\mathbf{y_t} = \mathbf{c} + \mathbf{A_1 y_{t-1}} + \cdots + \mathbf{A_p y_{t-p}} + \mathbf{u_t} \, . \tag{2.6}$$

Let $\mathbf{y_t}$ be an $n \times 1$ vector of observables of length T. The subsequent analysis of the responses of the U.S. financial market to our identified news shock is based on a range of data series, with a particular focus on indicators of market expectations, covering the period between January 1999 and November 2015.

The short-term interest rate, sr_t, our primary indicator of monetary policy, is a composition of the effective federal funds rate and the shadow short rate provided by Wu and Xia (2016). We use the shadow short rate in order to incorporate the Fed's unconventional policy measures, such as forward guidance and asset purchases, implemented after 2008.[4]

While we interpret the short rate as the lower end of the yield curve, we incorporate the two-year $\left(r_t^{2y}\right)$, five-year $\left(r_t^{5y}\right)$, and ten-year $\left(r_t^{10y}\right)$ bond yields taken from Adrian et al. (2013) to map a broader spectrum of the yield curve.

Furthermore, to encompass changes in expectations about the future interest rate path we withdraw the outlook for the T-bill four quarters ahead from the Survey of Professional Forecasters $\left(spf_t^{Tbill}\right)$. Ordering the monetary policy residual first, the vector of endogenous variables, $\mathbf{y_t}$, thus reads

$$\mathbf{y_t'} = \begin{bmatrix} mpr_t & sr_t & spf_t^{Tbill} & r_t^{2y} & r_t^{5y} & r_t^{10y} \end{bmatrix} \, . \tag{2.7}$$

The remainder is standard in the VAR literature. The $n \times n$ matrices $\mathbf{A}_i$ capture the coefficients for lags $i = 1, ..., p$, c is an $n \times 1$ vector of constants and u_t the $n \times 1$ vector of reduced-form innovations with variance-covariance matrix $\mathbf{\Sigma}$. The lag order is denoted by p and set to six following the Schwarz information criterion. The reduced-form moving average representation of this specification can be rewritten as

$$\mathbf{y_t} = \mathbf{B(L)u_t} \, , \tag{2.8}$$

[4] We have also carried out our analyses with an *mpr* based on the effective federal funds rate, as shadow short rates are generated regressors from term structure models and their path thus heavily depends on the underlying assumptions, as shown by Krippner (2020). Our results remain the same. Nevertheless, we will address this issue in greater detail in Section 5.

with $\mathbf{B(L)} = \sum_{i=0}^{p} \mathbf{B_i L}^i$ as an $n \times n$ matrix polynomial in the lag operator, $\mathbf{L}$, of moving average coefficients.

Assume the existence of a linear mapping between the prediction errors $\mathbf{u_t}$ and the mutually orthogonal shocks $\epsilon_\mathbf{t}$, i.e.

$$\mathbf{u_t} = \mathbf{P}\epsilon_\mathbf{t} \ , \tag{2.9}$$

with variance-covariance matrix $\mathbf{\Sigma} = E\left[\mathbf{u_t u_t'}\right]$. From equation (2.9) we see that the key restriction on the impact matrix $\mathbf{P}$ is that it must satisfy $\mathbf{PP'} = E\left[\mathbf{P}\epsilon_\mathbf{t}\epsilon_\mathbf{t}'\mathbf{P'}\right] = \mathbf{\Sigma}$. However, $\mathbf{P}$ is not unique. Let $\tilde{\mathbf{P}}$ be a valid alternative orthogonalization, e.g. a Cholesky decomposition. Hence, we can rewrite the space of permissible impact matrices as

$$\tilde{\mathbf{P}}\mathbf{Q} = \mathbf{P} \tag{2.10}$$

where $\mathbf{Q}$ is an orthonormal matrix ($\mathbf{Q'} = \mathbf{Q}^{-1}$ and $\mathbf{QQ'} = \mathbf{I_n}$) and therefore $\tilde{\mathbf{P}}\tilde{\mathbf{P}}' = \mathbf{\Sigma}$.

C. *Identification of News Shocks*

From equations (2.8) - (2.10) we can deduce the h-step ahead forecast error as

$$\mathbf{y_{t+h}} - \hat{\mathbf{y}}_\mathbf{t+h} = \sum_{\tau=0}^{h} \mathbf{B}_\tau \tilde{\mathbf{P}}\mathbf{Q}\epsilon_{\mathbf{t+h}-\tau} \ , \tag{2.11}$$

where $\mathbf{B}_\tau$ denotes the matrix of moving average coefficients at horizon τ. The share of the forecast error variance of variable i attributable to a structural shock j at horizon h is then

$$\Omega_{ij}(h) = \frac{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau}\tilde{\mathbf{P}}\gamma\gamma'\tilde{\mathbf{P}}'\mathbf{B}'_{i,\tau}}{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau}\mathbf{\Sigma}\mathbf{B}'_{i,\tau}} \ . \tag{2.12}$$

The $n \times 1$ impulse vector $\tilde{\mathbf{P}}\gamma$ corresponds to the j-th column of a possible orthogonalization while $\mathbf{B}_{i,\tau}$ denotes the i-th row of the moving average coefficients matrix at horizon τ. Owing to the fact that the identification of news shocks requires the identification of a shock orthogonal to innovations in the monetary residual, the optimization problem can be expressed as

$$\gamma^* = \arg\max \sum_{h=0}^{H} \Omega_{1,2}(h) = \frac{\sum_{\tau=0}^{h} \mathbf{B}_{1,\tau}\tilde{\mathbf{P}}\gamma\gamma'\tilde{\mathbf{P}}'\mathbf{B}'_{1,\tau}}{\sum_{\tau=0}^{h} \mathbf{B}_{1,\tau}\mathbf{\Sigma}\mathbf{B}'_{1,\tau}} \tag{2.13}$$

subject to

$$\tilde{\mathbf{P}}(1,j) = 0 \quad \forall j > 1 \tag{2.14}$$

$$\gamma(1,1) = 0 \tag{2.15}$$

$$\gamma'\gamma = 1 \; . \tag{2.16}$$

The first two restrictions ensure that news shocks have no contemporaneous effect on the policy residual, while the third restriction imposes that γ is a column vector belonging to an orthonormal matrix.[5] Since we use monthly data, we set the truncation horizon to $H = 24$ months. Swanson and Williams (2014) and Hanson and Stein (2015), among others, argue that forward guidance operates within this window.[6]

D. *Estimation and Inference*

Estimation and inference is based on Bayesian techniques. We assume a Minnesota prior for the unknown reduced-form coefficients and a normal-inverted Wishard distribution for the variance-covariance matrix $\mathbf{\Sigma}$. Inference is then based on 2000 draws from the posterior, where we solve for $\gamma*$ each draw.

E. *Domestic Effects of U.S. News Shocks*

The restrictions we impose in order to identify a monetary news shock, zero contemporaneous impact on the short rate but maximum explanatory power in the future, allows us to capture all policies which are announced in period t but become effective later. Forward guidance is one candidate for a policy captured by this identification. Under forward guidance, the Fed announces today i.a. to maintain a lower level of the policy rate in the future than it would otherwise do. Hence, to the extent this announcement comes as a surprise, it should leave the contemporaneous short rate unaffected but drive future policy rates.

Nonetheless, forward guidance shocks are not the only candidates that fit this identification scheme. A Fed announcement of asset purchases commencing in the future should not only leave today's short rate unchanged, but at the same time, drive the future short rate and other forward-looking variables. Likewise, news shocks are also possible in periods in which monetary policy is not constrained by the effective lower bound on nominal interest rates. Take for example the Fed chair giving a speech hinting at future

[5] Regarding Uhlig (2004), this approach identifies the news shock as the first principal component of the monetary policy residual orthogonalized vis-à-vis its own innovation.

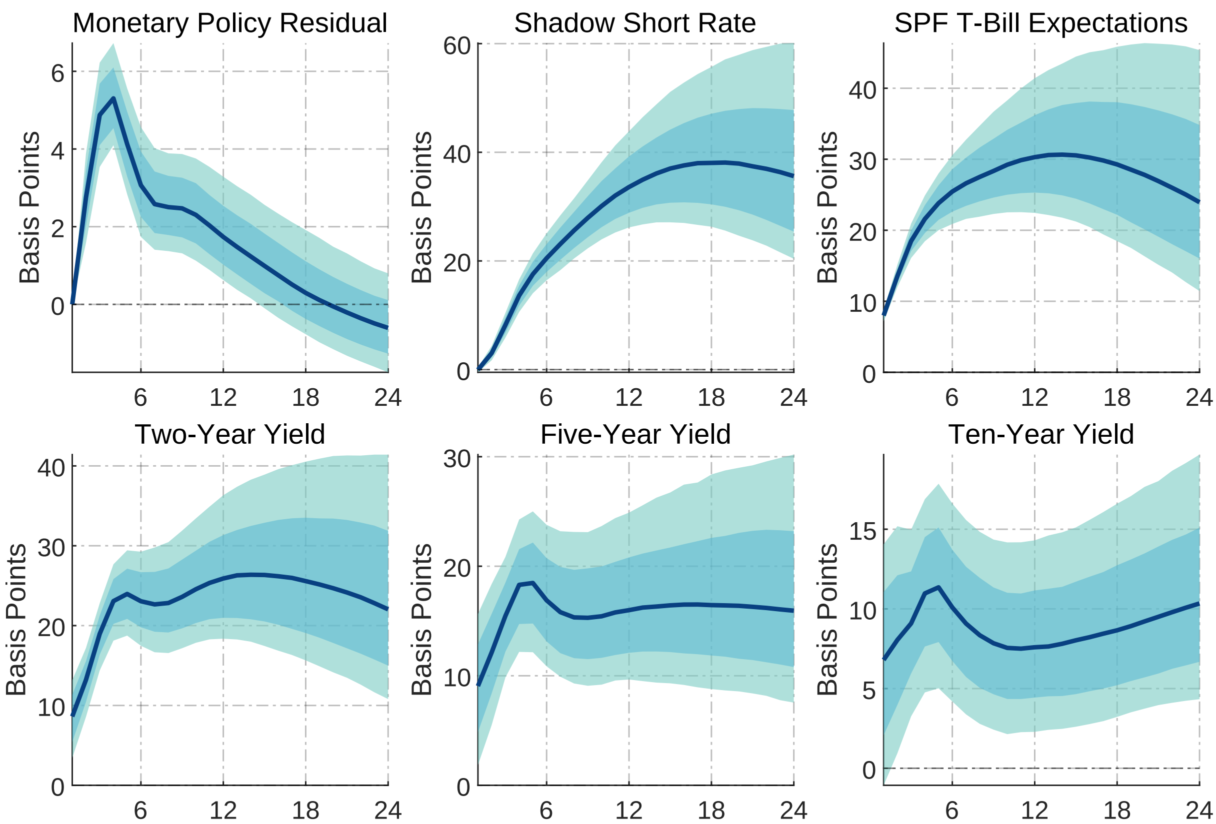
[6] However, robustness checks show that our results do not hinge on this specification. The results can be obtained upon request.

policy. To the extent this has not been anticipated, the news should drive forward-looking variables instantaneously, yet leave the short rate unchanged.

In what follows, we use the terms "news shock" and "forward guidance" interchangeably. However, we should keep in mind that the nature of the policy captured by these shocks goes above and beyond forward guidance in that sense.[7]

Figure 2 shows the median impulse responses to the identified monetary policy news shock along with 68% (dark area) and 90% (light area) posterior credibility intervals. On impact, the news shock does not move the *mpr*. This reflects the constraint imposed on the VAR system. Beyond period *t*, however, we find that the Fed tightens monetary policy with the *mpr* response peaking four months after the shock. Hence, the identified shock corresponds to a policy tightening announced in *t* becoming effective a few months later.

Figure 2: Domestic Responses to U.S. Monetary Policy News Shocks



Notes: Posterior median impulse responses to monetary news shocks (solid line). Dark (light) areas denote 68% (90%) probability masses.

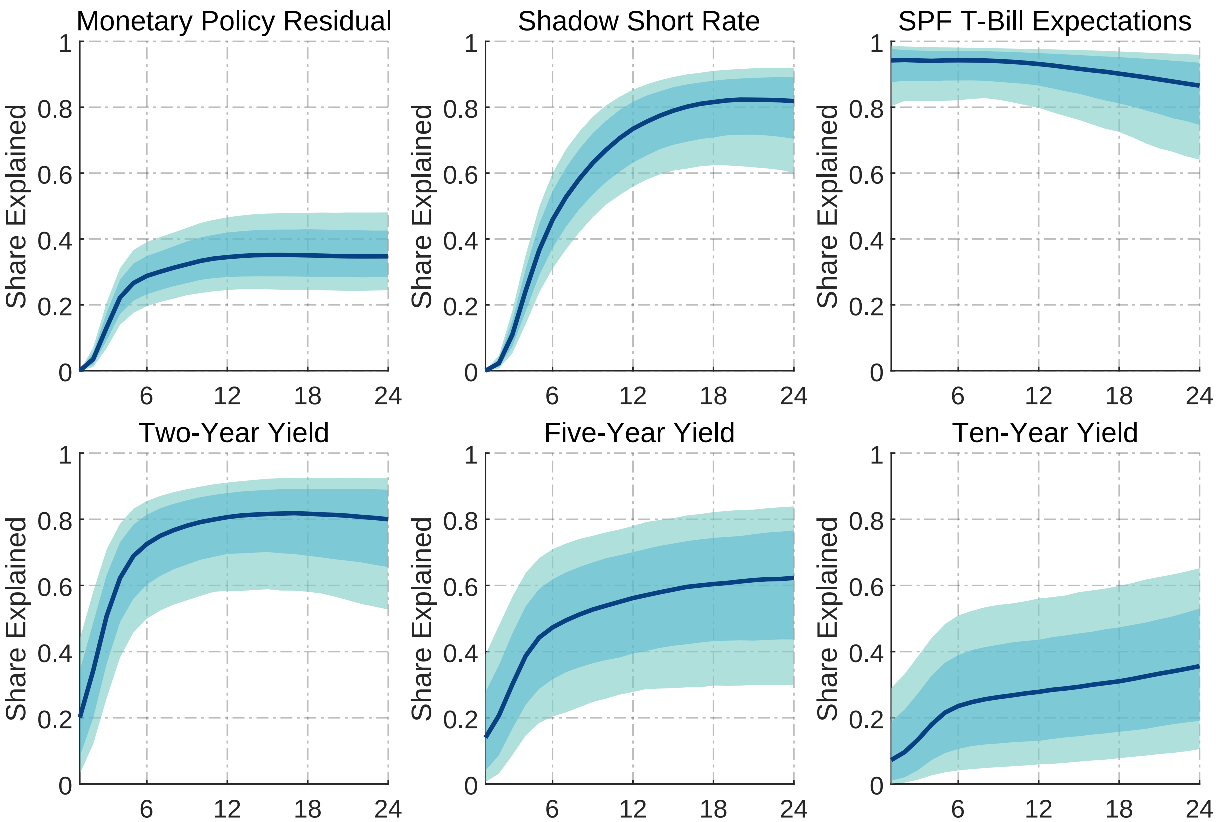
We also find that news about the forthcoming monetary policy tightening affect the entire term structure of interest rates. At the short end, the shadow short rate increases within a two-year window by almost 40 basis points. That is, contractionary monetary policy

[7] Our shocks can therefore be seen as a combination of unexpected disturbances of the *path*- and *QE*-factors, as in e.g. Swanson (2021) and Miranda-Agrippino and Nenova (2022) or as a mix of LSAP and central bank information shocks as in e.g. Georgiadis and Jarociński (2023).

materializes in increasing interest rates. That is to say – the Fed keeps her word. Market participants expect a notable increase in the T-bill rate four quarters in the future. The peak median response, 30 basis points, is only slightly smaller than the corresponding response of the short-term interest rate. Moreover, yields on two-, five-, and ten-year bonds increase by 25, 18, and 12 basis points, respectively. That is, the effect becomes smaller for longer maturities, which is in line with the findings of Gürkaynak et al. (2005), Gertler and Karadi (2015), Swanson (2021), and Jarociński (2024). Hence, news shocks do not only predict short.term interest rate movements but also successfully flatten the yield curve.

To get further insights into the relevance of our identified news shocks, we depict the share of the forecast error variance explained by said shocks in Figure 3.

Figure 3: FEV Explained by U.S. Monetary News Shocks



Notes: Fraction of the forecast error variance of each variable, explained by the median monetary policy news shock (solid line) along with posterior 68% (dark) and 90% (light) probability masses.

Over a 24 months horizon, news shocks explain up to roughly 35% of the variance of the monetary residual.[8] In other words, a notable fraction of the movements in the (unanticipated) interest rate path can be explained by news shocks – that is, anticipated Fed policy. News shocks explain up to 80% of the movement of interest rates at the short end of the yield curve.[9] Furthermore, almost the entire variance of T-bill expectations is

[8] Ben Zeev et al. (2020) report very similar contributions of their monetary news shocks.

[9] Ben Zeev et al. (2020) measure a maximum share of 47% in the federal funds rate. Our high value is probably

explained by news shocks. They therefore decisively shape market expectations. The explanatory power decreases with longer maturities of the underlying securities. Roughly 80% of the variance of two-year bond yields is explained by news shocks within a two-year horizon. Moreover, news shocks explain 60% and between 20% and 40% of the forecast error variance of five- and ten-year bond yields, respectively. Overall, our results suggest that forward guidance is successfully forming expectations concerning future interest rate policy.

Finally, to emphasize the role of forward guidance, we compare the influence of both, the monetary news shock identified before and a conventional monetary shock, i.e. a surprise policy tightening effective at time t.[10] In this context, Gürkaynak et al. (2005) provide a much-noticed work of the distinct impact of current shocks and news shocks.[11] For the sake of comparability with Gürkaynak et al. (2005) we adjust our analysis twofold: Firstly, in our baseline model we substitute the T-bill outlook with the three-month Eurodollar future to analyze the impact of news shocks on a comparable set of variables.[12] Unlike Gürkaynak et al. (2005), we include the three-month Eurodollar future instead of the one-year Eurodollar future due to data availability. Secondly, as Gürkaynak et al. (2005), we constrain the current shock to lead to the same peak median impulse response of the three-month Eurodollar future, as prompted by the news shock. To be more precise, we adjust the current shock to match the peak median response of the Eurodollar future to a news shock which we, in turn, cannot manipulate because the impulse vector is the result of an optimization procedure and restricted to have a length of one in order to belong to an orthonormal matrix. Thus, manipulating the news shock vector would violate the imposed restrictions.

Before we turn to the analysis of the impulse responses to both shocks and juxtapose our findings with Gürkaynak et al. (2005), it is worth noting that the size of our shock compared to Gürkaynak et al. (2005) differs. Thus, a quantitative comparison with their point estimates would be misleading.

However, we can evaluate our findings qualitatively. Figure 4 reveals the impulse responses to a current monetary policy shock (red) and a monetary policy news shock (blue).

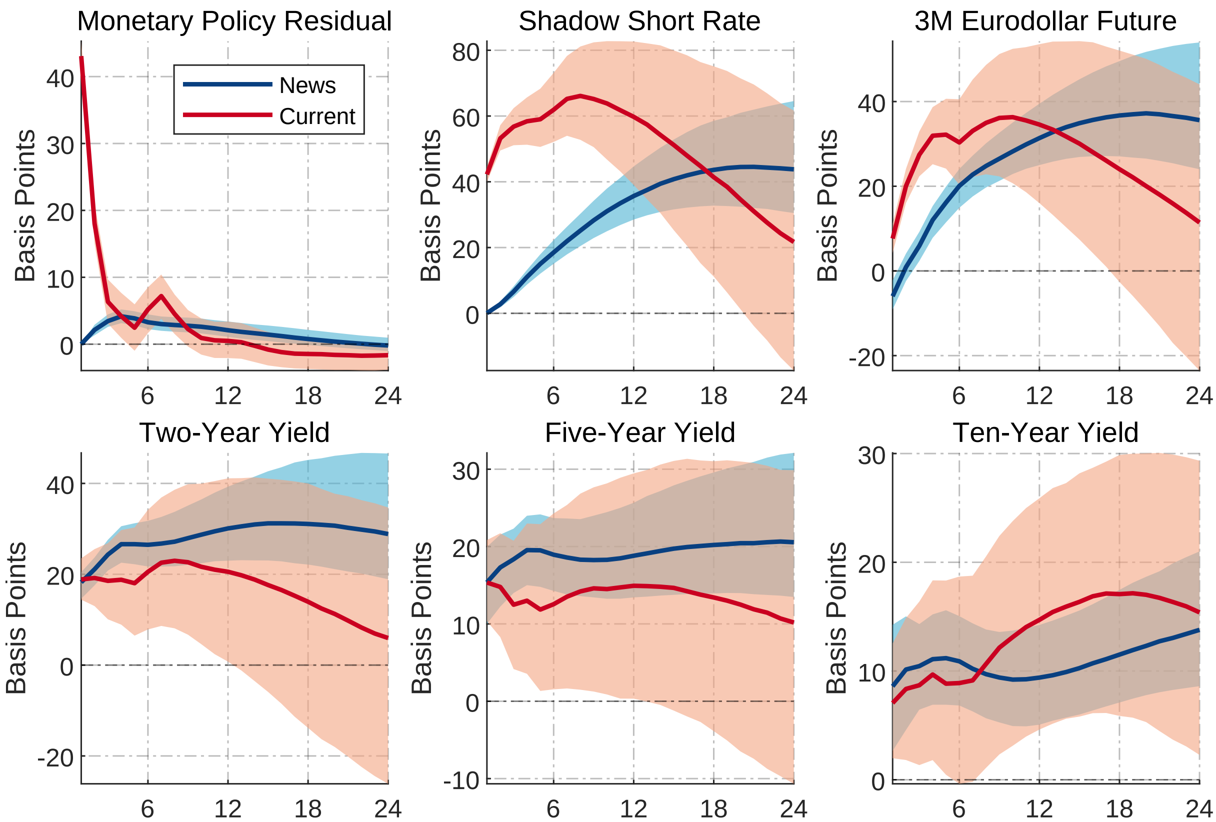
due to the use of a shadow short rate, which is largely determined by the interest rate structure at the middle and longer end of the yield curve. News shocks (are intended to) shape the yields in the aforementioned spectrum and explain a correspondingly high proportion in the forecast error variance, as also shown in Figure 3. This, in turn, cascades to the (hypothetical) short end of the shadow interest rate.

[10] The conventional monetary shock is identified based on a recursive Cholesky ordering of the variables. According to this ordering, the monetary policy shock is allowed to have a contemporaneous impact on all other variables, while monetary policy responds with at least a lag of one months to innovations in the other variables.

[11] The authors refer to the current shock as *target factor* and the news shock as *path factor*.

[12] Gürkaynak et al. (2005) identify their *path factor* through (unrestricted) principal components analysis given a set of high-frequency data. See also Nakamura and Steinsson (2018).

Figure 4: News Shock vs. Conventional Monetary Policy Shock



Notes: Median impulse responses to both, news shock (blue solid) and current monetary policy shock (red solid) along with their respective 68% posterior probability bands. The magnitude of the current shock is adjusted to lead to similar responses of the Eurodollar future as implied by news shocks.

Firstly, by construction, the peak median responses of the three-month Eurodollar future are akin, though the timing of the maximum response differs across shocks. As the current shock becomes effective immediately, the peak response of the three-month future is reached earlier. Not surprisingly, monetary surprises have an immediate (upscaled) 40 basis points impact on the interest rate, while news shocks, by definition, have no direct effect but materialize over time. The short rate increases by 65 basis points in response to a current shock and by 40 basis points to a news shock.

Returns on two-year government bonds respond on impact basically indistinguishable. While the impact of the news shocks remains quantifiable over the truncation horizon at approximately 30 basis points, the effect of the surprise dissipates over time and is no longer significant after 12 months due to the high degree of uncertainty surrounding it. Gürkaynak et al. (2005) find qualitatively similar responses to the two types of shocks at the short end of the yield curve. They estimate highly significant marginal effects on two-year yields of 48 and 41 basis points for the *target factor* and the *path factor*, respectively.

Our impulse responses of the five-year bond yield also resemble the findings of Gürkaynak et al. (2005). On impact, both shocks increase returns by 15 basis points. Over time, news shocks have been observed to have a somewhat greater effect on five-year bonds than monetary surprises. However, given the wide credibility interval of the response to monetary surprises, the results are statistically hardly distinguishable. Again, qualitatively our results do not differ much from the findings of Gürkaynak et al. (2005), who measure a slightly greater marginal effect of the *path factor*. Likewise, the response of the ten-year yield is comparable to the results in the literature.

To sum up, we are able to identify news shocks that lead to plausible responses of U.S. bond yields which are in line with the literature using alternative approaches.

3 How the Euro Area Responds to Expected Fed Policy

Are market participants in the euro area reshaping their expectations in light of an expected monetary tightening of the Federal Reserve? To answer this question, we estimate the spillover effects of news shocks within a VAR system similar to the one used in the previous section. The model incorporates both, U.S. and euro area variables. The primary objective of this paper is to examine the impact of U.S. news shocks on expectations in the euro area. To that end, we limit our focus to variables that measure sentiment and uncertainty. As a result, we exclude core economic variables from our analyses.

The U.S. variables consist of the monetary policy residual, the (shadow) short-term interest rate, the expected three-month T-bill rate, and the two-year yield. The rationale for the selection of variables is that forward guidance aims at forging the future interest rate path within a two year window, as stated by Campbell et al. (2012) and Gertler and Karadi (2015), among others. These four core variables are included throughout the subsequent analyses, while we substitute the five- and ten-year yields with survey data on sentiment and expectations about the future economic stance of the euro area. Since the news shock is restricted to be orthogonal to current short rate changes and to maximize the share of the forecast error variance of the U.S. monetary policy residual, the inclusion of additional euro area variables is innocuous.

To obtain insights into the role of U.S. news shocks for sentiment and expectations in the euro area, we consider aggregate survey responses from both, firms and households. Data on consumer sentiment and the business climate are taken from business and consumer surveys provided by the European Commission. This is also the source of the responses to expectations about prices, unemployment, consumption, and production. The ifo outlook for the euro area is provided by the CES ifo Group. Finally, the composite index for systemic stress (CISS) stems from the ECB data portal.

To make the responses of the various survey data to an U.S. news shock comparable, we transform them as follows: following the OECD CCI Harmonization Guidelines, we first normalize the survey data to have a mean of zero and a standard deviation of one. The data is then amplitude adjusted around 100. Finally, we take the natural logarithm and multiply it by 100. As a result, we can interpret the impulse responses as percentage changes following a U.S. news shock.

Figure 5 depicts the impulse responses of the euro area variables to U.S. monetary news shocks. First, regarding the sentiment indicators, U.S. news shocks lead to an improvement in both indicators by a similar magnitude within the truncation horizon. Consumer sentiment as well as business climate increase by about 0.1 percent due to a news shock. Moreover, news shocks contribute up to 30% (42%) to the forecast error variance of the indexes (not shown here). In other words, forward guidance by the Fed has a sizable effect on private sector's sentiment in the euro area.

In addition to an increase in sentiment, the economic outlook also appears to be improving, as indicated by the ifo index, which captures expectations about economic activity six months in the future. The ifo index jumps on impact by about 0.05 percent and reaches a maximum response of 0.1 percent five months after the impact of the shocks. Taken together, the responses of the ifo index and private sector sentiment suggest that an expected Fed tightening has expansionary effects in the euro area. This is consistent with the notion that a news shock reveals new information about the current and future business cycle. In the case of a positive news shock, the Fed reveals information about its assessment of a continuing boom in the U.S. economy, which spills over to the euro area. We will discuss the interpretation in detail below.

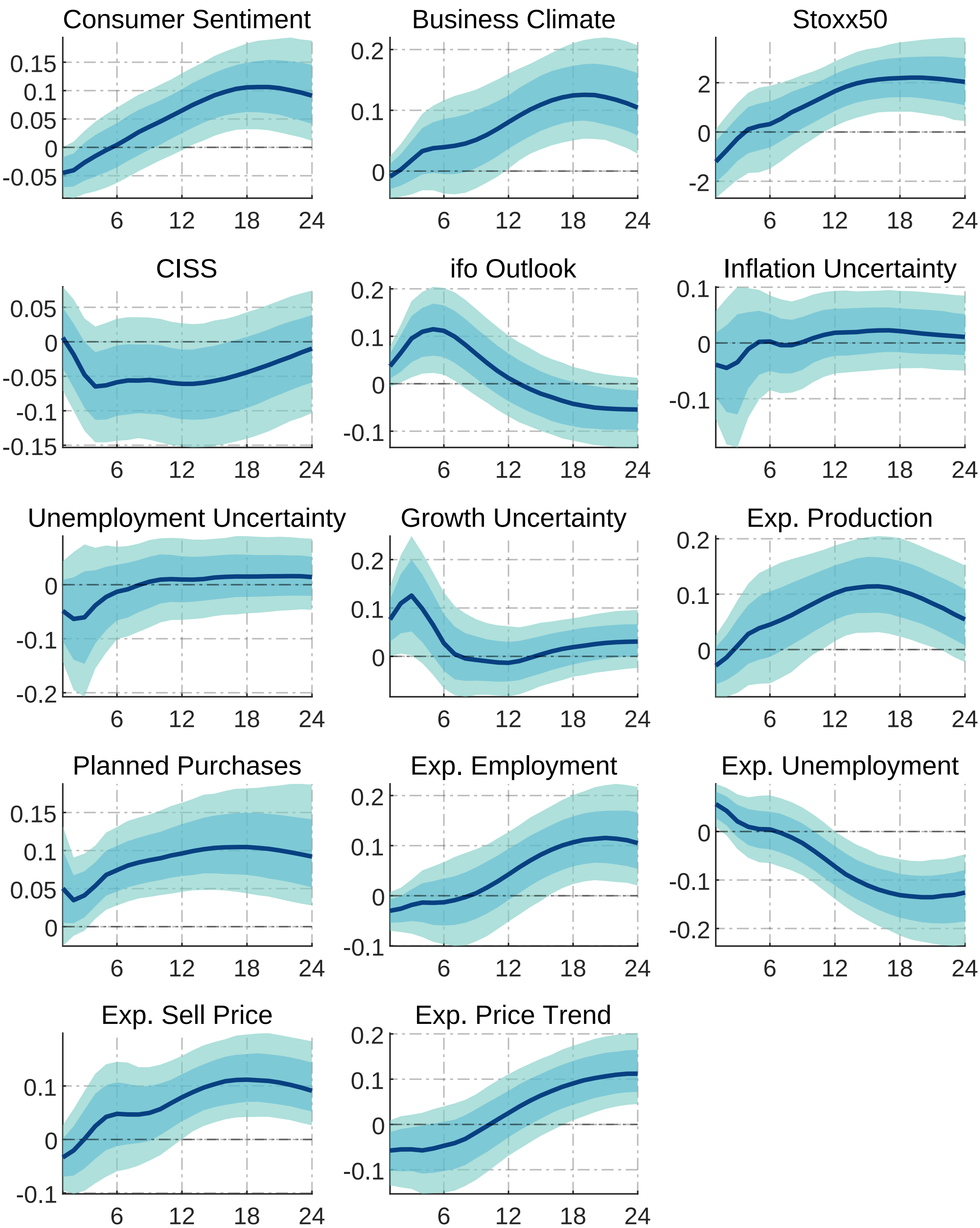
The positive tone is furthermore reflected in the response of the STOXX50, an index which comprises stocks of 50 blue-chips from the euro area. After an initial fall, the STOXX50 increases by up to 2 percent in response to the news shock. This reaction is in line with the findings in Jarociński and Karadi (2020).

The indicator for systemic stress in the euro area (CISS) decreases in a hump-shaped manner by up to 0.05 percent. This is consistent with the argument previously put forth: the economic outlook for the euro area improves and, hence, financial stress in the subsequent months falls.[13]

A prospective Fed tightening, as discussed below, reveals a favorable assessment of the current economic situation. This, in turn, could contribute to a reduction in economic uncertainty. Since the euro area business cycle expands upon the news originating from the Fed, we should also expect a reduction of macroeconomic uncertainty in the euro area. Indeed, uncertainty concerning inflation and unemployment in the euro area tends

[13]See Bachmann et al. (2013) for an analysis of the nexus between uncertainty and economic activity and Jarociński and Karadi (2020) for the accommodative effects of information shocks on financial condition. Bernal et al. (2016) provide an examination of the impact of economic policy uncertainty on risk spillovers within the euro area.

Figure 5: Euro Area Responses to U.S. Monetary Policy News Shock



Notes: Median impulse responses (solid lines) to anticipated U.S monetary tightening. Dark (light) areas depict 68% (90%) probability masses. Responses are in percentage changes.

to decrease, as shown in Figure 5. However, this effect is not significant. Uncertainty concerning future economic growth, on the other hand, increases by roughly 0.1 percent within the first year after the news shock appears. One potential explanation for this phenomenon is that, despite a general consensus regarding the direction of the future business cycle in the euro area, there is no consensus regarding the extent of economic growth. This lack of consensus translates into increased uncertainty.

Manufacturing firms in the euro area report increasing production expectations for the months ahead following the U.S. news shock. Firms report an increase in expected production by 0.1 percent. On the demand side, consumers report their intention to increase major purchases over the next 12 months by up to 0.1 percent. Both responses are statistically and economically significant.

Furthermore, the optimistic tone is mirrored by a positive response concerning the labor market. Producers report an anticipated increase in employment by 0.1 percent, whereas consumers forecast a decrease in unemployment of 0.15 percent.

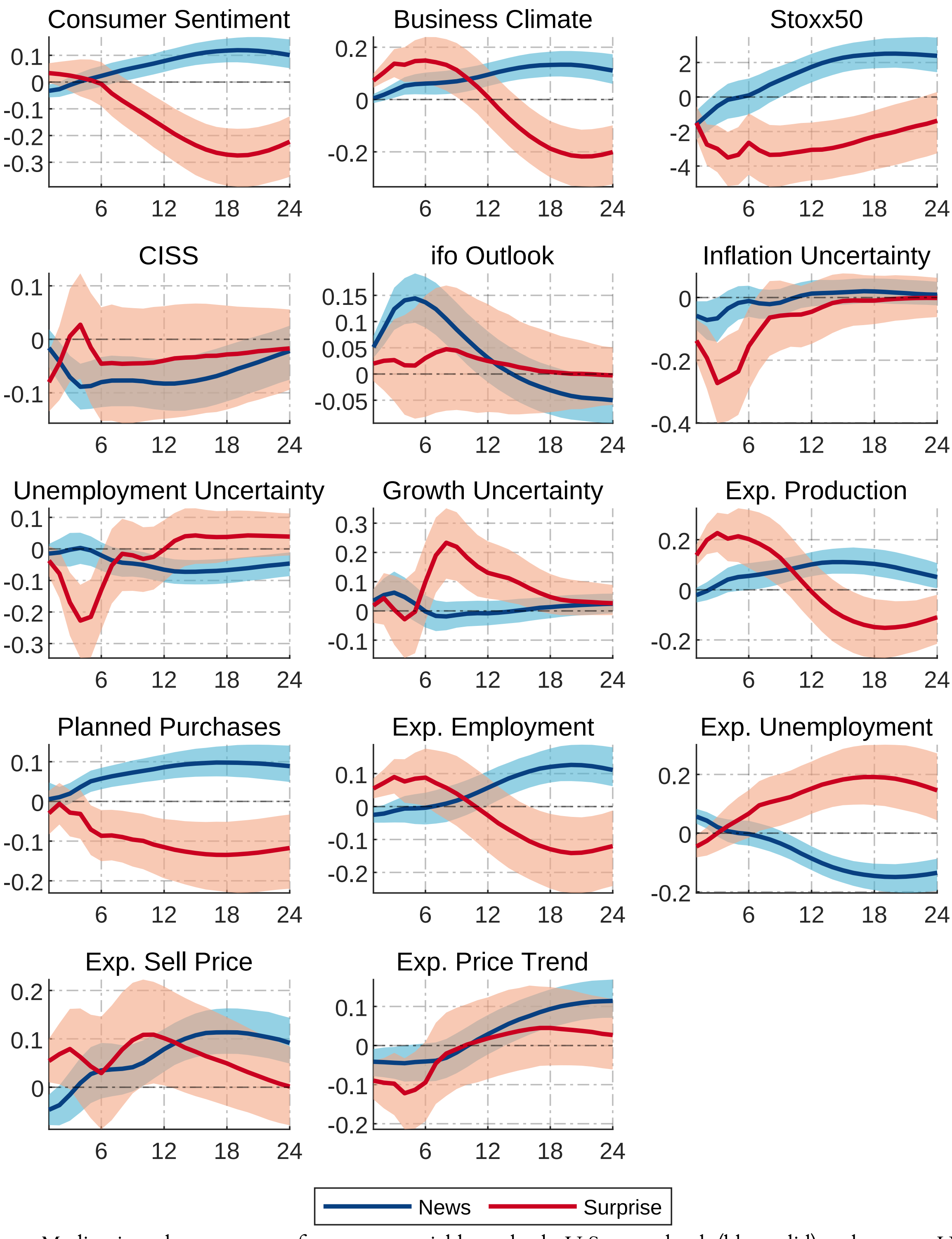
Figure 5 furthermore shows the responses of expected selling prices for the months ahead as stated by manufacturers and expected price trends over the next 12 months as stated by households. Both groups anticipate overall increasing prices within a 24 month horizon. The peak median responses are akin around 0.1 percent. Again, this is consistent with the good news emanating from the U.S., which have a favorable effect on the euro area economy. The additional demand causes price expectations to increase. Jarociński and Karadi (2020) show for the U.S. and the euro area that shocks that exhibit a concurrent co-movement of interest rates and stock markets lead to a notable increase in prices. Our results indicate that such shocks have considerable spillover effects.

Finally, we want to asses in how far the responses of expectations and sentiment to news shocks differ from their responses to a monetary surprise. Figure 6 plots findings discussed above (blue) and the responses to a U.S. monetary surprise (red) along with their respective posterior 68 percent probability masses.

In the majority of cases, the responses exhibit a notable disparity. We find that monetary surprises, that is, the contemporaneous implementation of a more restrictive monetary policy than expected, leads to a sizeable deterioration of consumer sentiment and business climate in the euro area. Both indicators decrease by more than 0.2 percent in response to a monetary policy tightening. Likewise, returns of the STOXX50 decrease immediately by two percent. The reason is that (i) real interest rates and risk premia increase and (ii) expected payoffs decline with the deteriorating outlook. Systematic stress is barely affected.

While inflation and unemployment uncertainty decrease, growth uncertainty increases. One reason could be that as central banks call out their interest rate decisions, they enable market participants to adjust their assessment concerning the state of the business cycle. Such information can decreases uncertainty. By contrast, an interest hike higher than expected could outface market participant's expectations concerning future business cycle movements.

Figure 6: News Vs. Surprise in the Euro Area



Notes: Median impulse responses of euro area variables to both, U.S.news shock (blue solid) and current U.S. monetary policy shock (red solid) along with their respective 68% posterior probability bands. Responses are in percentage changes.

The response of expected production within the next 12 months is puzzling. After a counter-intuitive increase, expected production eventually decreases, as higher interest rates slow down the economy, increase unemployment and thus decrease demand. As a consequence, firms respond with lower production. The decrease in demand becomes evident given the decrease in planned purchases by households. The decrease in supply and demand, and hence economic slowdown, gets further evident given the responses concerning expected employment and unemployment: firms report that they are expecting to employ less, while households report to be more likely unemployed within the next 12 months.

The responses of expected prices complete the overall picture. Within the first six months after the shock hits the economy, firms report decreasing expected selling prices.

It is worth noting that our findings concerning the role of news shocks and monetary surprises on (expectations about) inflation and economic activity are very similar to Jarociński and Karadi (2020) threefold. Firstly, our current monetary shock and their monetary surprise lead to similar responses. Secondly, the effect of our news shock is comparable to their information shock and thus emphasizes the vital role of central bank communication furthermore. Finally, our results indicate an asymmetric response to monetary surprises and news shocks. We find that expectations tend to respond stronger to an actual monetary tightening than to the accommodating information of news as such.

However, our findings stand out as we find that U.S. monetary news play a remarkable role in the expectation formation in the euro area.

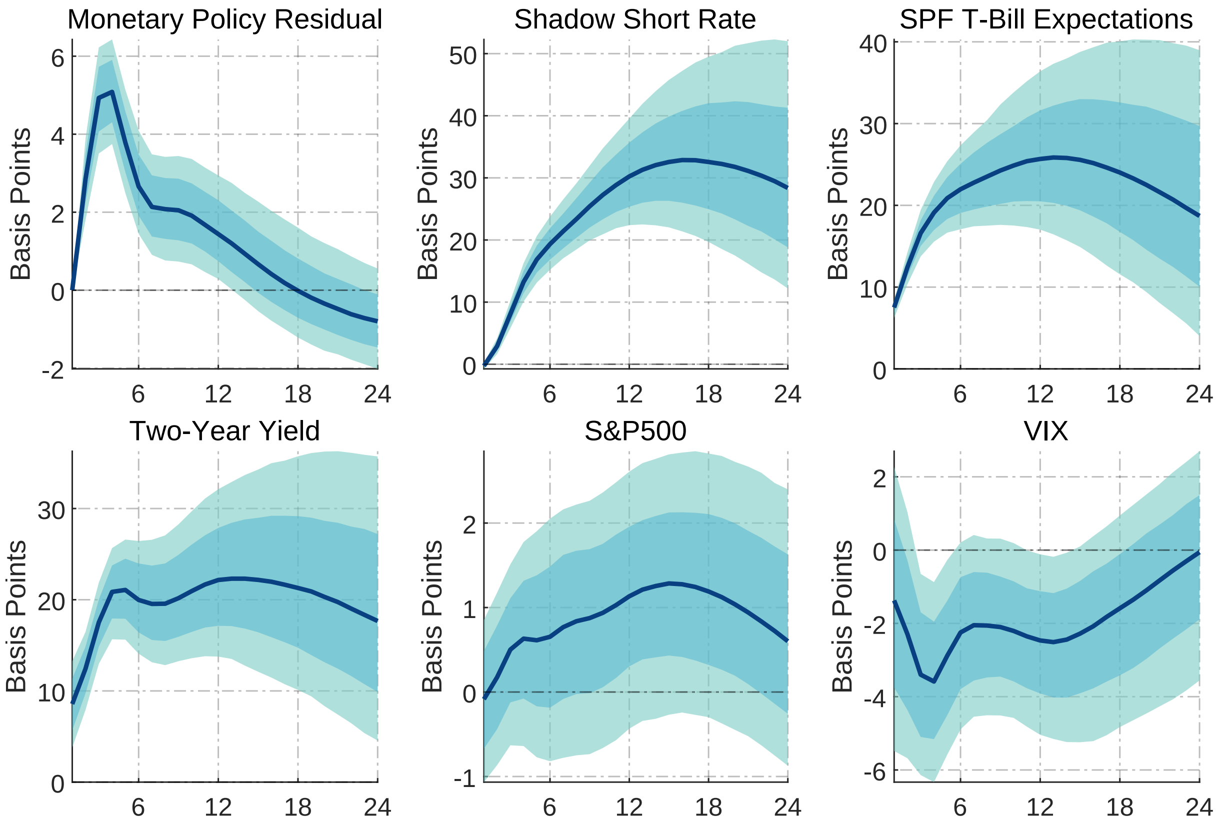
4 Black Clouds and Silver Linings

So far, our results suggest that a monetary news shock, which raises expected interest rates in the U.S., has expansionary effects in the euro area. A contemporaneous Fed tightening, in contrast, has contractionary effects on expectations in the euro area and leads to a fall in uncertainty. These opposing responses between an expected and current policy tightening are consistent with the notion that news shocks convey favorable information about the business cycle, which spill over to the euro area.

In this section, we provide evidence for this interpretation of our results. For that purpose, we jump back to the model for the U.S. economy and study the effects of news shocks on equity prices and volatility. A negative co-movement of anticipated interest rate hikes and stock returns would indicate that market participants expect the present value of future payoffs to decline because (i) real interest rates and risk premia increase and (ii) the expected payoffs decline with the deteriorating outlook caused by the indicated policy tightening. However, news concerning current and future monetary policy are to some extend based on information that are not open to the public. Thus, a concurrent co-movement between expected interest rate tightenings and stock returns reveals that market participants construe the announced policy action as a measure to counteract the impact of current and future demand conditions on the economy.

Figure 7 shows that our identified news shocks lead to an appreciation of equity prices as reflected by the S&P 500 index.[14] The effect is highly significant at the 68 percent level. That is, expected future corporate earnings increase upon receiving the news about the intentions of the Fed. Hence, the news shock can also be seen as an information shock in the sense of Jarociński and Karadi (2020) or a Delphic shock as in Lakdawala and Schaffer (2019) or Jarociński (2024).

Figure 7: Monetary News Shocks and the U.S. Stock Market



Notes: Posterior median impulse responses to monetary news shocks (solid line). Dark (light) areas denote 68% (90%) probability masses.

Figure 7 further reveals that monetary news entering the market not only increase stock returns, but also decrease volatility. The VIX index of implied volatility falls by almost 2 basis points on impact and reaches its through at nearly 4 basis points five months after the news shock hits the economy.As new information concerning future monetary policy enters the market, whether through FOMC statements or speeches, uncertainty decreases notably. Since elevated levels of uncertainty are typically seen as depressing economic activity, see Bachmann et al. (2013), the fall in the VIX index is again consistent with the favorable information content of the news shock and the responses of sentiment and expectations in

[14] We take data of the monthly average of daily S&P500 returns from Yahoo Finance. VIX data stem from FRED St. Louis database.

the euro area.

Another way to infer the information content of news shocks is to take a closer look at changes in forecasters expectations concerning future macroeconomic outcomes. If the inherent news carry a positive tone, forecasters should revise their outlook concerning i.a. expected prices and output upward. For this task, we compute the revision of CPI and real GDP expectations as the difference in the forecaster's assertion of the respective variables' value four quarters ahead and the respective statement in the previous forecast vintage.[15] Formally, we compute

$$rev_t = E_t x_{t+4} - E_{t-1} x_{t+4} \ , \tag{4.1}$$

where x_{t+4} is either CPI or real GDP.

Figure 8 reveals that there is a movement in the same direction between interest rate expectations and projections of real GDP as well as prices in the presence of news shocks. In this sense, our results confirm the findings of Campbell et al. (2017), whereupon Delphic forward guidance reveals information about macroeconomic fundamentals, and are similar to the effects that the *information shock* by Jarociński and Karadi (2020) to real GDP and inflation generates.

Moreover, the positive change in expected real GDP is consistent with the upward revision of prices. Note that this does not imply that forecasters do not believe that a future interest rate hike is not effective in fighting inflation. Such revisions only state that forecasters initially underestimated the true state of the business cycle and believe that the Fed is capable to assess the state of the economy more correctly and thus adjust their expectations upward.

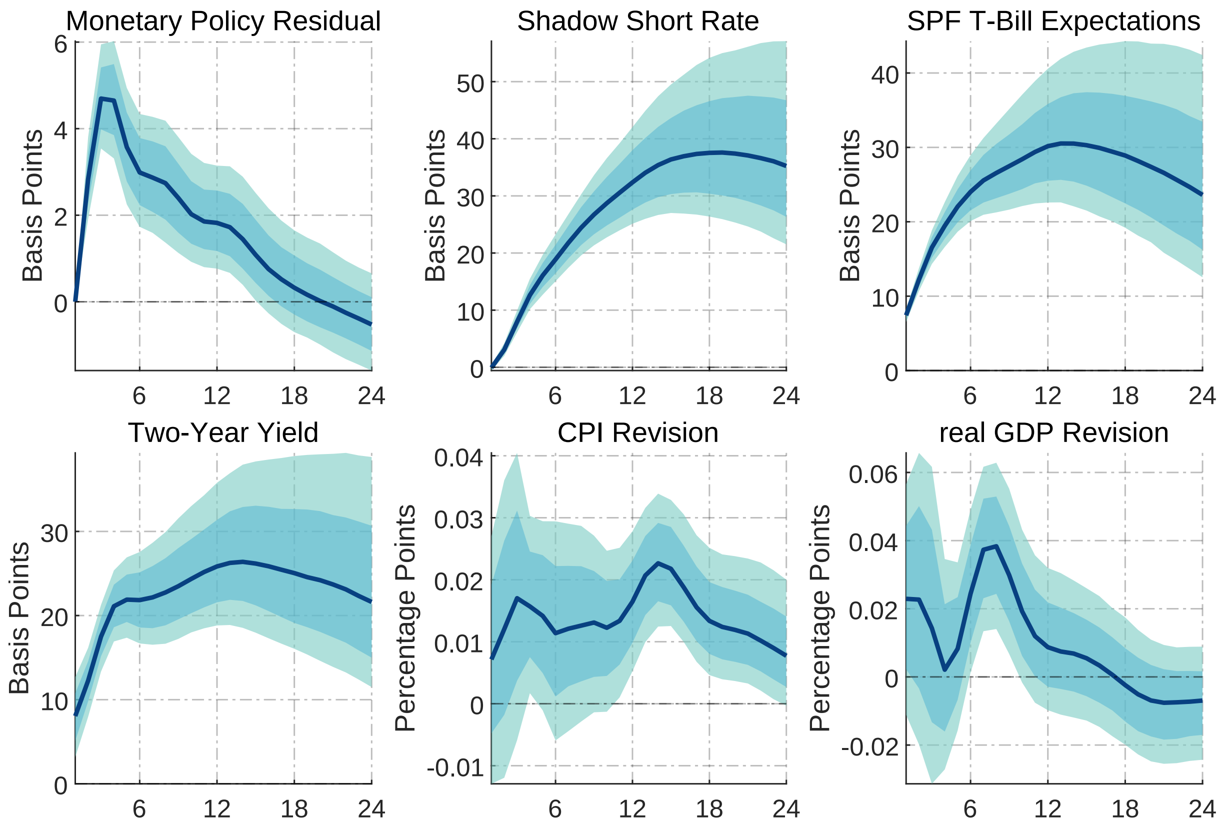
5 Robustness

Our analysis crucially depends on the monetary policy residual. In our baseline setup, we use the Wu and Xia (2016) shadow rate as a proxy for the monetary stance. The interest rate utilized itself is a point estimate, as shadow short rates are not observable and are therefore estimated from term structure models. Consequently, some degree of uncertainty surrounds them. Moreover, their path is heavily dependent on the model assumptions, as demonstrated by Deutsche Bundesbank (2017) and Krippner (2020).

In what follows, we therefore estimate alternative monetary policy residuals entirely based on the (observed) federal funds rate. In doing so, we use policy rules closely related to

[15] Data on CPI and real GDP expectations are taken from the survey of professional forecasters (SPF). Data is available only on a quarterly frequency. To get monthly data, we convert them using the technique of *quadratic-match average*.

Figure 8: Monetary News Shocks and SPF Expectations



Notes: Posterior median impulse responses to monetary news shocks (solid line). Dark (light) areas denote 68% (90%) probability masses.

Coibion and Gorodnichenko (2012). Among their variations, the authors incorporate i.a. Tealbook forecasts and a higher lag order of the interest rate.

A. *Incorporating Tealbook CPI Forecasts*

The Tealbook is prepared by the Research staff at the Board of Governors and contains projections for various variables about how the economy will fare in the future; including inflation expectations. With this information at hand, we estimate

$$i_t = \mu + \rho_1 i_{t-1} + \rho_2 i_{t-2} + \phi_\pi E_t \pi^{tb,cpi}_{t+2,t+1} + \phi_{dy} E_t dy^{tb}_t + \epsilon^{mpr}_t \ , \tag{5.1}$$

for the period 1999m01 to 2015m11. Here, i_t is the effective federal funds rate with its lagged values i_{t-1} and i_{t-2}. $E_t \pi^{tb,cpi}_{t+2,t+1}$ is the average Tealbook forecast of CPI inflation over $t+1$ and $t+2$, and $E_t dy^{tb}_t$ is the Tealbook now-cast for the contemporaneous growth rate of real output.[16]

[16]The now-cast for the contemporaneous growth rate refers to the current quarter of data collection. As before, we transform the data to a monthly frequency. In contrast to Coibion and Gorodnichenko (2012), we do not incorporate the now-cast of the contemporaneous output gap due to data availability. As the Tealbook is produced *before* each meeting of the Federal Open Market Committee, the data contained therein are thus

It is worth mentioning that we do not have to transform the data from a quarterly to monthly frequency because FOMC meetings usually take place eight times a year which provides us 8/12 observations a year on a monthly basis. We calculate the missing four observations as the average between the prior and subsequent forecast.[17]

Figure 9 reveals that our results are robust to this alternative specification. All median impulse responses from the baseline model (dashed lines) are located within the posterior credibility bands. The most striking difference is the response of the monetary policy residual. We will also see this noticeable feature in the subsequent robustness exercises. The observation that the effect of news shocks is more pronounced in the baseline model can be attributed to the use of the shadow interest rate. This is estimated or calibrated using term structure models, which makes it particularly responsive to anticipated future interest rates. Furthermore, the response of the alternative MPR is less persistent which is likely due to the additional interest rate lag in the policy rule.

B. *Incorporating Core Personal Consumption Expenditure*

One could argue that core personal consumption expenditures (PCE) inflation is the more appropriate inflation indicator to describe policy decisions by the Fed.[18] To evade potential misspecification, we therefore estimate (5.1) using average Tealbook forecasts for core PCE inflation over $t+1$ and $t+2$ instead of CPI inflation. That is, we estimate

$$i_t = \mu + \rho_1 i_{t-1} + \rho_2 i_{t-2} + \phi_\pi E_t \pi_{t+2,t+1}^{tb,pce} + \phi_{dy} E_t dy_t^{tb} + \epsilon_t^{mpr} \,, \tag{5.2}$$

where $E_t \pi_{t+2,t+1}^{tb,pce}$ is the average Tealbook forecast of PCE core inflation over $t+1$ and $t+2$. In this exercise, our sample is slightly shorter, as Tealbook core PCE forecasts are available only from January 2000.

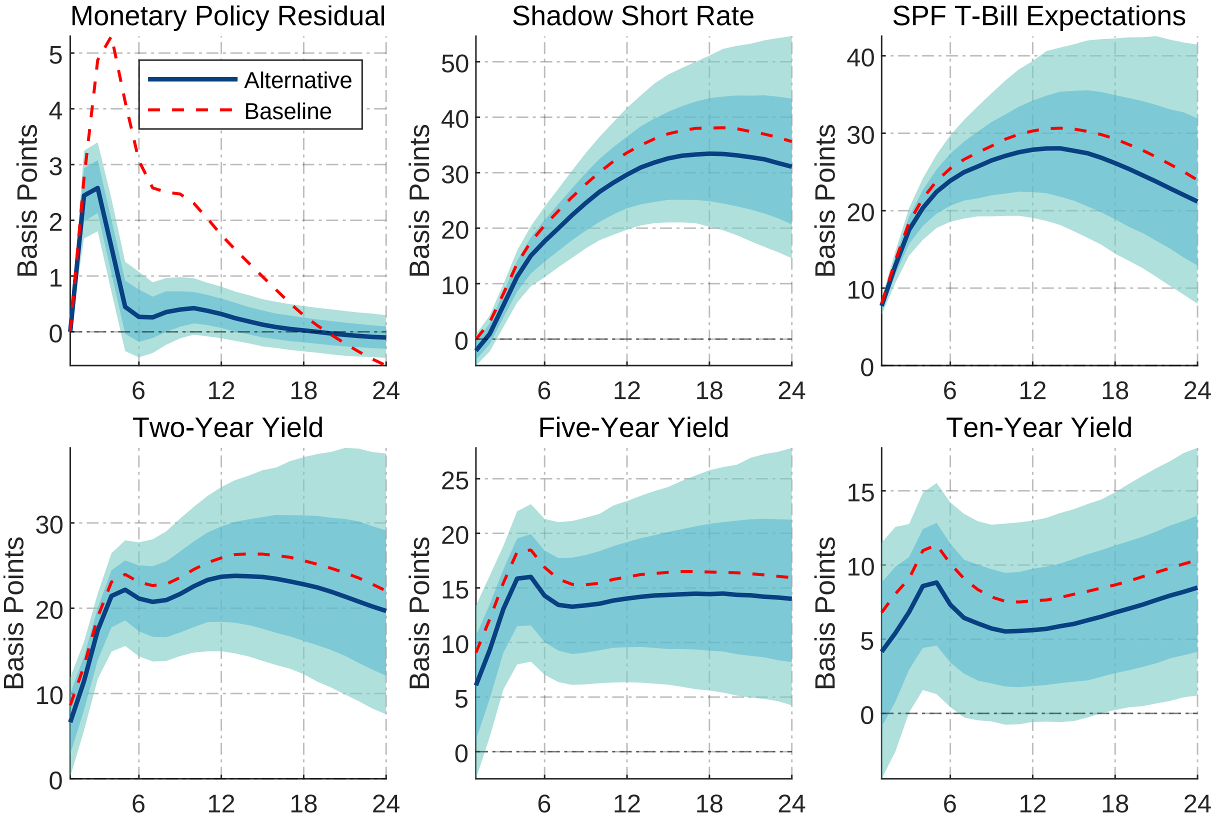
The results are shown in Figure 10. Yet again, our results are robust to this alternative. It is striking that all median responses (solid lines) in this setup are consistently below the respective median response of the baseline model (dashed lines). Nevertheless, they lie well within the probability masses of the alternative specification.

exogenous to interest rates and can consequently be estimated using OLS without posing an endogeneity problem.

[17] For example, the January 1999 ($t = 99,1$) now-cast for dy is $E_{99,1}dy_{99,1} = 2.7$. The respective now-cast for March 1999 ($t = 99,3$) is $E_{99,3}dy_{99,3} = 3.4$. Thus, we calculate the missing now-cast for February 1999 ($t = 99,2$) as $E_{99,2}dy_{99,2} = (E_{99,1}dy_{99,1} + E_{99,3}dy_{99,3})/2$. We do the same for core PCE inflation forecasts.

[18] For example, during the FOMC meeting in December 1999, Chairman Greenspan provided a clear statement as to why to prefer the PCE price index to the CPI.

Figure 9: Interest Rate Rule with Tealbook CPI Forecasts



Notes: Posterior median impulse responses (solid lines) to monetary news shocks as in equation (5.1). Dark (light) areas denote 68% (90%) probability masses. Dashed lines depict median impulse responses from the baseline model.

C. *Considering Market Expectations*

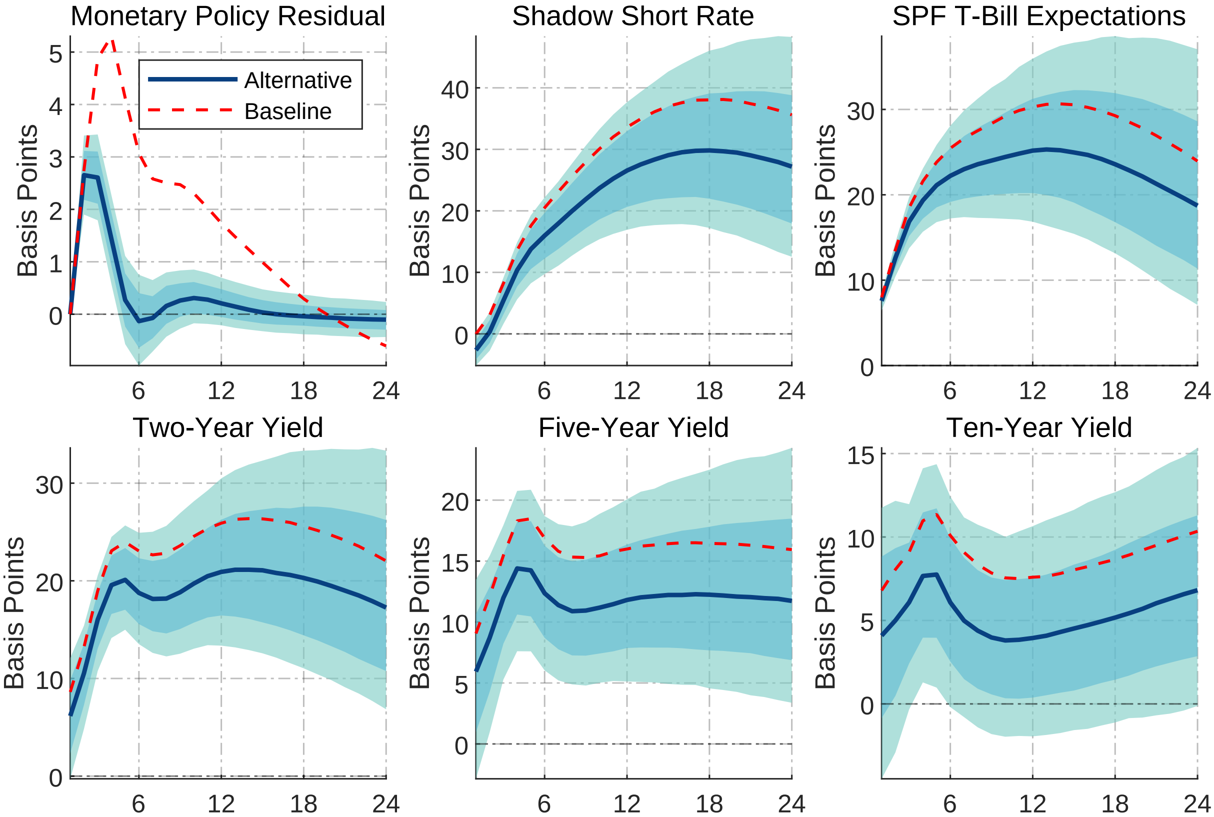
Especially in the course of the 2007-08 financial crises and the subsequent recession with interest rates at the zero lower bound, central bank communication and expectation formation became increasingly important. At the same time, the Fed faced a trade-off between flexibility in and commitment to its designated monetary policy. To avoid financial stress and uncertainty, the Fed might therefore take market expectations into account. To control for that possibility, we estimate

$$i_t = \mu + \rho_1 i_{t-1} + \rho_2 i_{t-2} + \phi_\pi E_t \pi^{tb,cpi}_{t+2,t+1} + \phi_{dy} E_t dy^{tb}_t + \phi^d_\pi \left(E_t \pi^{tb,cpi}_{t+2,t+1} - E_t \pi^{spf,cpi}_{t+2,t+1} \right) + \phi^d_{dy} \left(E_t dy^{tb}_t - E_t dy^{spf}_t \right) + \epsilon^{mpr}_t \,. \quad (5.3)$$

The term $E_t \pi^{tb,cpi}_{t+2,t+1} - E_t \pi^{spf,cpi}_{t+2,t+1}$ captures discord in expectations concerning CPI inflation between the Fed and the market. The divergence in expectations concerning real output growth is captured by $E_t dy^{tb}_t - E_t dy^{spf}_t$. The results are depicted in Figure 11. Once more, our baseline results are robust to this alternative specification.

Lastly, we want to assure that the responses of the euro area are robust to the alternative

Figure 10: Interest Rate Rule with core PCE Forecasts



Notes: Posterior median impulse responses (solid lines) to monetary news shocks as in equation (5.2). Dark (light) areas denote 68% (90%) probability masses. Dashed lines depict median impulse responses from the baseline model.

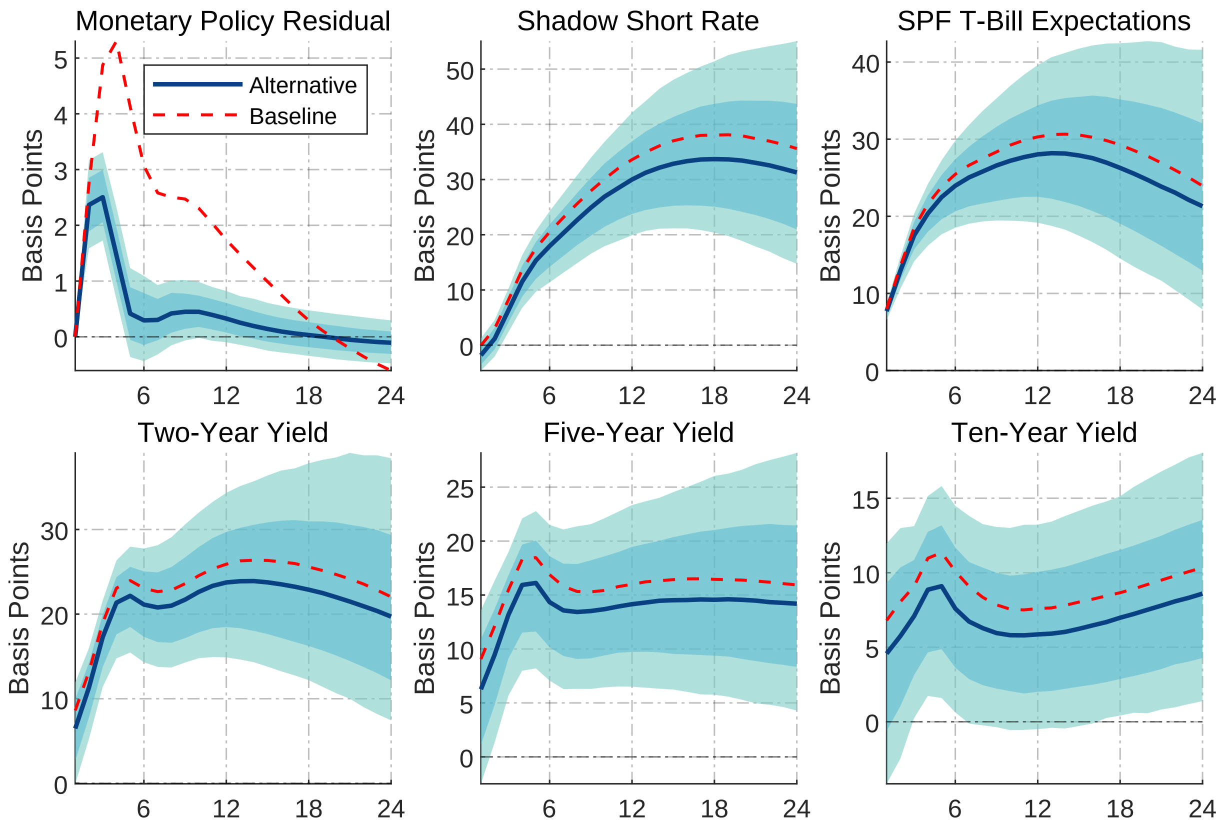
specification. We therefore take the MPR as in equation (5.3) and look at the impulse responses of our euro area variables, which are depicted in Figure 12. The alternative specification corroborates our previous findings that anticipated future interest rate hikes by the Federal Reserve induce a positive sentiment within the euro area.

6 Conclusion

This paper quantifies spillovers of U.S. monetary news shocks to the euro area. News shocks originate from anticipated Fed policy actions such as credible forward guidance. We identify news shocks based on a VAR approach and estimate the responses of euro area variables to an anticipated Fed tightening.

Our main results are twofold. First, we find significant spillovers. Variables such as asset prices, expectations, and sentiment indicators in the euro area respond to an anticipated Fed policy. Hence, our analysis underlines the relevance of policy spillovers among advanced economies. Our second finding pertains to the sign of these spillover effects. An expected Fed tightening is shown to be expansionary for the euro area, rather than

Figure 11: Interest Rate Rule with Expectation Discord



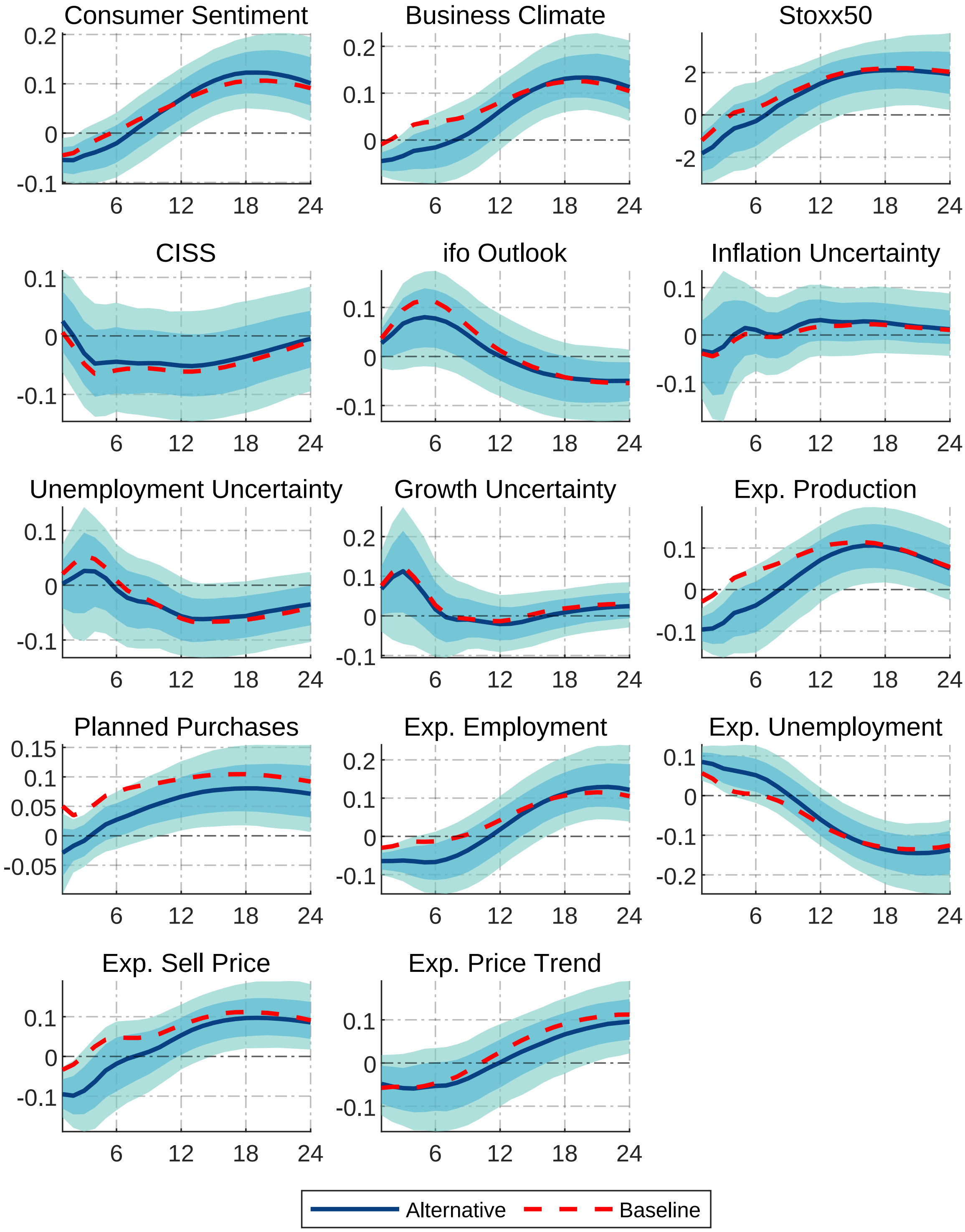
Notes: Posterior median impulse responses (solid lines) to monetary news shocks as in equation (5.3). Dark (light) areas denote 68% (90%) probability masses. Dashed lines depict median impulse responses from the baseline model.

contractionary. Confidence indicators improve and uncertainty tends to decrease after the anticipated tightening. Likewise, stock prices appreciate in the euro area.

At first, this pattern is difficult to reconcile with economic intuition. However, these findings are in line with the notion that an announcement issued today about a future tightening reveals private information the Fed might have about the state of the U.S. economy. This favorable news trigger an upward revision of sentiment indicators in the euro area. We underline this interpretation by showing that the news shocks, although raising expected future interest rates, also raise equity prices in the U.S. and lower equity market volatility. Hence, it is the new information about a stronger than expected economic expansion that spills over to the euro area. This logic also implies that an anticipated policy *easing* in the U.S., such as the one implemented at the zero lower bound, had *contractionary* effects on the euro area as the policy step reveals worse than expected fundamentals.

Our results shed new light on the discussion of policy spillovers. Traditionally, the literature studies spillovers with an opposite sign: a policy tightening in the U.S. reduces euro area exports, which has contractionary effects on the economy. Tighter monetary

Figure 12: Euro Area Responses to Alternative News Shock



Notes: Posterior median impulse responses (solid lines) to monetary news shocks as in equation (5.3). Dark (light) areas denote 68% (90%) probability masses. Dashed lines depict median impulse responses from the baseline model.

conditions in the U.S., the argument goes, also raise global interest rates and lead to capital outflows back into the U.S. dollar, which is contractionary abroad. Most policy prescriptions to deal with this kind of spillover effects are based on this notion of policy spillovers. For example, small open economies often ease monetary conditions as a result of the Fed tightening in order to reduce the fallout from the contraction in the U.S. economy. Hence, spillovers in this sense lead to a divergence of policy stances between the U.S. and other economies.

The notion of spillovers highlighted in this paper, however, suggests that an *anticipated* U.S. tightening can be expansionary abroad, such that the monetary policy response in the euro area is also a policy tightening. Thus, the spillovers shown here lead to a convergence of policy stances. This, in turn, reduces the scope for international policy coordination.

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Essay III:

Do Credit Supply Shocks Have Asymmetric Effects?

This paper has been published as:

Finck, David, and Paul Rudel, “Do credit supply shocks have asymmetric effects?," *Empirical Economics*, 2023, *64*(4), 1559–1597.

Acknowledgement

We thank an anonymous referee and Peter Tillmann for very helpful comments and suggestions. Vanessa Thelen, Katrin Luise Gärtner-Rudel and Karsten Kucharczyk provided insightful comments. We also thank Egon Zakrajšek and Luca Gambetti for providing their data. We thank the Fritz Thyssen Stiftung for financial support (grant no. 10.16.2.004WW).

This essay is a revised edition of the published version.

Do Credit Supply Shocks Have Asymmetric Effects?

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Abstract

They do. Partly. We identify credit supply shocks via sign restrictions in a Bayesian VAR and separate them into positive and negative. Using local projections, we find that positive credit supply shocks leave notably different prints in private debt, mortgage debt, and debt:GDP, as opposed to negative credit supply shocks. This pattern is caused by the response of household mortgage debt. Furthermore, we find evidence that positive credit supply shocks are the driving force behind boom-bust cycles. Yet, developments behind the boom-bust cycle cannot explain the strong and persistent response in debt; but house prices tend to. However, if we abstract from potential asymmetries, we get rather mild results, which underestimate the true effects of credit supply shocks.

The views expressed in this paper are those of the authors and do not necessarily represent those of the Deutsche Bundesbank or the Eurosystem.

Keywords: Credit supply shocks, household debt, asymmetry, local projections

JEL classification: C11,E21, E22, E32

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1 Introduction

The financial crisis and the subsequent Great Recession made sternly clear that credit markets can take a leading role for economic activity. As such, there is a renewed interest in the nexus between credit supply shocks and economic activity.

One common finding in the literature is that an unexpected contraction in credit conditions has adverse effects. For example, Gambetti and Musso (2017) estimate a time-varying vector autoregressive (VAR) model with drifting parameters and stochastic volatility for the U.S., the UK, and the euro area for 1980 to 2011. They find significant effects of credit supply shocks which increase over time. Their results also imply that the effects of credit market distortions are stronger during recessions. In another seminal paper, Gilchrist and Zakrajšek (2012) show that lower credit spreads improve the costs of debt finance, which increases spending and production and, in turn, increases asset prices and thus stimulates economic activity through the financial accelerator mechanism (for further recent contributions, see Jordà et al., 2013; Mumtaz et al., 2018; Mian et al., 2017; and Gertler and Gilchrist, 2018, among others). However, these analyses have in common that they examine symmetric responses to distortions in credit supply, i.e. the impact of a positive shock is identical to the impact of a negative shock in absolute terms.

The contribution of this paper is to examine asymmetries (and potentially non-linearities) in the propagation of credit supply shocks. The objective here is to provide new evidence on the transmission of credit supply shocks by relying on a simple, yet flexible framework. We follow Tenreyro and Thwaites (2016), who investigate asymmetric effects of monetary policy shocks on key macroeconomic variables via local projections. The advantages of local projections over vector autoregression (VAR) models are well documented (Jordà, 2005). Above all, it is not necessary to impose dynamic restrictions as is done in VAR models. Moreover, local projections allow us to parsimoniously test for asymmetric effects. We do so by splitting an identified credit supply shock à la Gambetti and Musso (2017) into its positive and negative parts which are then planted into a set of seemingly unrelated equations. This allows us to directly evaluate the effect of a credit supply shock for different adjacent horizons.[1] Our set of variables includes key variables for the U.S. on the overall debt cycle of households, but also various variables describing real activity as well as the demand and supply side of the economy ranging from the early 1970s until late 2018.

Overall, our results clearly point to asymmetric effects concerning the different debt

[1] Such a credit supply shock can be associated with various events, such as unexpected changes in bank capital availability for loans due to changes in regulatory capital ratio requirements or unanticipated changes in the degree of competition in the banking sector. More precisely, an exogenous drop in credit supply is assumed to lead to an increase in the lending rate, which ultimately leads to a drop in economic activity and deflationary pressure.

measures considered in this paper. More specifically, we find that the response of overall household indebtedness to an unexpected increase in credit supply is substantially stronger in absolute terms than in the opposite case of an unexpected decrease. That is, we find that an expansionary shock of one standard deviation leads to a significant increase of household indebtedness by about 1.5 percent after roughly three years. However, a negative shock of the same size leads to a decrease of household indebtedness which is significant only for the first year and also significantly different from the response following a credit supply easing. Importantly, this result is shown to clearly be driven by the responsiveness of households' mortgages. Also, we find key macro headline variables (prices, production, short-term interest rate) as well as some key variables determining the demand and supply side of the economy to respond asymmetrically. Overall, following an expansionary shock of credit supply, our results clearly point to the well established boom-bust cycle. In the opposite case we do not observe such a pattern.

While our framework allows us to flexibly uncover asymmetric responses following shocks, tracking the exact mechanisms that drive our results is beyond the scope of this model and, thus, of this paper.

Nevertheless, a large body of literature points at amplifications and asymmetries in the propagation of sudden (financial) distortions as, for example, (i) occasionally binding borrowing constraints, (ii) market imperfections (in terms of asymmetric information), or (iii) the role of asymmetric central bank behavior.

Regarding occasionally binding constraints, suppose an unexpected easing of credit conditions. In this case, both, firms and households that previously were excluded from the credit market are now able to borrow. The resulting increase in demand will in turn stimulate the economy. Following an unexpected deterioration in credit conditions, in contrast, the credit constraint could eventually become binding for both, households and firms. In this case, firms and households alike could either (i) no longer being able to rely on financial intermediaries to borrow externally or (ii) not being able to borrow the amount demanded.[2]

Another important mechanism relies on the role of asymmetric information. In general, the external finance premium is the premium that banks charge due to asymmetric information regarding a project to be financed. As such, the balance sheet or net worth is of particular importance for the financing decision. Fluctuations in the net worth could thus increase the effect of shocks hitting the economy. Consider again a negative credit

[2] In this respect, as pointed out by Sedláček and Sterk (2017) and emphasized by Barnichon et al. (2022), episodes of high financial stress can prevent high-potential firms to emerge. More precisely, Sedláček and Sterk (2017) show that cohorts of large firms tend to be born during periods of booming consumer demand, i.e., when it is easy for firms to acquire new customers. Phases of booming consumer demand, in turn, may depend on credit conditions.

supply shock which reduces the availability of credit in the economy. In this case, the role of the balance sheet with respect to the credit conditions of firms will become more important than before. A positive credit supply shock, in contrast, increases the availability of credit. A firm with a given balance sheet may therefore find it easier to borrow money, but disproportionately more difficult to borrow money in the case of a negative shock.

Finally, the central bank may play an important role in the transmission of credit supply shocks. Central banks monitor the lending behavior to firms and households very closely. Eventually, the central bank has asymmetric preferences when it comes to stabilizing shocks stemming from the credit market. For example, it is possible that the central bank reacts stronger during boom phases than during bust phases. Also, the central bank eventually reacts different when overall credit conditions are loose already. Finally, the reaction of the central bank may also depend on the zero lower bound. For example, if the key interest rate is close to zero, the central bank has less scope to counter inflationary pressures and may have to resort to unconventional monetary policy measures. These effects on the systematic component of monetary policy can all contribute to making the transmission of credit supply shocks non-linear or asymmetric.[3]

Overall, our paper fits well into a relatively new strand of literature which investigates non-linearities and asymmetries in the transmission of credit supply shocks. The first paper to mention is of Colombo and Paccagnini (2020), who estimate a smooth transition VAR (STVAR) and investigate the role played by credit supply shocks across the business cycle. They find that contractionary credit supply shocks trigger asymmetric and negative effects. However, the paper that fits closest is Barnichon et al. (2022), who estimate a vector moving-average (VMA) with functional approximations of impulse responses. They find that the effects of financial shocks on the economy depend on their sign and size. That is, their results imply that the mild and short-lived effects of financial market disruptions typically found in SVAR models can be explained by asymmetric effects. However, we do not solely focus on key macro variables, but also investigate whether asymmetric effects can be found in credit volumes as well as different measures of both, aggregate supply and aggregate demand. Finally, investigating asymmetries helps not only to get a better understanding of the consequences of credit supply shocks but rather is crucial for policymaking. This is because the events leading to and following the latest financial crisis raised the question whether monetary policy should take credit developments into account when making policy decisions. For this reason, it is not surprising that many economists propose that the central bank should eventually lean against the credit cycle. If this is the case, it is crucial for policy design to know whether

[3] As will be shown in the robustness section, we find that the central bank's systematic response to credit volumes and lending conditions has no important role in the transmission of credit supply shocks and is thus not a driving force for the asymmetric effects we find in our paper.

credit shocks propagate symmetric or asymmetric before adjusting the short-term nominal interest rate.

The remainder of this paper is organized as follows. Section 2 explains the methodology. Section 3 contains our main results. In Section 4, we conduct a battery of robustness checks. Section 5 concludes.

2 Methodology

Before we show our results, we introduce our methodological approach in this section. First, we describe the derivation of our credit supply shock. We then explain our econometric methodology to uncover asymmetries in the transmission of these shocks. Finally, we set out our approach to statistical inference.

A. *Deriving the Credit Supply Shock*

In order to derive a credit supply shock, we use an auxiliary structural VAR model identified by means of sign restrictions for the U.S. Let $\mathbf{y}_t$ be an $n \times 1$ vector including real GDP, consumer prices, loan volumes, a composite lending rate, and a reference short-term (shadow) interest rate. The SVAR reads

$$\mathbf{y}_t'\mathbf{A}_0 = \sum_{j=1}^{J} \mathbf{y}_{t-j}'\mathbf{A}_j + \mathbf{c} + \varepsilon_t' , \tag{2.1}$$

where ε_t is an $n \times 1$ vector of structural shocks, $\mathbf{A}_j$ is an $n \times n$ matrix of structural parameters for $0 < j \leq J$ lags with $\mathbf{A}_0$ invertible and $\mathbf{c}$ is a $1 \times n$ vector of parameters.

The SVAR model in (2.1) can be rewritten as

$$\mathbf{y}_t'\mathbf{A}_0 = \mathbf{x}_t'\mathbf{A}_+ + \varepsilon_t' , \tag{2.2}$$

where $\mathbf{A}_+' = [\mathbf{A}_1', ..., \mathbf{A}_J', \mathbf{c}']$ and $\mathbf{x}_t' = [\mathbf{y}_{t-1}', ..., \mathbf{y}_{t-J}', 1]$ for $1 \leqslant t \leqslant T$. Hence, we estimate the reduced-form VAR

$$\mathbf{y}_t = \mathbf{x}_t'\mathbf{B} + \mathbf{u}_t' , \tag{2.3}$$

where $\mathbf{B} = \mathbf{A}_+\mathbf{A}_0^{-1}$, $\mathbf{u}_t' = \varepsilon_t\mathbf{A}_0^{-1}$, and $\mathbf{E}[\mathbf{u}_t\mathbf{u}_t'] = (\mathbf{A}_0\mathbf{A}_0')^{-1}$.
Since the structural parameters are not identified, we need to impose some restrictions. We therefore rely on the identification strategy of, among others, Gambetti and Musso (2017) who draw inference concerning the response of (log) real GDP, (log) consumer prices, (log) loan volumes, a composite lending rate, and a reference short-term interest rate to four structural shocks: (i) aggregate supply, (ii) aggregate demand, (iii) monetary policy, and (iv)

credit supply.[4] The latter is of main interest for our further analysis. Table 1 summarizes

Table 1: Identification Restrictions

Shock	Real GDP	Prices	Short-term interest	Lending rate	Loan Volume
Aggregate Supply	+	–	No restriction	No restriction	No restriction
Aggregate Demand	+	+	+	+	No restriction
Monetary Policy	+	+	–	No restriction	No restriction
Credit Supply	+	+	+	–	+

Notes: The identifying assumptions are imposed on impact, where '+' means an increase and '–' a decrease in the underlying variable. All shocks are normalized as leading to an increase in real GDP.

the identification restrictions. The identification of an aggregate supply shock, an aggregate demand shock and a monetary policy shock is quite standard, we therefore will not discuss it here.[5]

The identification of the expansionary credit supply shock, on the other hand, deserves further discussion. As pointed out by, inter alia, Christiano et al. (2010) and Gambetti and Musso (2017), a credit supply shock can be associated with various events, such as unexpected changes in bank capital availability for loans due to changes in regulatory capital ratio requirements or unanticipated changes in the degree of competition in the banking sector. The identification we use can be thought of as (i) shocks to the bank funding technology or bank reserve demand, as in Cúrdia and Woodford (2010), as well as (ii) shocks to bank's capital quality and bank's net worth, as in Gertler and Karadi (2011). An expansionary credit supply shock consequently leads to an increase in real GDP and prices. This notion is in line with the identification scheme of all model-specific credit supply shocks in the models of Cúrdia and Woodford (2010) and Gertler and Karadi (2011) as well as some specific credit supply shocks in Gerali et al. (2010) and Christiano et al. (2010).

An exogenous increase in loan supply (credit supply) is also assumed to lead to a contemporaneous drop in the lending rate as well as an increase in the short-term interest rate, which is under the control of the central bank. An exogenous expansion of the supply of loans to the private sector via a decrease in the lending rate has expansionary effects as the lower costs of external funds enable to expand consumption while firms can expand their investments.[6] The central bank counteracts the resulting price pressure by increasing the short-term interest rate.

[4] In order to estimate (2.3), we rely on Bayesian techniques using a Minnesota prior. Inference is based on 20,000 draws, where the first 10,000 draws are discarded, as samples that have been generated in early iteration steps are likely to be not representative for the true posterior distribution. Data is compiled as in Gambetti and Musso (2017) (see supplementary material therein) and extended until 2018Q4.

[5] For a comprehensive description, see Gambetti and Musso (2017).

[6] We take a closer look at this transmission channel in Section 3.

Finally, note that while it is common practice to derive shocks from an auxiliary SVAR model, our hybrid VAR-LP approach is internally inconsistent. This is because in the SVAR model, structural shocks are identified under the assumption that the data generating process is linear and symmetric, as pointed out by Barnichon et al. (2022).[7] Of course, one might consider deriving the structural shock in a state-dependent local projections model as well. However, this approach has two limitations: first, also within an LP approach along the lines of Plagborg-Møller and Wolf (2021), we need to proceed in two steps, where, in the first step, a linear local projections model is fitted to the observed data to extract a credit supply shock. In a second step, this shock is then used in another local projections model to uncover possible asymmetries in the transmission of credit supply shocks. The reason is that within both, an LP framework as well as a VAR framework, it is not possible to separately identify positive and negative credit supply shocks a priori without knowing the shock in advance. The second point is more of a technical nature. Structural identification in a local projection approach works very similarly to a VAR approach, whereby the variance-covariance matrix is derived from the $h = 1$ projection residuals for the identification. The (only) crucial difference, as pointed out by Plagborg-Møller and Wolf (2021), is that within a local projections framework, the reduced-form impulse responses come directly from the direct projections rather than from iterative forecasts as in a VAR model. Importantly, as pointed out by Plagborg-Møller and Wolf (2021), the projection residuals from a local projections approach equal these Wold innovations. As a result, the variance-covariance matrix $\boldsymbol{\Sigma}$ as obtained within a local projections framework contains the same information as obtained from a VAR framework. Hence, if and only if we restrict the responses of the endogenous variables on impact only, as is done in this paper, then we get the same set of structural shocks in the local projections framework as in the VAR framework. Since we are not interested in the impulse responses from the first stage but only in the identified credit supply shock for the second stage, it makes no difference to us whether we identify our shock in a VAR framework or a local projections framework.

Nevertheless, we use an alternative measure of a credit supply shock obtained from a proxy SVAR in the robustness section.

B. *Econometric Setup*

In order to uncover the asymmetric effects of structural shocks, we follow Tenreyro and Thwaites (2016) and rely on local projections, as proposed by Jordà (2005). The local projection method provides a flexible framework and is easy to implement. Moreover, it is

[7] They directly estimate a vector moving-average model to derive financial shocks and rely on functional approximations of impulse responses (FAIR). However, their robustness checks imply that a hybrid VAR-LP approach (as ours) and the internally-consistent approach using FAIR yield very similar results.

well documented that local projections have several advantages over VAR models. Above all, local projections are more robust to possible misspecifications, at least under a finite lag structure. Moreover, they allow us to parsimoniously model asymmetric effects and, in effect, saves degrees of freedom relative to a multivariate approach. That is, even though we lose observations from adjusting for leads and lags, we ultimately save degrees of freedom because our set of control variables on the right-hand side is relatively sparse as we do not need to describe the dynamics of the endogenous variables conditional on the shock.

Local projections base on the idea to directly regress the dependent variable at different horizons $t+h$ for $h = 0, 1, ..., H$, conditional on an information set Ω_t that consists of a set of control variables. In the linear case, the regression equation reads

$$y_{t+h} = \alpha_h + \gamma_h \mathbf{x}_t + \beta_h shock_t + e_{t+h} \ , \tag{2.4}$$

where y_{t+h} is the variable of interest at horizon $t+h$, $\mathbf{x}_t$ is a vector of control variables, and $shock_t$ is the identified structural shock.[8] The coefficient β_h measures the average response of the dependent variable to the shock that hits the economy at time t. Thus, one constructs the impulse responses as a sequence of the β_h's estimated in a series of separate regressions for each horizon.

Note that (2.4) is easily adapted to estimate a model that allows for non-linear effects. More precisely, we want to test whether positive shocks have the same impact as negative shocks. This can be done by regressing

$$y_{t+h} = \alpha_h + \gamma \mathbf{x}_t + \beta_h^+ \max\{shock_t, 0\} + \beta_h^- \min\{shock_t, 0\} + e_{t+h} \ . \tag{2.5}$$

While the information sets in (2.4) and (2.5) do not differ, the coefficients β_h^+ and β_h^- do now allow us to test for sign-dependent impulse responses. In particular, the response of y_{t+h} on a shock in t is now given by

$$\frac{\partial y_{t+h}}{\partial shock_t} = \begin{cases} \beta_h^+, \text{ if } & shock_t \geqslant 0, \\ \beta_h^-, \text{ if } & shock_t < 0. \end{cases} \tag{2.6}$$

It is important to stress that a perfectly symmetric transmission of credit supply shocks would imply that $\beta_h^+ = \beta_h^-$. That is, exogenous expansions and contractions of credit supply would have the same effects in absolute terms. Contrary to this, we would point to asymmetric effects when the divergence between β_h^+ and β_h^- is significantly different from zero.

[8] More precisely, $\mathbf{x}_t$ summarizes p lagged values of a vector of control variables, $controls_t$, and q lagged values of the dependent variable. Hence, we get $\gamma_h \mathbf{x}_t \equiv \gamma_h^{controls} \sum_{j=1}^{p} controls_{t-j} + \gamma_h^{y} \sum_{k=1}^{q} y_{t-k}$.

Our vector $\mathbf{x}_t$ contains control variables that are supposed to have an effect on the endogenous variable y_t. We therefore include $p = 2$ lagged values of the short-term federal funds rate, the consumer price index, and real GDP, where consumer prices and real GDP are in logs and multiplied by 100. Finally, $\mathbf{x}_t$ also includes $q = 3$ lags of the dependent variable.[9]

C. *Inference*

Regressing the dependent variable at different horizons on the same set of control variables will likely result in autocorrelated residuals. In order to calculate standard errors that account for the possibility of serially correlated residuals within and across equations, we follow Ramey and Zubairy (2018) and Tenreyro and Thwaites (2016) and estimate seemingly unrelated equations as proposed by Driscoll and Kraay (1998). To be more precise, we estimate the parameters of interest of each equation separately and, in a second step, average the moment conditions across horizons $h = 0, ..., H$ when deriving Newey-West standard errors. In effect, the Driscoll-Kraay standard errors account for autocorrelation across both, time t and horizons h. We follow standard practice (see Jordà, 2005) and set the maximum autocorrelation lag for the Newey-West procedure $L = h + 1$.

3 Results

In this section, we present the baseline results of our paper. In the baseline setting, the idea is to uncover possible asymmetries in the responses of the economy to a credit supply shock. Hence, the baseline regression focuses on the asymmetric effects of positive and negative shocks on the economy. The sample size covers data from 1975Q3 to 2018Q4, consisting of 174 observations. After adjusting for leads and lags, the effective sample size starts in 1976Q2 and ends in 2013Q4 and, hence, consists of 151 observations.

A. *Baseline Results*

Do credit supply shocks have asymmetric effects? Before we answer this question, it is important to bear in mind that throughout the paper, we present impulse response coefficients rather than impulse responses.[10] So, for example, a *positive* value of β_h^- indicates

[9] The choice of p and q is based on the Schwartz Bayesian Information Criterion given by $-2\ln(\widehat{L}) + k\ln(n)$, where k is the number of parameters, $(\widehat{L})$ is the maximized value of the likelihood function, and n is the effective sample size after adjusting for leads and lags. We tried different combinations of p and q ranging from 1 to 4 lags each. For each combination of p and q, we follow the strategy of Tenreyro and Thwaites (2016) and sum up the resulting information criteria over both, the horizon h and over all different dependent variables. Finally, the minimum value of this operation results in the optimal lag length of $p = 2$ and $q = 3$.

[10] In order to get impulse responses, one simply needs to flip the impulse response coefficients.

that after a *negative* shock (i.e., an unexpected credit curtailment), the effect, i.e. impulse response, is *negative*. In other words, there is a uniflow response to the shock.

This being said, Figures 1 - 4 read as follows: The rows correspond to the dependent variables that are affected by the credit supply shocks. The first column depicts the impulse response coefficients β_h^+ (red-solid lines) following a positive credit supply shock. In contrast, the second column depicts the impulse response coefficients β_h^- (red-solid lines) describing the response following a negative credit supply shock to the particular dependent variable, both accompanied by their respective 90 percent confidence bands. For further comparison, dashed lines represent the impulse response coefficients from the linear model (equation 2.4), i.e. β_h.

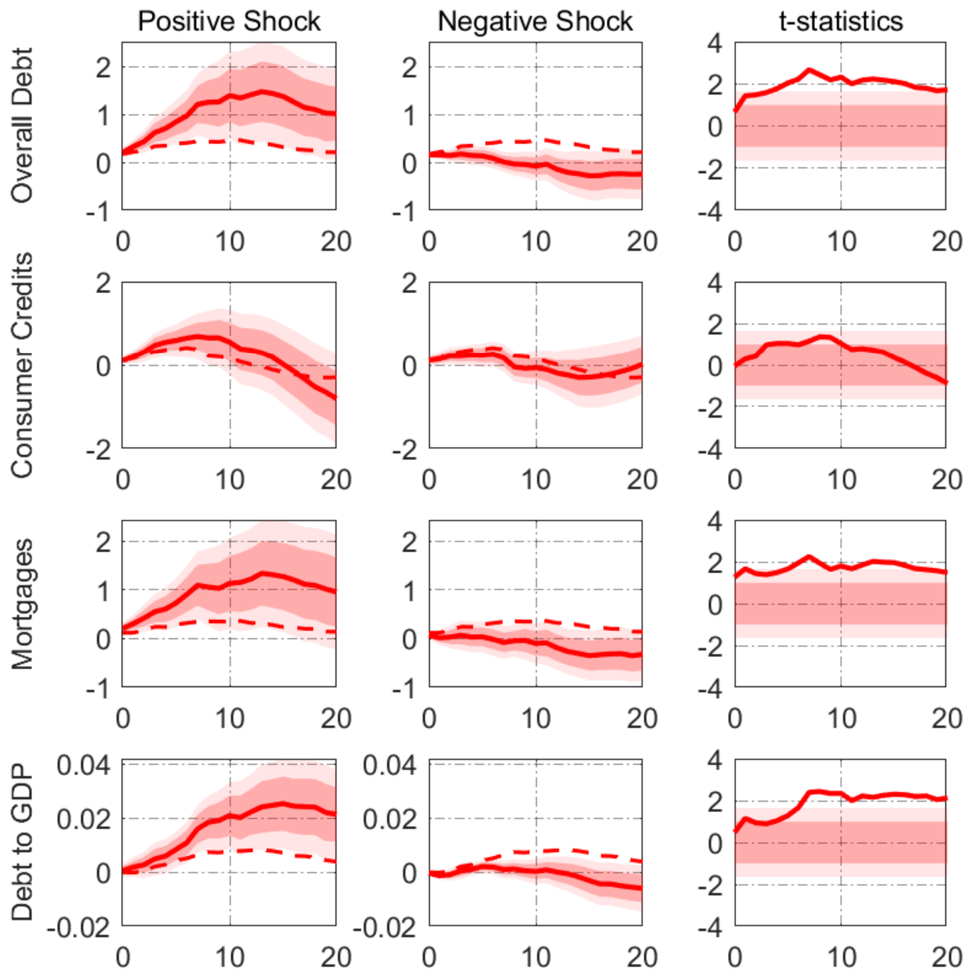
The third column shows $t-$statistics testing the null hypothesis $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for adjacent horizons $h = 0, ..., H$, where the shaded area covers the $t-$critical values for a 90 percent confidence interval, i.e. ±1.645. If the $t-$ statistics (red-solid) lies outside the shaded-area, we reject the null that the difference in the response of the endogenous variable is not distinguishable from zero in favor of the alternative hypothesis that they are significantly different from zero at the 90 percent confidence level and thus, indicate non-negligible asymmetric effects.

Figure 1 shows the impulse response coefficients corresponding to different debt volumes, namely overall household debt, consumer credit, mortgages, as well as the response of debt:GDP for each horizon h (x-axis) after a shock hits the economy in t. Given a positive credit supply shock, overall debt steadily and significantly increases by 1.5 percent. This effect is highly persistent as it holds for more than 20 quarters. The volume of consumer credit increases significantly, reaching a peak of 0.9 percent after ten periods before it wears out. The effect of a credit supply shock on consumer credit is more short-lived than overall debt. The response of mortgages shows where the sluggish behavior of overall debt stems from: mortgages respond very similar to a positive credit supply shock as does overall debt in both, magnitude and duration.[11] The positive effect proceeds over more than 20 quarters with a peak response of 1.5 percent. Debt:GDP shows a picture similar to both, the response of overall debt and mortgage debt. The positive response, which peaks at 0.025 percent, becomes significant after five periods and remains thereafter, shows evidence that debt is more sensitive to a credit supply shock than real GDP.

Turning to the responses to a negative shock, recall that a positive response coefficient indicates a concurrent reaction such that, e.g. concerning overall debt, a detrimental credit supply shock leads to a decrease in overall debt for two quarters. In the medium-term, i.e.

[11] This comes at no surprise as the share of mortgage credit to the overall indebtedness amounts to over 90 percent in the mid-2000's which further explains the results.

Figure 1: Response of Credit Volumes to Credit Supply Shocks



Notes: The first column shows the impulse response coefficients (red-solid) β_h^+ for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock, the second column shows the impulse response coefficients (red-solid) β_h^- for a negative (one standard deviation) credit supply shock. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval, relying on Driscoll-Kraay standard errors. The red-dotted lines in the first two columns show the impulse response coefficients β_h from a linear model without testing for asymmetric effects. The third column shows the t−statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t−critical values for a 68 (90) percent confidence interval, i.e. ±0.995 (±1.645). The rows show, from top to bottom, the responses of overall debt volume (in percent), the volume of consumer credit (in percent), mortgage credit volume (in percent), and the share of debt:GDP (in percentage points).

after roughly ten quarters, the negative shock goes into reverse and leads to an increase of debt, though not significant, as the confidence bands of the response coefficients comprise zero. This is true for all debt categories, as well as the debt:GDP ratio. Above all, it stands out that the responses are in all cases other than the response of consumer credit, less pronounced than in the case of a positive credit supply shock. By the same token, when not accounted for asymmetries, one gets misleadingly rather mild responses to credit supply shocks.[12]

Furthermore, the responses in all cases are more sticky than in the case given a positive shock. Even though the response of the overall indebtedness, mortgage debt, and the debt:GDP ratio is slightly significantly different from zero, the concurrent effect is short-lived, at most, and tends to increase debt in the medium-term, with response coefficients significantly different from zero at the 90 percent confidence level.

Most importantly, in all cases except consumer credit, the responses to a positive (negative) shock reside well above (below) their symmetric counterparts, indicating that there are non-negligible asymmetric effects.

The third column of Figure 1 underpins this visual impression. The $t-$statistics for overall debt, mortgage debt, and the debt:GDP ratio show that we reject the null whereupon private debt equally responds to positive and negative shocks. Solely for consumer credit, we do not reject the null hypothesis based on our $t-$statistics and conclude that, following an exogenous shock to credit supply, consumer credit responds similarly in absolute terms.

Three insights from this first exercise need to be highlighted: first, in the linear model, the responses are driven by the positive component of the shock, thus, suppressing a debt-increasing effect of adverse shocks in the medium-run, as seen in the second column of Figure 1.[13] Second, the differences in the responses between the linear and non-linear models are most pronounced for overall debt, mortgage debt, and debt:GDP; measures that are central to the debate whether central banks should actively lean against the credit cycle in their policymaking.[14] Third, not accounting for asymmetries leads to misleadingly attenuated responses of the aforementioned debt measures.

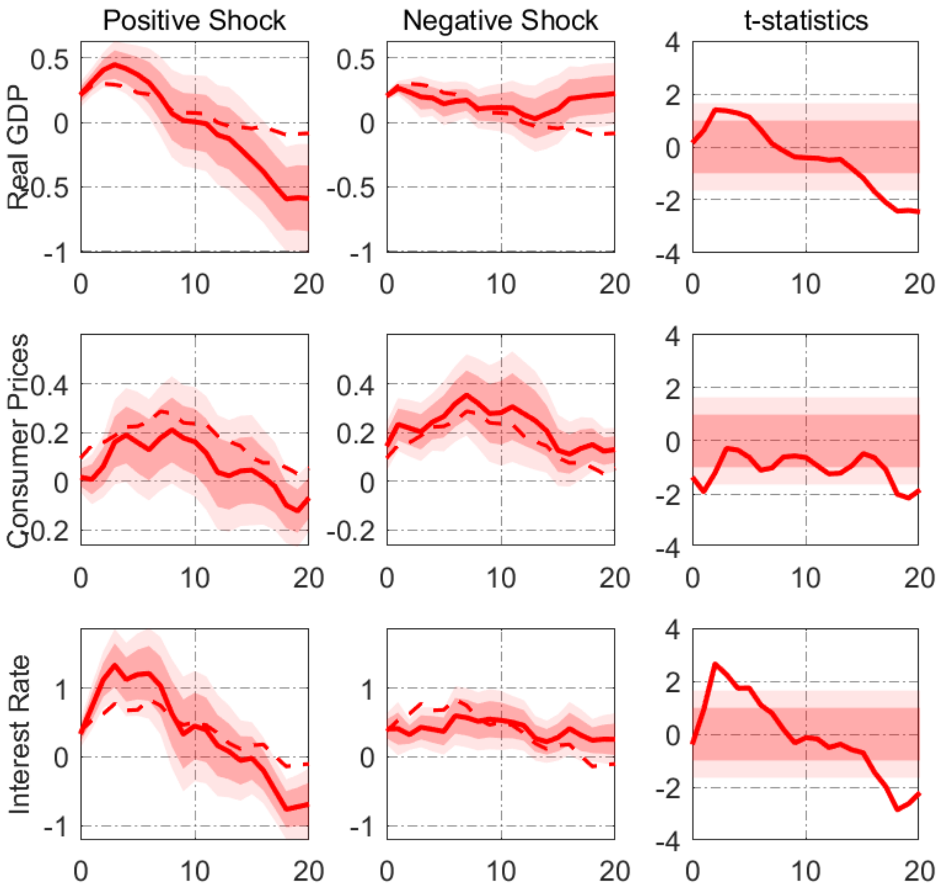
Turning to the effects on key macro variables, the first column of Figure 2 reports the results for real GDP and consumer prices (both in logs) as well as for the short-term (shadow) interest rate. Following a positive credit supply shock, real GDP increases immediately by about 0.25 percent, peaking at 0.5 percent after four quarters and steadily reverts afterward. This effect is significant for about seven periods. What stands out is that the effect of the

[12]A finding in line with Barnichon et al. (2022) statement regarding financial shocks.

[13]For example, the response coefficient for mortgage debt given an expansionary credit supply shock is three times higher than the equivalent response coefficient from the linear model.

[14]See, for example, Lambertini et al. (2013) and Svensson (2017). In the robustness section, we evaluate the role of monetary policy in the transmission of credit supply shocks in a counterfactual experiment and derive policy implications.

Figure 2: Credit Supply Shocks and Headline Variables



Notes: The first column shows the impulse response coefficients β_h^+ (red-solid) for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock, the second column shows the impulse response coefficients β_h^- (red-solid) for a negative (one standard deviation) credit supply shock. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval, relying on Driscoll-Kraay standard errors. The red-dotted lines in the first two columns show the impulse response coefficients β_h from a linear model without testing for asymmetric effects. The third column shows the t−statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t−critical values for a 68 90 percent confidence interval, i.e. ±0.995 (±1.645). The first row shows the response of real GDP (in percent), the second row the response of consumer prices (in percent), and the third row shows the response of the effective federal funds rate (amended by the Wu-Xia shadow rate) in percentage points.

shock does not wear out but instead leads to a subsequent decline in real GDP. After 16 quarters, there is a significant drop in output of 0.5 percent. This is in line with the well-established notion that credit supply expansions lead to subsequent episodes of economic downturn, as in e.g. Schularick and Taylor (2012) or Mian et al. (2017).

The economic upturn caused by additional availability of credit leads to an increase (though not significant) in consumer prices by up to 0.2 percent which starts to decline after 10 quarters. As real GDP subsequently decreases, so do prices, leading to deflationary pressure after 18 quarters which is significantly different from zero. In light of the responses of debt:GDP both, the responses of real GDP and prices add up to Fisher's *debt-deflation hypothesis* whereupon an economic slowdown increases the real burden of debt, which in turn puts downward pressure on aggregate demand, slowing down economic activity even further.

As the monetary authority responds to output and prices in the conduct of its policies, it follows the boom-bust pattern. First, it increases its short-term interest rate in response to the increase in those indicators. The peak response is an increase of one percentage point after four quarters. As the economic downturn comes into action, interest rates respond with a substantial decrease.

The effects following an unexpected credit crunch are not very different to those from the linear model. A negative credit supply shock leads to a significant decrease in output and prices, and as such, interest rates decrease to counteract the economic downturn. Here, after four years, prices hint to patterns of asymmetry, mounting to a stronger deflationary pressure in the presence of negative shocks. This also explains the asymmetric effects of real debt variables in the mid-run, because the strong response of prices following a negative shock seem to dampen the overall response of real debt following an unexpected negative credit supply shock.

Summing up, our results point to symmetric effects in the short-run, as the *t*-statistics fluctuate within, rather than outside of its critical values for the first four years or so. Thereafter, however, we find that all three key variables respond asymmetrically. More precisely, in all three cases, the response following a positive credit supply shock is stronger in absolute values than in the case of a negative credit supply shock. Furthermore, it is worth noting that our results suggest that in the presence of a negative shock, prices exhibit stronger deflationary pressure, which are underestimated in a linear model.

B. *Digging Deeper*

There are different channels through which a credit supply deterioration can transmit into the (real) economy. An expansion in credit supply, therewith decrease in lending rates, could, for example, boost the supply side of the economy through additional (funds for and realizations of) investments due to decreasing credit costs, as argued by inter alia Gilchrist and Zakrajšek (2012), which in turn would lead to an increase in employment. Aggregate demand, on the other hand, can be stimulated by means of credit expansion by enabling households to increase consumption as their balance sheets improve, as noted by i.a. Mian and Sufi (2014) and Gertler and Gilchrist (2018). For this reason, we search for traces of asymmetry in the responses of some surrogates for both, aggregate supply and aggregate demand to credit supply deteriorations.

Beginning with the supply side, Figure 3 shows how external financing, measured via the credit spread provided by Gilchrist and Zakrajšek (2012), the total non-farm payroll employment, investments, and real credits to non-financial corporations respond.

As the top panel shows, we find that, following a negative credit supply shock, the response of the external finance premium is different from zero only on impact and indistinguishable from zero afterwards. This is contrary to the response following a positive credit supply shock. Here, we see no significant response on impact and the subsequent three years. Afterwards, however, the finance premium increases, which coincides with the responses to the bust pattern we observe for our macroeconomic variables.[15]

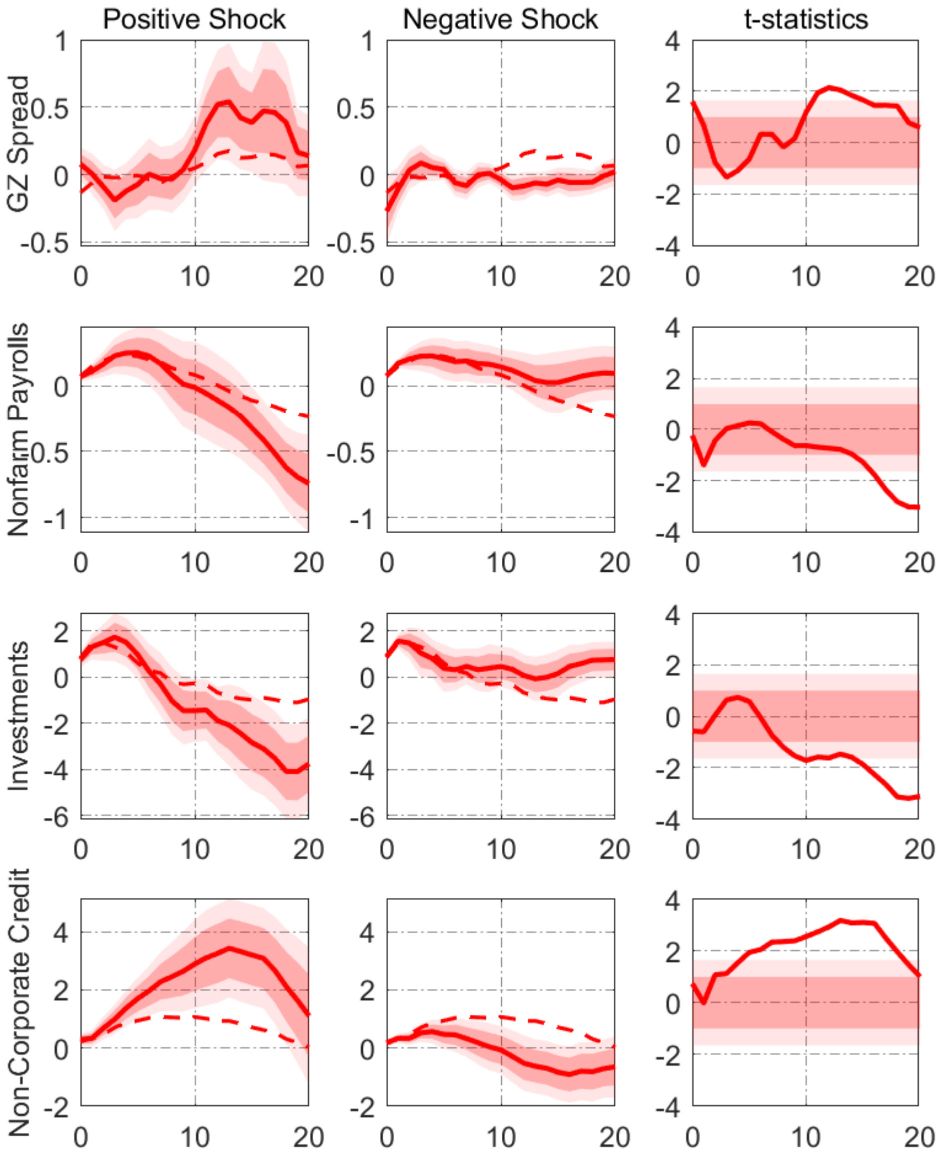
In the case of employment, total non-farm payrolls clearly exhibits the boom-bust pattern. If a positive credit supply shock hits the economy, employment significantly increases on impact by 0.05 percent and increases up to 0.2 percent before it reverts and becomes significantly negative after almost four years. In the case of a negative credit supply shock, total non-farm payrolls co-move by 0.1 percent for 12 periods, which translates into an decrease in payrolls. Both results are mostly indistinguishable, except, as before, at the long-end of our analysis, and a result of the changes in economic activity given the respective shocks.

Investment responds very similarly to both, positive and negative credit supply shocks, as does real GDP. After a significant and somewhat persistent increase on impact, peaking at 1.5 percent, the response mean-reverts and becomes significantly negative by 1.5 percent after 11 quarters. As before, we observe asymmetric effects after 16 quarters, i.e. at the farther end of our projection. Also here, we find that the response of a positive credit supply shock is stronger in absolute value than in the case of a negative credit supply shock, as indicated by the significantly negative t-statistic in the respective panel.

Taken together, the responses of the external finance premium, non-farm payrolls, as well as real investments represent the well established boom-bust cycle caused by a credit supply

[15] As financing conditions can play a crucial rule for economic fluctuations (see, for example, Adrian et al., 2010 or Bruno and Shin, 2015), we have also looked at the subcomponents of the Chicago Fed National Financial Conditions Index (NFCI), which comprise a wide range of indicators concerning volatility and funding risk, credit conditions, as well as debt and equity measures. In short, the impulse responses of the subindexes are remarkably similar to the impulse responses of the GZ spread, which is why we refrain from presenting them in the paper. Of course the results are available upon request.

Figure 3: Credit Supply Shocks and the Supply Side



Notes: The first column shows the impulse response coefficients β_h^+ (red-solid) for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock, the second column shows the impulse response coefficients β_h^- (red-solid) for a negative (one standard deviation) credit supply shock. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval, relying on Driscoll-Kraay standard errors. The red-dotted lines in the first two columns show the impulse response coefficients β_h from a linear model without testing for asymmetric effects. The third column shows the t–statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t–critical values for a 68 (90) percent confidence interval, i.e. ±0.995 (±1.645). The first row shows the response of the Gilchrist and Zakrajšek (2012) spread (in percentage points), the second depicts the response of total non-farm payrolls (in percent), the third shows the response of real investments (in percent), and the last row shows the response of real credits to non-financial corporations (in percent).

deterioration.

Finally, real credits to non-financial corporations exhibit a significant and persistent increase in response to a positive credit supply shock. The peak median response, which amounts to 3.4 percent, is observed after 13 quarters, before the response reverses. The timing also matches the responses of overall debt and mortgage debt, which comes at no surprise, as these variables follow the same cycle. The same is true in the case of a negative credit supply shock: the initial decrease in real credits wears out after roughly two years and tends to increase thereafter. As in the case of the other credit variables, the responses show significant asymmetries.

Mian et al. (2017) stress that the boom-bust cycles of the past four decades were primarily driven by household debt operating through the household demand channel. For example, the combination of rising house prices (and thus improvement in the household's balance sheet) and declining lending rates (i) led to an increase in residential investments and (ii) enabled additional consumption of both, domestic and foreign goods and services.[16] Hence, we take a look at the responses of house prices, real residential investments, and real household expenditures, which are depicted in Figure 4.

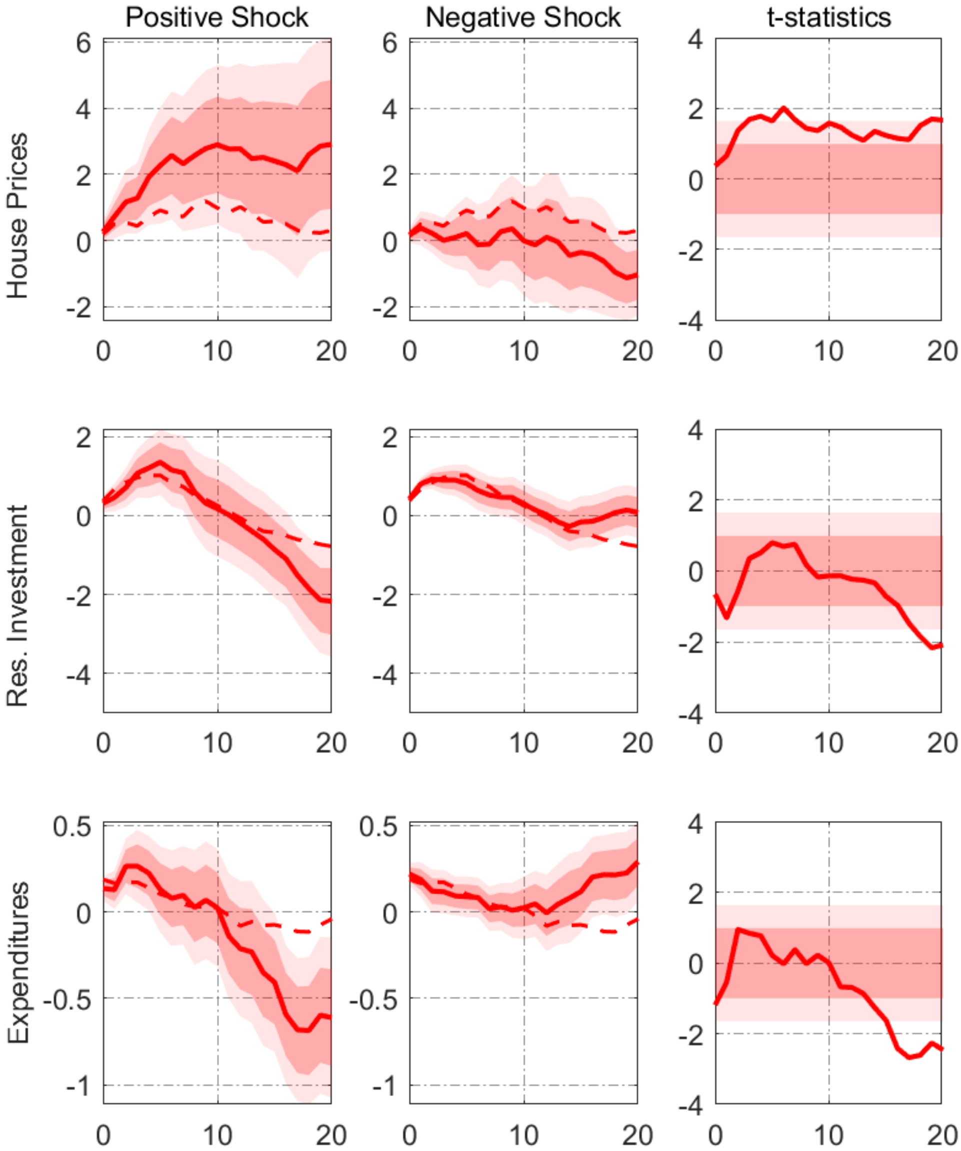
The first row shows that the response of house prices (real Shiller Index) resembles remarkably well the response of mortgage debt. Positive credit supply shocks lead to a persistent and also significant increase in house prices. While negative shocks lead to quite similar opposite effects, we find clear patterns of asymmetry as the t-statistics are very close at or above the critical values from quarter 4 onwards. This is because, at the back-end, house prices (i) remain on a relatively high level after a positive shock and (ii) tend to exhibit mean-reverting behavior after a negative shock, which in turn increases the difference between the β coefficients. Furthermore, the linear response is mitigated by the response to a negative shock, underestimating the stark effect of positive credit supply shocks on house price inflation.

The response of residential investment is similar to the response of total investments. This can be explained by higher demand for housing due to an improvement in the household's balance sheets. The response of residential investment peaks at one percent after one year before it mean-reverts, exhibiting the boom-bust pattern. After 20 quarters, residential investments significantly decrease by approximately two percent. Concerning a negative credit supply shock, the same story applies as in the case of total investments.

It stands out that for both shocks, consumption expenditures follow the response of consumer credit and real GDP very closely. Given a positive credit supply shock, expenditures increase initially and show mean-reverting behavior that eventually results in a significant decrease. That is, beneficial credit conditions improve the household's balance

[16]For further impressions, see the evolution of real mortgage rates depicted in Figure A.1 in the appendix.

Figure 4: Credit Supply Shocks and the Demand Side



Notes: The first column shows the impulse response coefficients β_h^+ (red-solid) for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock, the second column shows the impulse response coefficients β_h^- (red-solid) for a negative (one standard deviation) credit supply shock. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval, relying on Driscoll-Kraay standard errors. The red-dotted lines in the first two columns show the impulse response coefficients β_h from a linear model without testing for asymmetric effects. The third column shows the t–statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t–critical values for a 68 (90) percent confidence interval, i.e. ± 0.995 (± 1.645). The first row shows the response of house prices (real Shiller index, in percent).The second row depicts real residential investments (in percent). The last row shows the response of real personal expenditures (in percent).

sheets (e.g. through higher asset prices such as housing) such that they increase borrowing (especially consumer credit) with which they expand consumption. In the case of a contractionary credit supply shock, expenditures decrease significantly by 0.2 percent and tend to remain declining in the long-run.

To summarize, three things stand out: First, the responses of consumer credit, real GDP, the interest rate, non-farm payrolls, total and residential investment, as well as personal expenditures to a positive credit supply shock all contribute to the notion that credit supply expansions lead to a vicious boom-bust cycle.

Second, the response of credits to non-financial corporations, house prices, and mortgage debt is highly persistent and does not follow the boom-bust pattern. One explanation could be the following: Positive credit supply shocks increase funding possibilities for corporations as well as house prices and, thus, stimulate economic activity, which in turn leads to an increase in demand for (new or the expansion of existing) mortgage loans. As the economy, however, transits into the bust-phase, monetary policy steps into place, decreasing interest rates. This decrease, in turn, leads to an increase in asset prices, such as house prices. Thus, while the economy shows the boom-bust pattern, house prices do not. For example, a closer look at the responses of house prices and real GDP reveals that the pace of change in house prices decreases after 6 to 10 quarters; the period where the boom goes bust.

Last, asymmetries appear in the back-end of the responses and are primarily driven by the positive portion of the shock.[17] In turn, this implies that not accounting for asymmetries leads to underestimated effects of credit supply shocks in the medium to long-run.[18]

4 Sensitivity Analysis

So far, our results indicate that the transmission of credit supply shocks is asymmetric. This section seeks to underpin our results via a battery of robustness checks, including an alternative choice of credit supply shock as well as several alternative model specifications.

[17] At the back-end, the t-statistics are either (i) overwhelmingly negative, as in the case of consumer prices, non-farm payrolls, as well as total and residential investments or (ii) significantly negative, as consumer prices, non-farm payrolls, investment:GDP, and expenditures, which indicates stronger responses to positive than negative shocks.

[18] Another observation, that an anonymous referee thankfully brought to our attention, is that we observe a boom-bust pattern in the impulse responses of economic variables, on the one hand, but no such pattern in the responses of the debt variables, on the other hand. One potential reason is the difference in the underlying cycles. As far as credit and debt variables are concerned, these variables are rather sluggish compared to classical economic variables and are merely linked to the credit cycle. There is much evidence that the letter is twice as long as the business cycle (see, for instance, Alpanda and Zubairy, 2019). This could explain why, for some variables, we do not yet observe a change in the sign of the response over our 20-quarter horizon.

A. *Credit Supply Shocks from a Proxy SVAR*

Our results in Section 3 rely on the identification strategy following Gambetti and Musso (2017) through sign restrictions. Since the identified credit supply shock comes from a different model and enters our local projection framework exogenously, we crosscheck our results using an alternative credit supply shock. Using a Monte Carlo experiment, Mumtaz et al. (2018) provide detailed evidence that the performance of various structural vector autoregression models seeking to identify credit supply shocks varies substantially.[19] Using data for the U.S., they find that the Gambetti and Musso (2017) identification performs well in replicating DSGE model-implied impulse response functions. Several other authors use alternative proxies for credit supply, including Gilchrist and Zakrajšek (2012), Bassett et al. (2014), and Lown and Morgan (2006), and use it as an endogenous variable in an otherwise standard VAR, where a shock to the proxy is interpreted as a credit supply shock. However, Mumtaz et al. (2018) show that proxy variables in a recursive SVAR do not perform well due to a large attenuation bias increasing in the variance of the measurement error. They also show that the measurement error has little effect on the performance of proxy VARs because the proxy of credit supply does not enter the model directly. We, therefore, extend the sample of Mumtaz et al. (2018) and estimate a proxy SVAR model where the excess bond premium of Gilchrist and Zakrajšek (2012) is considered as an instrument rather than an additional endogenous variable.[20]

The correlation of the estimated credit supply shock from our proxy SVAR and our credit supply shock identified as in Section 2 is 0.59. Both series show the same pattern most of the time and the dynamics during periods of financial turmoil as in 2008 overlap almost perfectly.[21]

Figures A.2 to A.5 in the appendix show that in most cases, the qualitative directions of the impulse responses do not change. Also, the difference between the coefficients β_h^+ and β_h^- looks very much like in our benchmark case. However, while the $t-$statistics for the macro variables still point to asymmetric effects, uncertainty in the impulse response

[19] The authors consider three different DSGE models featuring credit supply in order to construct artificial data, namely the DSGE model by Gertler and Karadi (2011), the estimated DSGE model from Christiano et al. (2014) and, finally, the model by Cúrdia and Woodford (2010). In a nutshell, Mumtaz et al. (2018) use these DSGE models as the true data generating processes and consider various competing SVAR models with different identification strategies in order to shed light on their replication performance of the true impulse responses following the model-implied credit supply shocks.

[20] We use the same time span as in Section 3, namely 1975Q3 to 2018Q4. Our estimation is based on one lag, as suggested by the Bayesian Schwartz Information Criterion. For details on the estimation, see Mumtaz et al. (2018) Section 2.2.

[21] The reliability statistic proposed by Mertens and Ravn (2014), as the squared correlation between the proxy and the credit supply shock, is 0.16 in our case and notably higher as in Mumtaz et al. (2018), thus indicating higher reliability as a strong instrument. Most strikingly, however, is that all impulse responses within our proxy SVAR show the expected sign. This is interesting from the standpoint that in our proxy SVAR, the identification is far less restrictive than in our baseline model from Section 2.

coefficients of debt volumes after a positive shock is remarkably higher than after negative shocks, resulting in t-statistics that are not statistically different from zero. Overall, we conclude that our results still point to asymmetric effects in most cases when we use a credit supply shock from a proxy SVAR instead of a shock identified by means of sign restrictions.

B. *A Note on the Role of Estimation Uncertainty Surrounding the Shock*

So far, our impulse response coefficients are the mean responses to the median of a series of identified shocks, that satisfy the imposed restrictions. Consequently, estimation uncertainty surrounding the shock is not taken into account. Our set of $B = 10,000$ draws for the credit supply shock from the VAR nevertheless allows us to test how representative our shock is. For each series $shock_t^{(1)}, ..., shock_t^{(10,000)}$, we therefore estimate our baseline model and report the uncertainty across all draws. Note that the potential disadvantage of the median is that the median in t and $t+1$ can come from different draws (and thus different models, see Fry and Pagan, 2011 on this). By using the entire time series for each draw, we avoid this inconsistency.

Figure 5 reports the baseline point estimates (red-solid) with the 68 percent and 90 percent confidence bands (red-shaded areas) as well as the median over all point estimates (black-solid) and 90 percent (black-dashed) confidence intervals across all $10,000$ draws. It stands out that our median shock seems to be very representative of the population, as the median across all $10,000$ estimates is very close to our baseline impulse responses.

C. *Is Monetary Policy a Potential Cause for Asymmetric Effects*

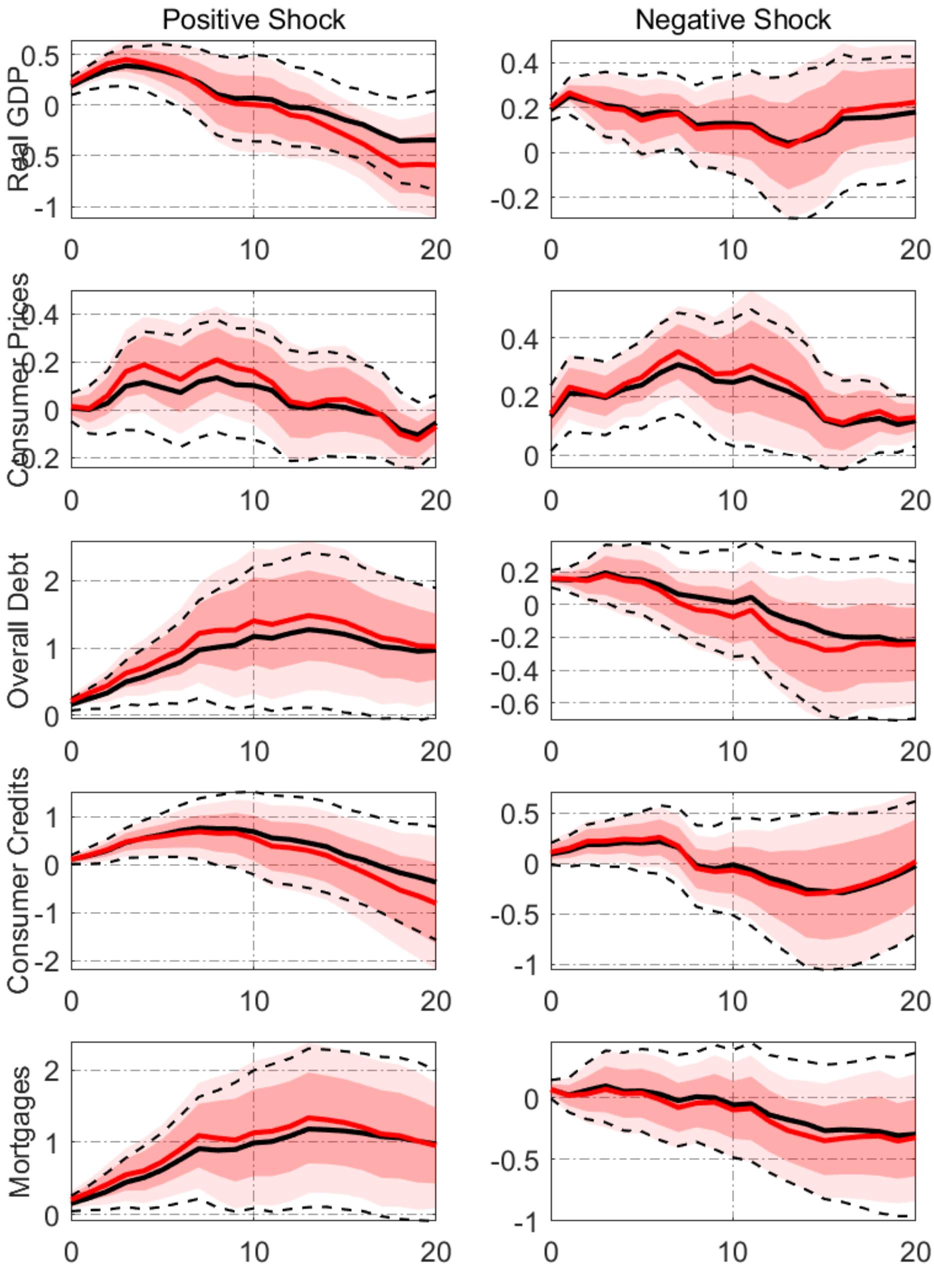
As mentioned in the introduction, it is quite conceivable that monetary policy decisions can be a cause of asymmetric responses, if, for example, monetary policy systematically responds differently to expansionary shocks than to contractionary shocks. To examine the role of monetary policy in the transmission of credit supply shocks in our setup, we re-estimate the VAR model based on the assumption, that the policy rate does not react to contemporaneous and past movements of the composite lending rate and credit volumes by means of block exogeneity. In this scenario, the policy rate only reacts to movements in those variables via feedback from the remaining variables of the model, but not directly to movements of those variables.

In a second step, we repeat our baseline estimation

$$y_{t+h} = \alpha_h + \gamma_h \mathbf{x}_t + \beta_h^+ \max\left\{shock_t^{cf}, 0\right\} + \beta_h^- \min\left\{shock_t^{cf}, 0\right\} + e_{t+h},$$

where y_{t+h} is the variable of interest at horizon $t+h$, $\mathbf{x}_t$ is a vector of control variables, and $shock_t^{cf}$ is the credit supply shock of this counterfactual exercise.

Figure 5: Impulse Responses Across All Draws of the Credit Supply Shock



Notes: Point estimates (red-sold) with the 68 and 90 percent confidence bands (red-shaded areas) from the baseline model as well as the median over all point estimates (black-solid) and 90 percent (black-dashed) confidence bands across 10,000 draws.

Figure 6 compares the credit supply shock from our baseline setup with the shock we obtain in this exercise. Here, the red-solid line reports the mean of the baseline specification with the corresponding 90 percent confidence bands (shaded area), respectively. In contrast, the black-solid line corresponds to the median shock of the counterfactual scenario. As can be seen, the two shocks mostly overlap.

Figure 6: Baseline Shock vs Counterfactual Shock

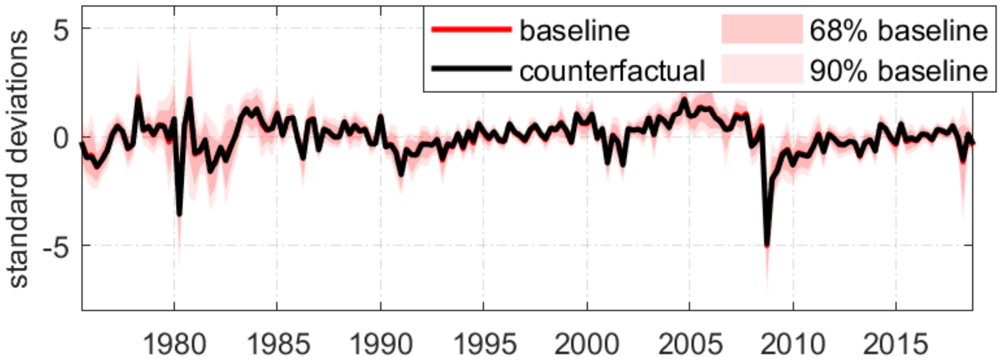


Figure 7 reports the corresponding impulse response coefficients for this exercise together with the original impulse response coefficients for a subset of our endogenous variables, in order to conserve space.[22] The red-solid line corresponds to the baseline impulse response coefficients, whereas the black-solid line corresponds to the impulse response coefficients obtained from the counterfactual experiment credit supply shock. Note that we only report the baseline specification's 68 percent and 90 percent confidence bands.

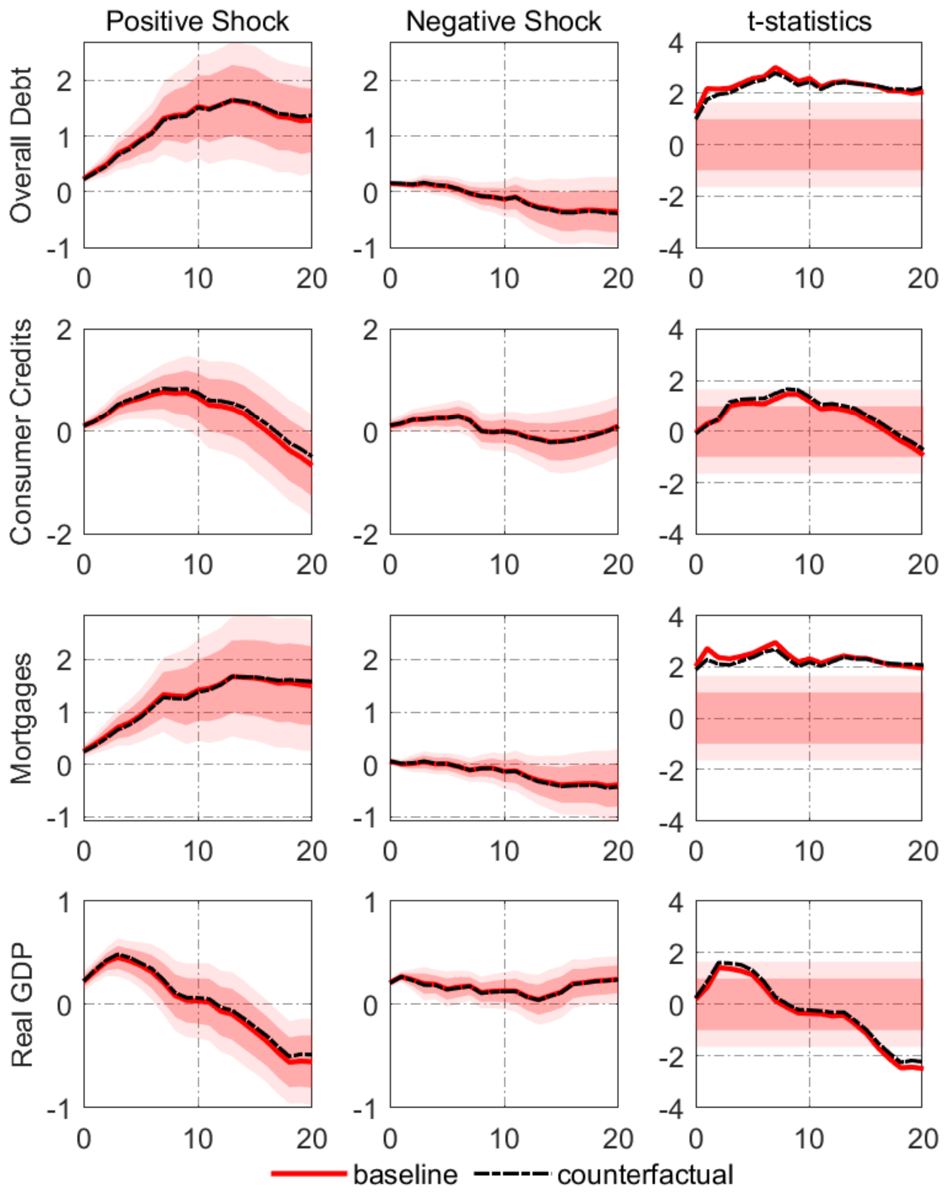
In all cases, there is virtually no difference in the responses to the shocks, as the impulse response coefficients are basically alike. In other words, our findings suggests that the central bank's systematic response to credit volumes and lending conditions has no important role for the transmission of credit supply shocks and is thus not a driving force for the asymmetric effects we find in our results.

What are the policy implications for monetary policy? The results of the counterfactual analysis by no means imply that monetary policy does not influence the transmission of the credit supply shock at all. This is because the restriction within the counterfactual experiment merely restricts the central bank's systematic response to credit volumes and the composite lending rate. However, a credit supply shock also affects other variables, including real GDP and prices, i.e. variables to which the central bank reacts. Consequently, monetary policy acts in the background, but is not in the position to directly influence the course of events. In other words, leaning against the credit cycle would not meet the desired objectives.

Hence, from a policy point of view, it is necessary to asymmetrically respond to

[22] The impulse responses for the remaining variables are available on request.

Figure 7: Baseline IRFs vs. Counterfactual IRFs



Notes: Impulse response coefficients for the baseline (red-solid) and counterfactual (black-solid) credit supply shocks. Dark (pale) red-shaded areas are the 68 (90) percent confidence intervals of the responses to the baseline shock, relying on Driscoll-Kraay standard errors. The last column shows the t−statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. Here, the dark (pale) red-shaded areas cover the t−critical values for a 68 (90) percent confidence interval, i.e. ±0.995 (±1.645). All responses are expressed in percent.

unexpected disruptions in the credit market by means of macroprudential activity. One conceivable measure would be to implement buffers whose amount is aligned with the sign or size of the credit shock – similar to the counter-cyclical capital buffers, which are determined by the business cycle. However, we would like to leave a more thorough analysis of this to further research.

D. *The Effects of the Overall Business Cycle and Credit Conditions*

One explanation for our observed asymmetries could be that the distribution of our identified credit supply shocks itself is asymmetric, depending on either the overall business cycle or credit conditions. First, we devote ourselves to the effects of the overall business cycle.

One could argue that positive credit supply shocks occur mainly during periods of expansion, while adverse credit supply shocks could predominantly occur during recessions. If this was the case, we probably would have to account for this state dependence in our regression analysis. In order to test for this possibility, we compare the distribution of shocks during different phases of the business cycle. To do so, we follow the procedure of Tenreyro and Thwaites (2016), which amounts to estimating state-depending probability distributions via a smoothly increasing logistic function $F(z_t)$ as a weighting function of the kernel, where z_t is an indicator of the state of the economy. To do so, we take the annualized quarterly growth rate of real GDP. Since this series is very volatile, we smooth out short-term volatility by filtering the series using a seven-quarter moving average. Subsequently, we calculate the logistic function over time. We follow Teräsvirta and Granger (1993) and employ a function of the form

$$F(z_t) = \frac{\exp\left(\kappa \frac{z_t - \mu}{\sigma_z}\right)}{1 + \exp\left(\kappa \frac{z_t - \mu}{\sigma_z}\right)}, \tag{4.1}$$

where μ is used to control the proportion of the sample the economy spends in either state (boom or recession), and σ_z is the sample standard deviation of the state variable z_t. The parameter κ controls how abruptly the economy switches from one state to the other following movements of the state variable. That is, higher values of κ mean that rather small movements of the state variable are needed to induce a switch from one regime to the other. We follow Auerbach and Gorodnichenko (2012) and Tenreyro and Thwaites (2016) and choose a value of $\kappa = 3$, indicating an intermediate degree of intensity of the regime-switching. We calibrate μ such that we spend 11.3% of the time in recessions. According to the NBER recession indicators, this corresponds to the share of periods we spend in recessions within our sample.

With the logistic function at hand, we estimate both, a probability density function (PDF) and cumulative density function (CDF) using our logistic function $F(z_t)$ and $1 - F(z_t)$, respectively, for weighting our (Normal Gaussian) kernel function in order to get state-dependent distributions of our credit supply shock. The resulting state-depending PDFs and CDFs are shown in Figure 8. The bottom panel shows the weighting function $F(z_t)$ (black-solid line), where the red-shaded areas highlight NBER recessions. As expected, we observe drops in our function $F(z_t)$ during recessions. This happens with a short delay since we use a moving average.

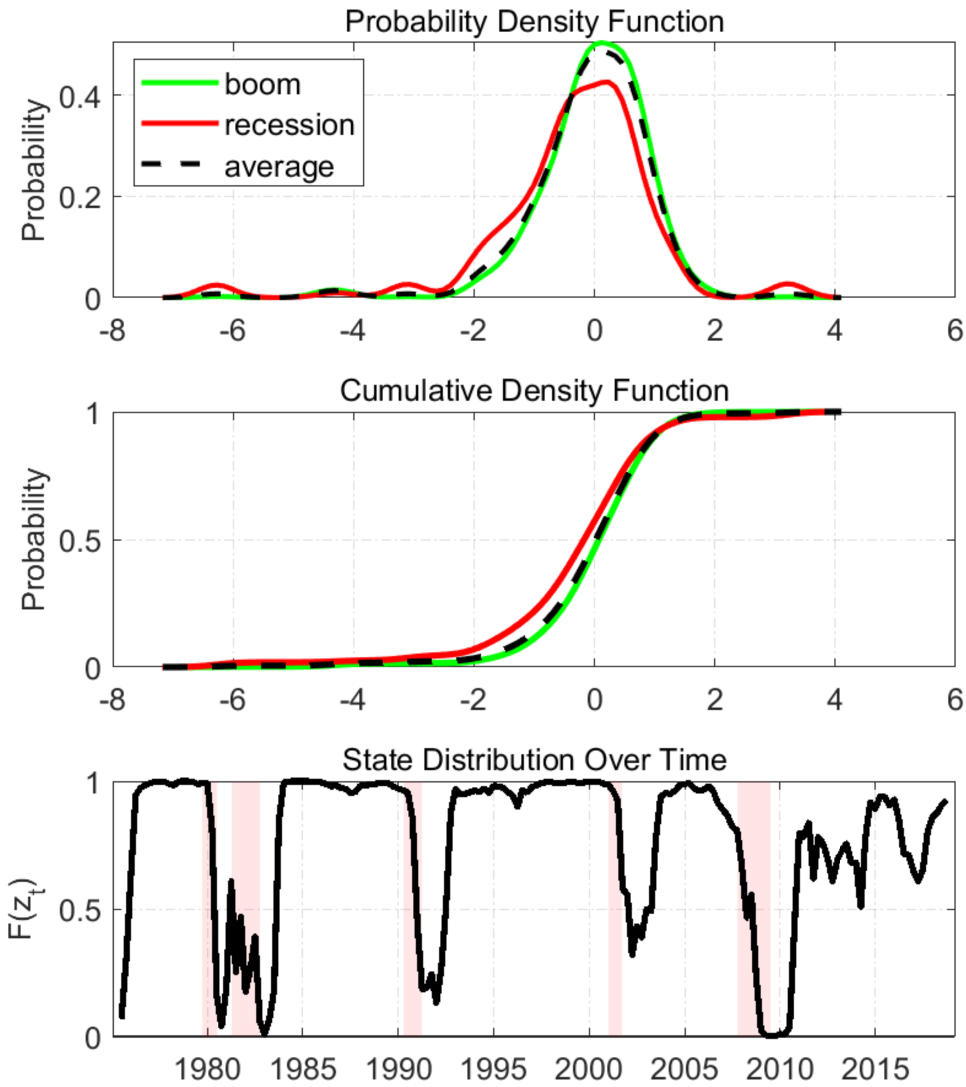
Turning to the estimated probability distribution functions, the average PDF of our credit supply shock appears to be normally distributed, which is not surprising because our shock is distributed as $shock_t \sim \mathcal{N}(0, I)$ by construction within our VAR. The distribution during booms almost perfectly overlaps the average distribution. The estimated PDF during recessions is also clearly centered around zero. Not surprisingly, we observe that large (negative) shocks occur mainly during recession. This is also visible in the estimated CDF, where the probability of getting a shock of minus one standard deviation or less (in absolute terms) in size is slightly higher during recessions. Nevertheless, the overall picture clearly points to common central tendencies of the distributions across the business cycle. We therefore conclude that the distribution of shocks does not depend on the business cycle.

However, it is possible that positive credit supply shocks primarily occur when financial conditions are looser than average, whereas negative credit supply shock may predominantly occur when financial conditions are tighter than average. If we find this to be true, this would imply that we possibly would have to take different states of financial conditions into account and therefore have to adjust our regression. We, therefore, take the NFCI Credit subindex and repeat our exercise in order to investigate whether the distribution of our credit supply shock systematically depends on financial credit conditions.[23]

Starting with the dynamics of $F(z_t)$ at the bottom panel of Figure 9, it turns out that whenever we are in a recession as indicated by the red-shaded area, credit conditions are above average, i.e. tighter than average. The estimated probability density functions at the top panel show that small shocks in absolute values are slightly more likely when credit conditions are below average, i.e., when credit conditions are relatively loose (red line), whereas larger shocks in absolute terms seem to be somehow more common during periods of credit tightening (green line). However, both estimated state-dependent distributions are clearly centered around zero and not much different from the estimated average probability

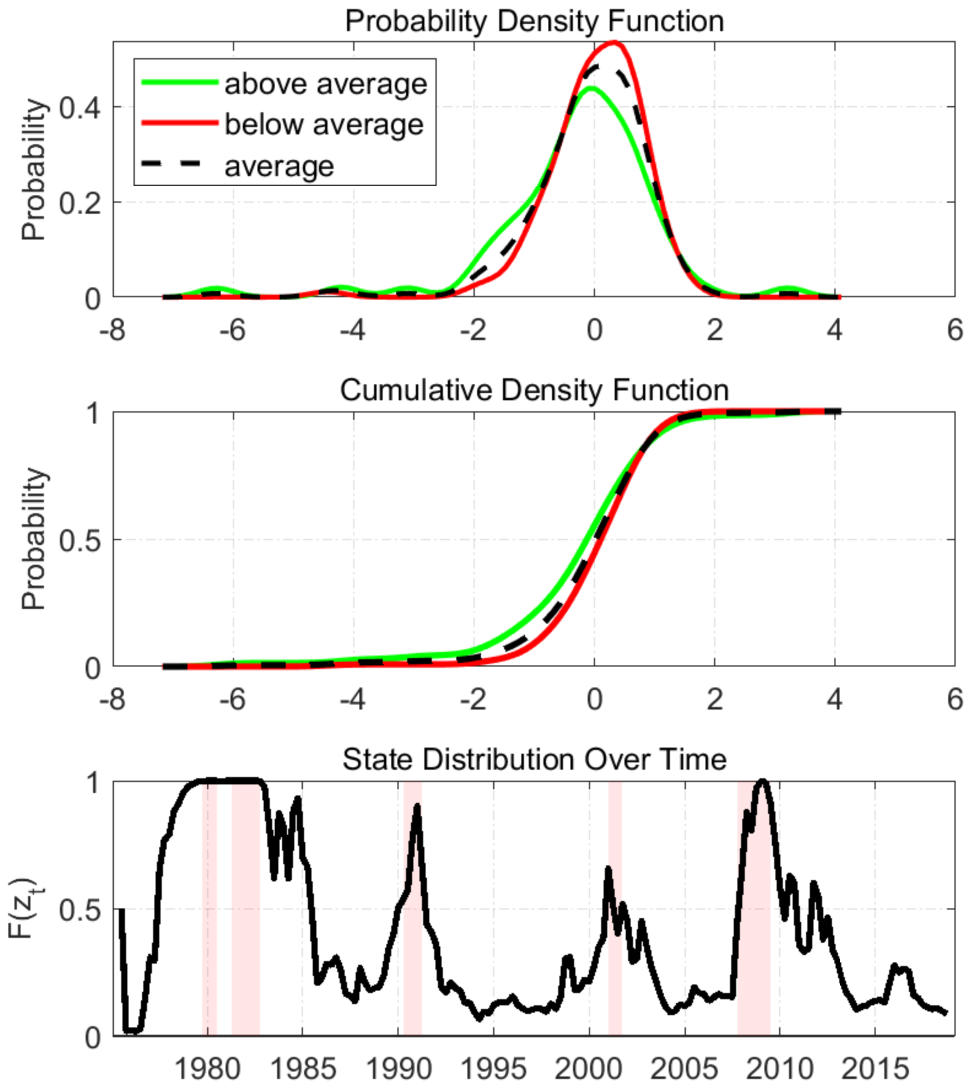
[23] We repeat this exercise for different state variables, namely, the output gap and the adjusted Chicago Fed National Financial Conditions Index. The resulting estimated probability density functions as well as the estimated cumulative density functions can be found in appendix B, Figures B.1 and B.2, respectively.

Figure 8: Estimated State-Dependent PDFs and CDFs



Notes: Estimated probability density functions (top panel), cumulative density functions (middle panel) and transition function $F(z_t)$ (bottom panel) over time. The green lines show the estimated distributions of credit supply shocks during booms, and the red lines show the estimated distributions during recessions using $F(z_t)$ and $1-F(z_t)$ for weighting our kernel function. The black-dotted lines correspond to the average distributions of credit supply shocks using a normally distributed kernel. In the bottom panel, the red-shaded areas highlight NBER recession dates.

Figure 9: Estimated State-Dependent PDFs and CDFs | z_t : Financial Conditions Credit Subindex



Notes: Estimated probability density functions (top panel), cumulative density functions (middle panel) and transition function $F(z_t)$ (bottom panel) over time. The green lines show the estimated distributions of credit supply shocks during booms. The red lines show the estimated distributions during recessions using $F(z_t)$ and $1 - F(z_t)$ for weighting our kernel function. The black-dotted lines correspond to the average distributions of credit supply shocks using a normally distributed kernel. In the bottom panel, the shaded areas highlight the NBER recession dates.

distribution. This finding is mirror-imaged in the middle panel, where the cumulative probability distributions do not differ notably. We conclude that, similar to the previous exercise, the distributions of credit supply shocks both, when credit conditions are above and below average, follow common central tendencies.

E. *Altering Specifications*

In order to further stress test our results, we make changes to the sample size as well as take a closer look at the role of lags and trends in order to ensure that these factors do not distort our results.

First, we take a look at the role of the Great Recession. Throughout the paper, we estimate our model over an effective period from 1975Q3 to 2013Q3. The asymmetric effects we found so far could possibly be a relic of the Great Recession. We test for this possibility and estimate our model, excluding NBER recession dates that mark the Great Recession. The blue-dashed line in Figures A.6–A.9 in the appendix show the results of this exercise. In short, the results are generally similar to our baseline such that we conclude that our findings are not driven by the Great Recession.

The next exercise is to investigate the effects of lags and trends. In our baseline setting, we do not include a log-linear trend into our regression equation in order to keep the regression equation consistent across our endogenous variables.[24] This subsection examines whether adding a trend changes our main results. We do so by estimating

$$y_{t+h} = \delta t + \alpha_h + \gamma \mathbf{x}_t + \beta_h^+ \max\{0, shock_t\} + \beta_h^- \min\{0, shock_t\} + e_{t+h} \, , \tag{4.2}$$

where δ denotes the effect of a log-linear time trend t, while the remainder is similar to our baseline regression (2.5). The results do not change, as can be seen form the course of the black-dotted line in Figures A.6–A.9.

As explained in Section 2, the choice of lags for both, the endogenous variable as well as the set of control variables other than the endogenous variables, relies on the Bayesian Schwartz Information Criterion. We, therefore, test whether the results change if our lag lengths are chosen according to the more restrictive Akaike Information Criterion (AIC) given by

$$2k - 2\ln(\widehat{L}) \, . \tag{4.3}$$

The AIC suggests $p = 4$ lags of the endogenous variable and $q = 3$ lags for the remaining

[24] Note that our effective sample size runs from 1975Q3 to 2013Q4. For some variables under consideration during this time span, it can be seen with the naked eye that adding a linear time trend would probably deliver misleading results.

variables, as opposed to the benchmark case where two lags of the endogenous variable have been used. Overall, we find that the choice of lags does not change our results remarkably, as the respective impulse responses (black-dashed line) are very similar to our baseline results (red-solid), as Figures A.6-A.9 show. Furthermore, the $t-$statistics as well show the same pattern as in Section 3.

5 Conclusion

The Great Recession has renewed the interest in the nexus between credit cycles and economic activity. One important finding is that credit developments can lead to vicious boom-bust cycles. That is, what starts with a stimulation of economic activity eventually results in economic downturn (e.g. Schularick and Taylor, 2012; Jordà et al., 2013). Another finding is that the boom-bust phases observed in the past four decades goes back to credit supply expansions (e.g. Mian et al., 2020; Justiniano et al., 2019). However, the research so far is limited to symmetric effects of credit supply developments. As pointed out by Barnichon et al. (2022), this may lead to somewhat counterintuitively lenient results. One reason is that originally differently operating shocks will eventually level out in a symmetric setup. This, as well as the theoretical literature that shows asymmetries (and non-linearities) in the response to financial shocks, raises the question, whether credit supply shocks cause asymmetric effects.

They do. Especially overall private debt, mortgage debt, debt:GDP, and house prices exhibit asymmetries in the response to credit supply shocks. In this respect, positive credit supply shocks tend to have stronger and more prolonged effects.

Furthermore, our results underpin the narrative of the boom-bust cycle in the presence of financial distortions which, again, is more pronounced in the presence of positive credit supply shocks. After an initial increase in economic activity (output, prices, investments, expenditures, and consumer credit) that lasts for five to ten quarters, the economy transits into a bust phase with a notable slowdown in economic activity. In contrast, negative credit supply shocks cause notably stronger deflationary pressure.

Looking at some surrogates of aggregate demand and aggregate supply, the boom-bust narrative is further confirmed, yet it does not explain the highly asymmetric and persistent response of overall debt, mortgage debt, and debt:GDP. However, even though this paper does not aim at tracing down the specific causes of asymmetries, we find that house prices, and thus the household-driven demand channel (e.g. Mian and Sufi, 2018) are key for the persistence in the response of mortgage debt and debt:GDP to credit supply shocks.

Lastly, if we abstract from asymmetries, we get relatively mild responses for debt and prices in the presence of credit supply shocks, such that the true effects tend to be underestimated.

However, we do not trace down the causes of asymmetries, which may be rooted in a variate of reasons: occasionally binding borrowing constraints, asymmetric information due to market imperfections, or behavioral biases, to name a few. We leave further going down the rabbit hole for future research.

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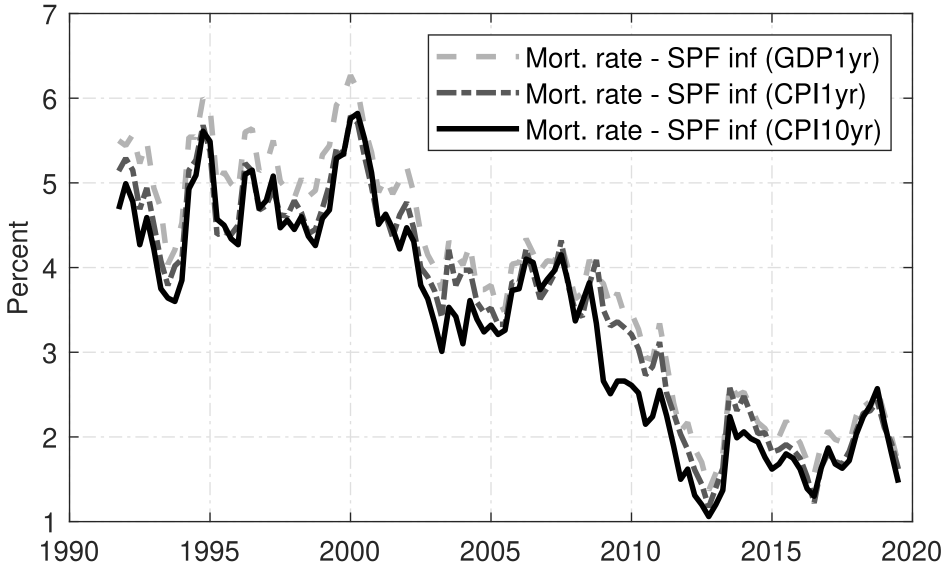
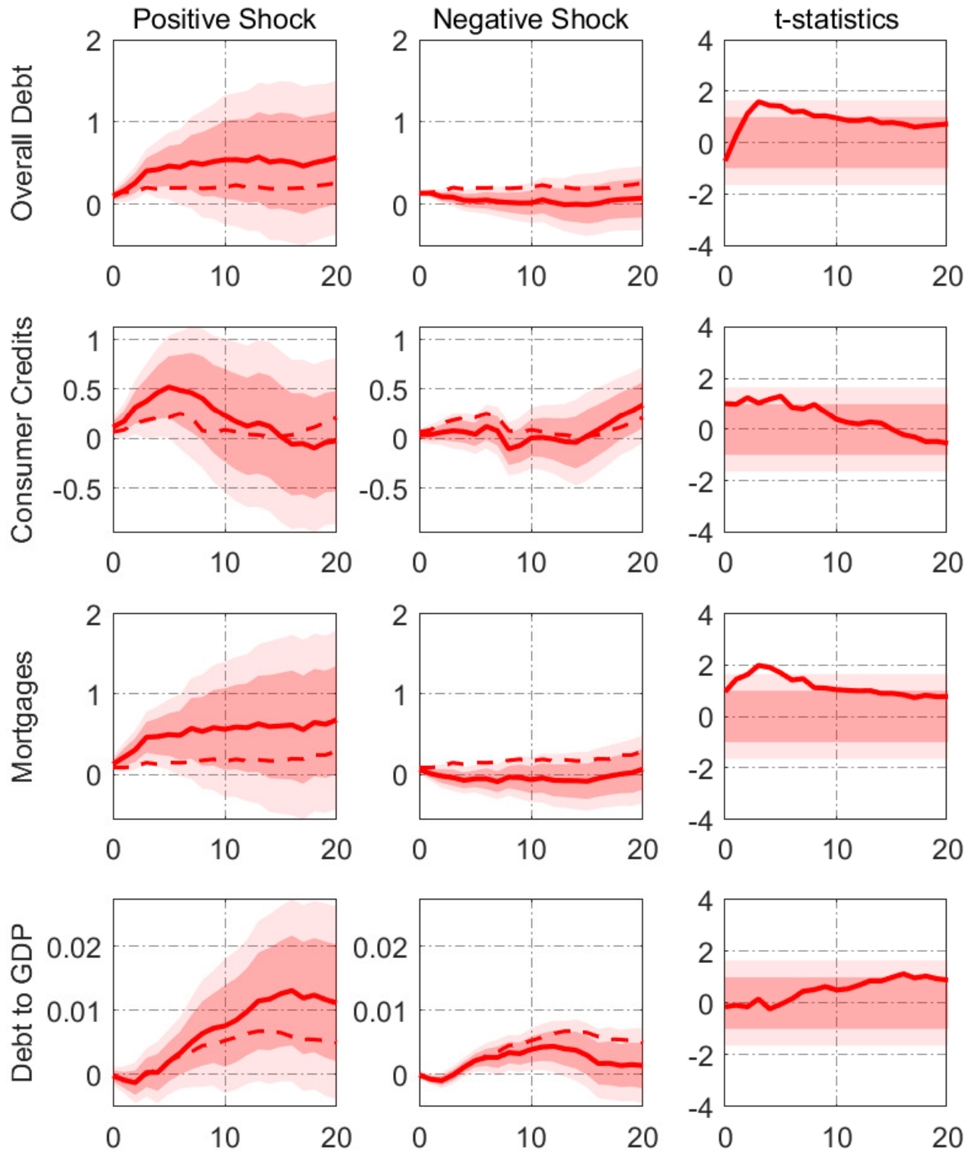
A Other Figures

Figure A.1: Real Mortgage Rates Over Time



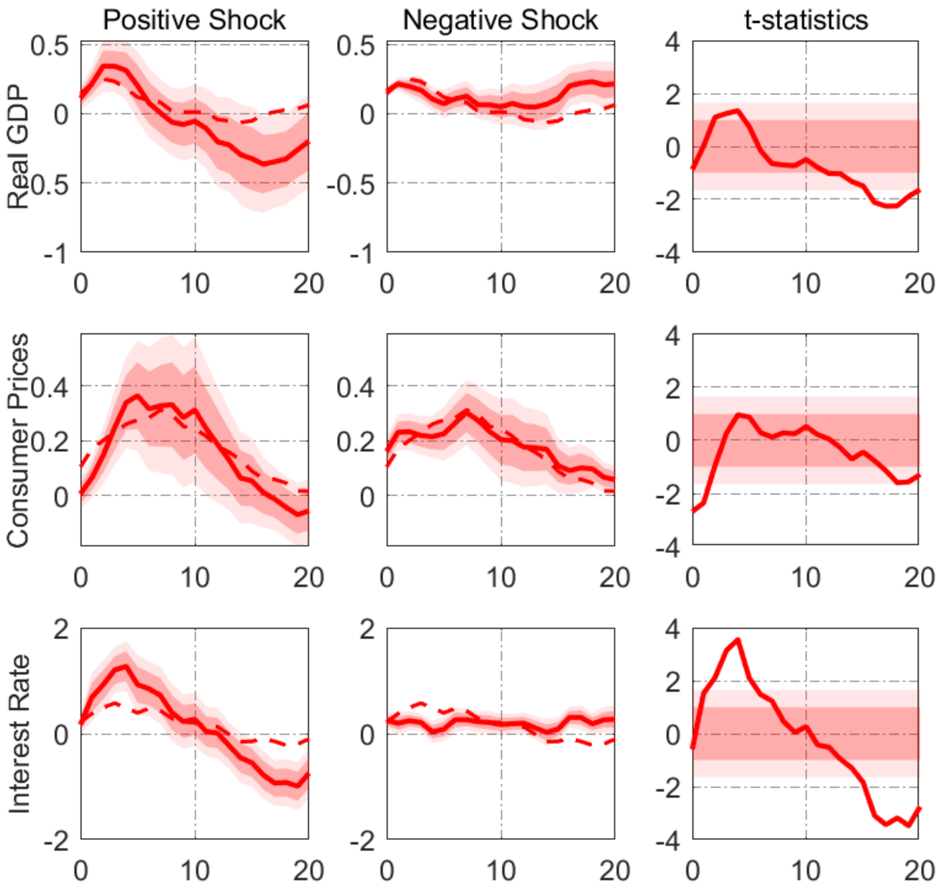
Notes: Real mortgage rate from 1990Q1 to 2019Q3 as the difference between the 30-year fixed mortgage rate and different measures of inflation expectations: GDP deflator-based one year-ahead inflation rate forecast (light grey-dotted), CPI-based one year-ahead inflation rate forecast (dark grey-dotted) and CPI-based 10 years-ahead inflation rate forecast (black-solid). The 30-year fixed mortgage rate is taken from the FRED, and the SPF forecasts are taken from the Philadelphia Fed.

Figure A.2: Impulse Response of Credit Volumes to Alternative Credit Supply Shock



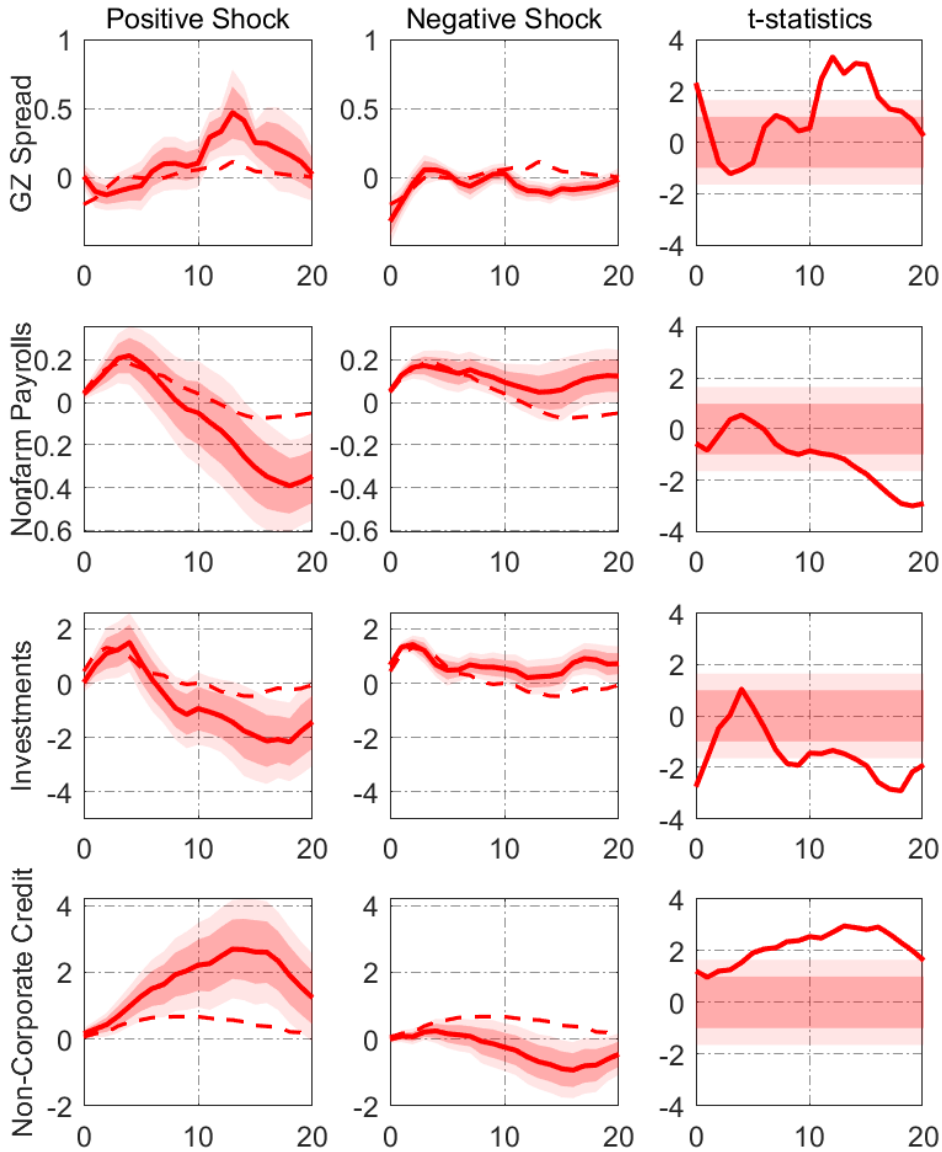
Notes: The first column shows the impulse response coefficients (red-solid) β_h^+ for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock from the proxy SVAR, the second column shows the impulse response coefficients (red-solid) β_h^- for a negative (one standard deviation) credit supply shock from the proxy SVAR. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval, relying on Driscoll-Kraay standard errors. The red-dotted lines in the first two columns show the impulse response coefficients β_h from a linear model without testing for asymmetric effects. The third column shows the $t-$statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the $t-$critical values for a 68 (90) percent confidence interval, i.e. ± 0.995 (± 1.645). The first row shows the response of overall debt volume (in percent), the second row the response of consumer credit volume (in percent), the third row the response of mortgage credit volume (in percent) and the fourth row shows the response of the share of debt:GDP (in percentage points).

Figure A.3: Impulse Responses of Headline Variables to Alternative Credit Supply Shock



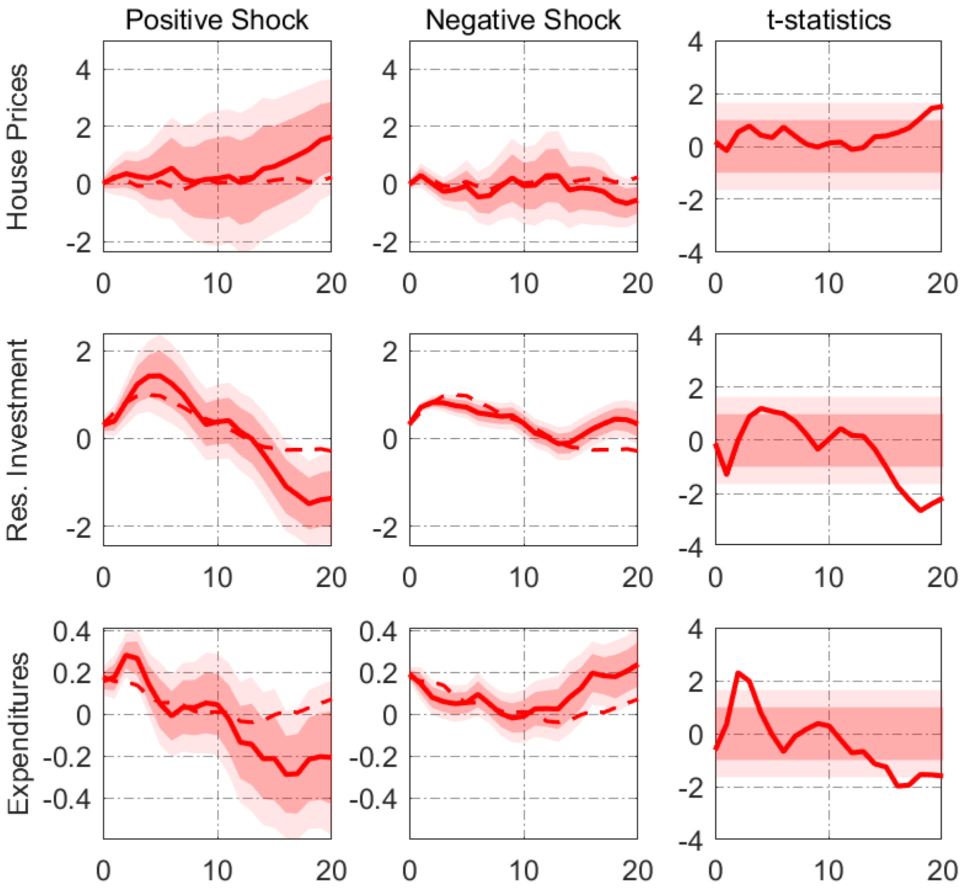
Notes: The first column shows the impulse response coefficients (red-solid) β_h^+ for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock from the proxy SVAR, the second column shows the impulse response coefficients (red-solid) β_h^- for a negative (one standard deviation) credit supply shock from the proxy SVAR. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval, relying on Driscoll-Kraay standard errors. The red-dotted lines in the first two columns show the impulse response coefficients β_h from a linear model without testing for asymmetric effects. The third column shows the t−statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t−critical values for a 68 (90) percent confidence interval, i.e. ±0.995 (±1.645). The first row shows the response of real GDP (in percent), the second row the response of consumer prices (in percent) and the third row shows the response of the effective federal funds rate (amended by the Wu-Xia shadow rate) in percentage points.

Figure A.4: Impulse Responses of Supply Side Variables to Alternative Credit Supply Shock



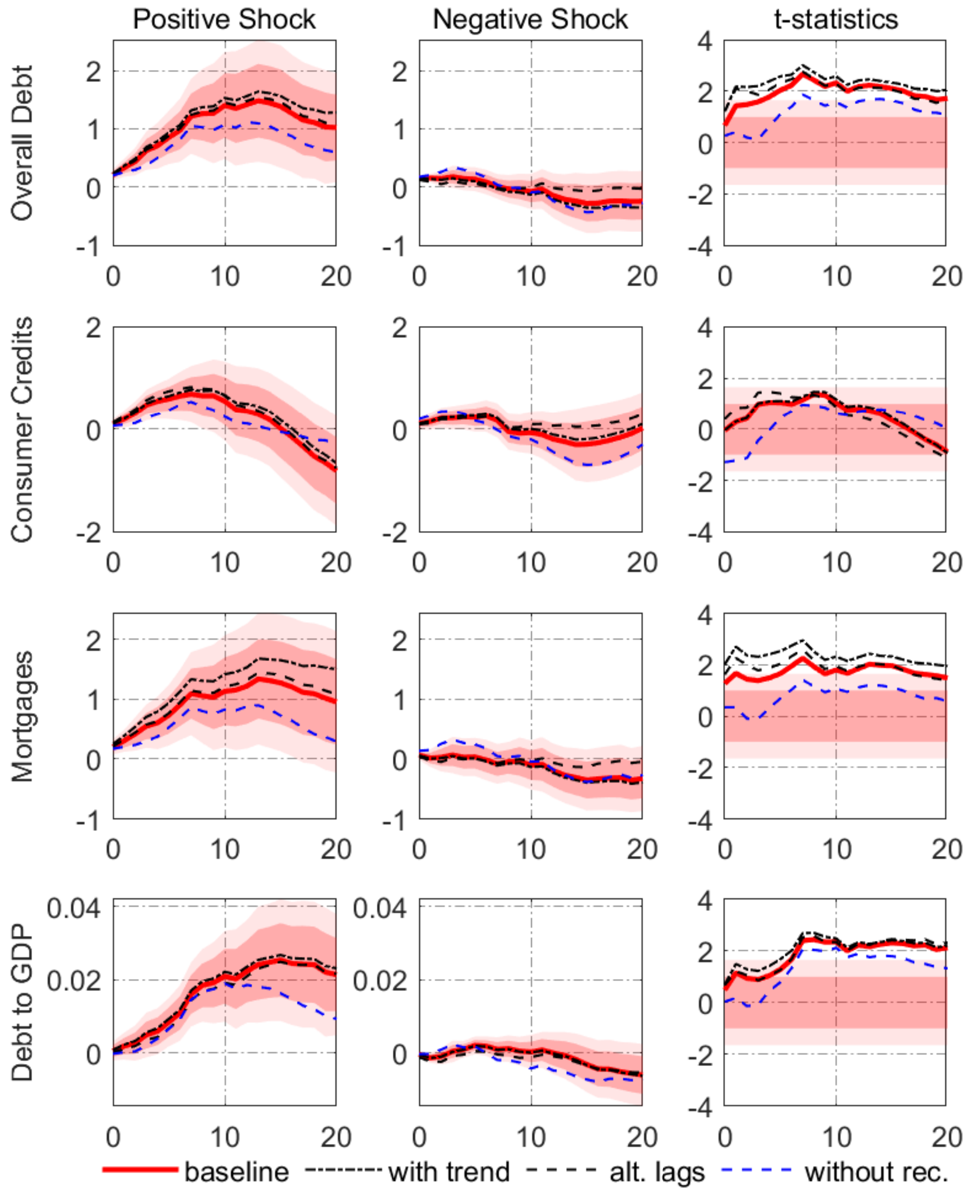
Notes: The first column shows the impulse response coefficients (red-solid) β_h^+ for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock from the proxy SVAR, the second column shows the impulse response coefficients (red-solid) β_h^- for a negative (one standard deviation) credit supply shock from the proxy SVAR. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval, relying on Driscoll-Kraay standard errors. The red-dotted lines in the first two columns show the impulse response coefficients β_h from a linear model without testing for asymmetric effects. The third column shows the t−statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t−critical values for a 68 (90) percent confidence interval, i.e. ±0.995 (±1.645). The first row shows the response of the Gilchrist and Zakrajšek (2012) spread (in percentage points), the second depicts the response of total non-farm payrolls (in percent), and the third shows the response of real investments (in percent).

Figure A.5: Impulse Responses of Demand Side Variables to Alternative Credit Supply Shock



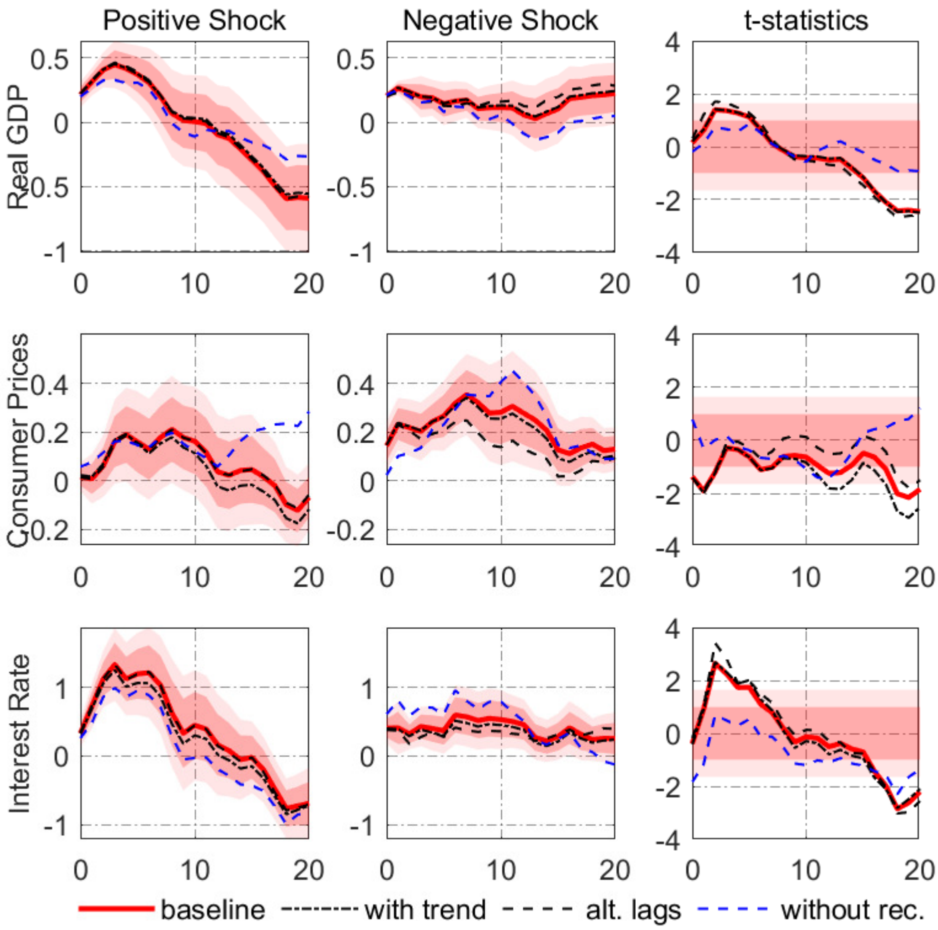
Notes: The first column shows the impulse response coefficients (red-solid) β_h^+ for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock from the proxy SVAR, the second column shows the impulse response coefficients (red-solid) β_h^- for a negative (one standard deviation) credit supply shock from the proxy SVAR. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval, relying on Driscoll-Kraay standard errors. The red-dotted lines in the first two columns show the impulse response coefficients β_h from a linear model without testing for asymmetric effects. The third column shows the t−statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t−critical values for a 68 (90) percent confidence interval, i.e. ±0.995 (±1.645). The first row shows the response of house prices (real Shiller index, in percent).The second row depicts real residential investments (in percent). The last row shows the response of real personal expenditures (in percent).

Figure A.6: Robustness Checks: Response of Credit Volumes



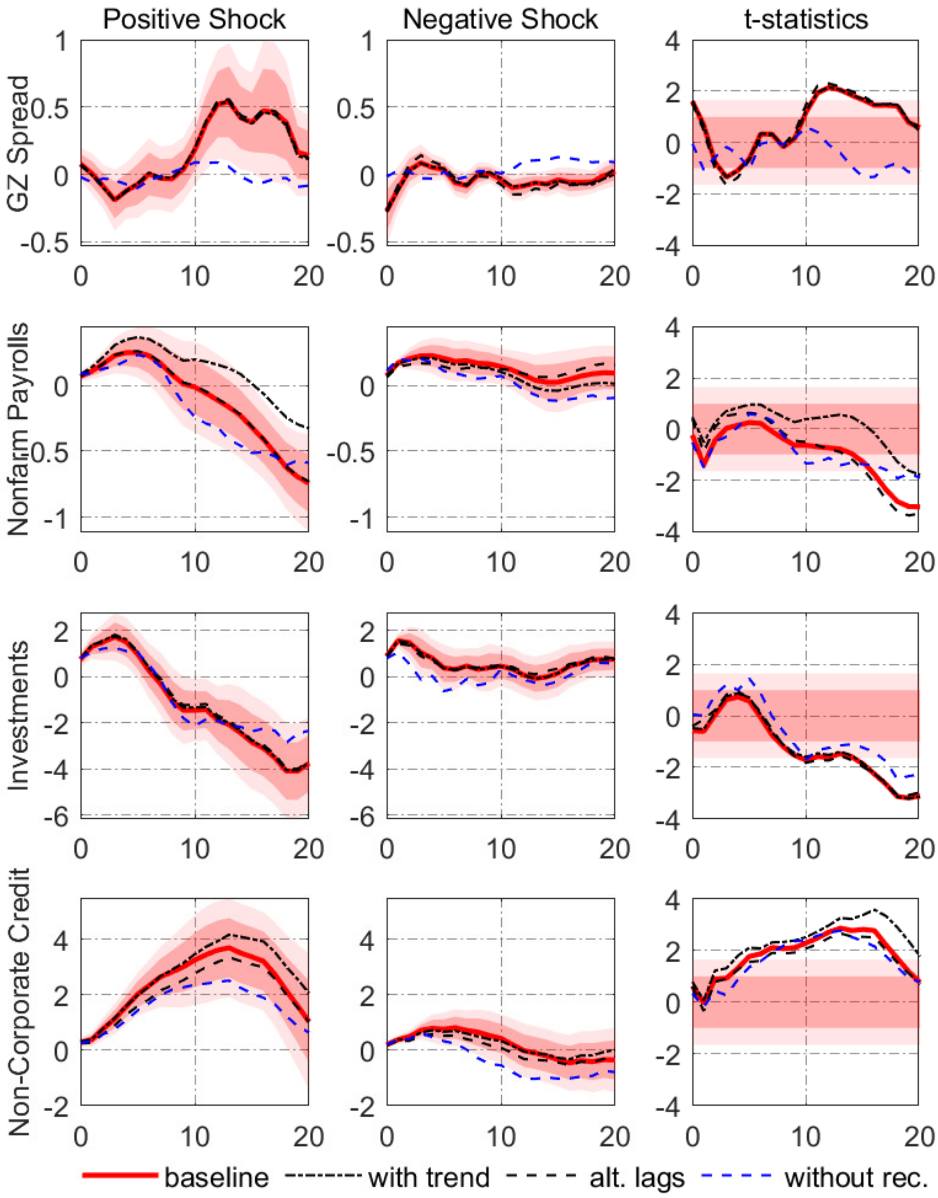
Notes: The first column shows the impulse response coefficients β_h^+ for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock from the baseline model (red-solid) alongside the impulse responses given alternative model specifications such as a model including a linear trend (black-dotted), a model with an alternative lag specification (black-dashed) as well as the results from an estimation of the baseline model, where the great recession has been excluded (blue-dashed). The second column shows the impulse response coefficients β_h^- for a negative (one standard deviation) credit supply shock. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval from the baseline model, relying on Driscoll-Kraay standard errors. The third column shows the corresponding t−statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t−critical values for a 68 (90) percent confidence interval, i.e. ±0.995 (±1.645), from the baseline model. The rows show, from top to bottom, the responses of of overall debt volume (in percent), the volume of consumer credit (in percent), the responses of mortgage credit volume (in percent), and the share of debt:GDP (in percent).

Figure A.7: Robustness Checks: Response of Headline Macro Variables



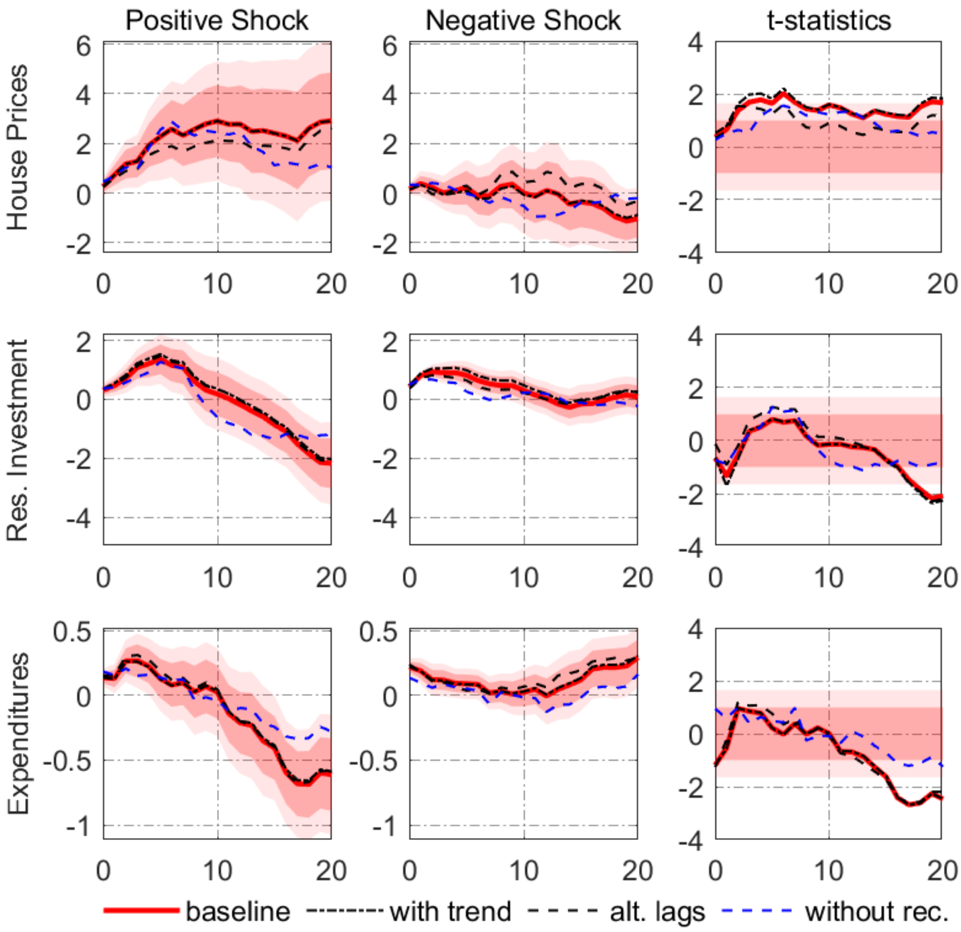
Notes: The first column shows the impulse response coefficients β_h^+ for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock from the baseline model (red-solid) alongside the impulse responses given alternative model specifications such as a model including a linear trend (black-dotted), a model with an alternative lag specification (black-dashed) as well as the results from an estimation of the baseline model, where the great recession has been excluded (blue-dashed). The second column shows the impulse response coefficients β_h^- for a negative (one standard deviation) credit supply shock. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval from the baseline model, relying on Driscoll-Kraay standard errors. The third column shows the corresponding $t-$statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the $t-$critical values for a 68 (90) percent confidence interval, i.e. ± 0.995 (± 1.645), from the baseline model. The first row shows the responses of real GDP (in percent).The second row depicts the responses of consumer prices (in percent). The last row shows the responses of the effective federal funds rate (amended by the Wu-Xia shadow rate (in percentage points).

Figure A.8: Robustness Checks: Supply Side Variables



Notes: The first column shows the impulse response coefficients β_h^+ for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock from the baseline model (red-solid) alongside the impulse responses given alternative model specifications such as a model including a linear trend (black-dotted), a model with an alternative lag specification (black-dashed) as well as the results from an estimation of the baseline model, where the great recession has been excluded (blue-dashed). The second column shows the impulse response coefficients β_h^- for a negative (one standard deviation) credit supply shock. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval from the baseline model, relying on Driscoll-Kraay standard errors. The third column shows the corresponding t−statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t−critical values for a 68 (90) percent confidence interval, i.e. ±0.995 (±1.645), from the baseline model. The first row shows the responses of the Gilchrist and Zakrajšek (2012) spread (in percentage points).The second row depicts the responses of total non-farm payrolls (in percent). The last row shows the responses of real investments (in percent).

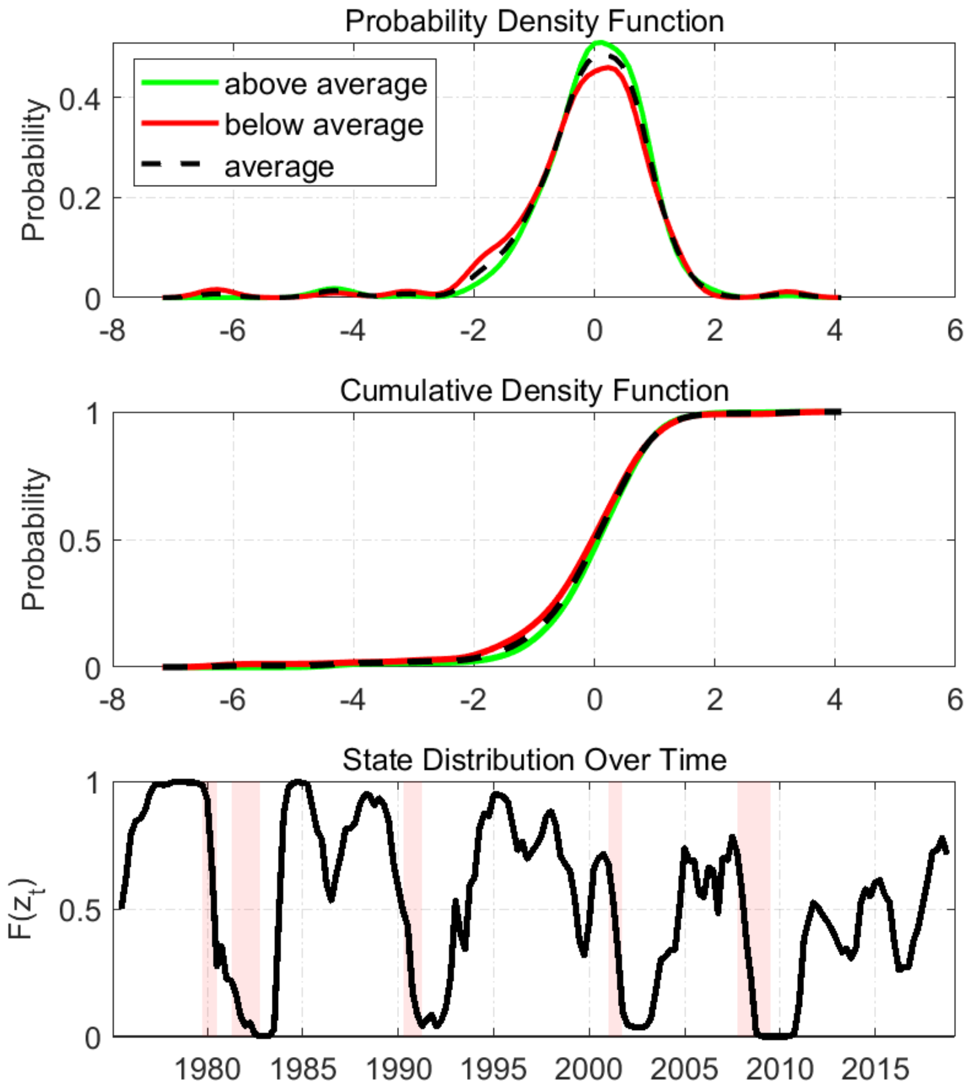
Figure A.9: Robustness Checks: Demand Side Variables



Notes: The first column shows the impulse response coefficients β_h^+ for $h = 0, ..., H$ for a positive (one standard deviation) credit supply shock from the baseline model (red-solid) alongside the impulse responses given alternative model specifications such as a model including a linear trend (black-dotted), a model with an alternative lag specification (black-dashed) as well as the results from an estimation of the baseline model, where the great recession has been excluded (blue-dashed). The second column shows the impulse response coefficients β_h^- for a negative (one standard deviation) credit supply shock. In both cases, the dark (pale) red-shaded area corresponds to the 68 (90) percent confidence interval from the baseline model, relying on Driscoll-Kraay standard errors. The third column shows the corresponding t−statistics testing the null that $H_0 : (\beta_h^+ - \beta_h^-) = 0$ for each horizon h using the Driscoll-Kraay method. The dark (pale) red-shaded area covers the t−critical values for a 68 (90) percent confidence interval, i.e. ±0.995 (±1.645), from the baseline model. The first row shows the responses of house prices (real Shiller index, in percent).The second row depicts real residential investments (in percent). The last row shows the responses of real personal expenditures (in percent).

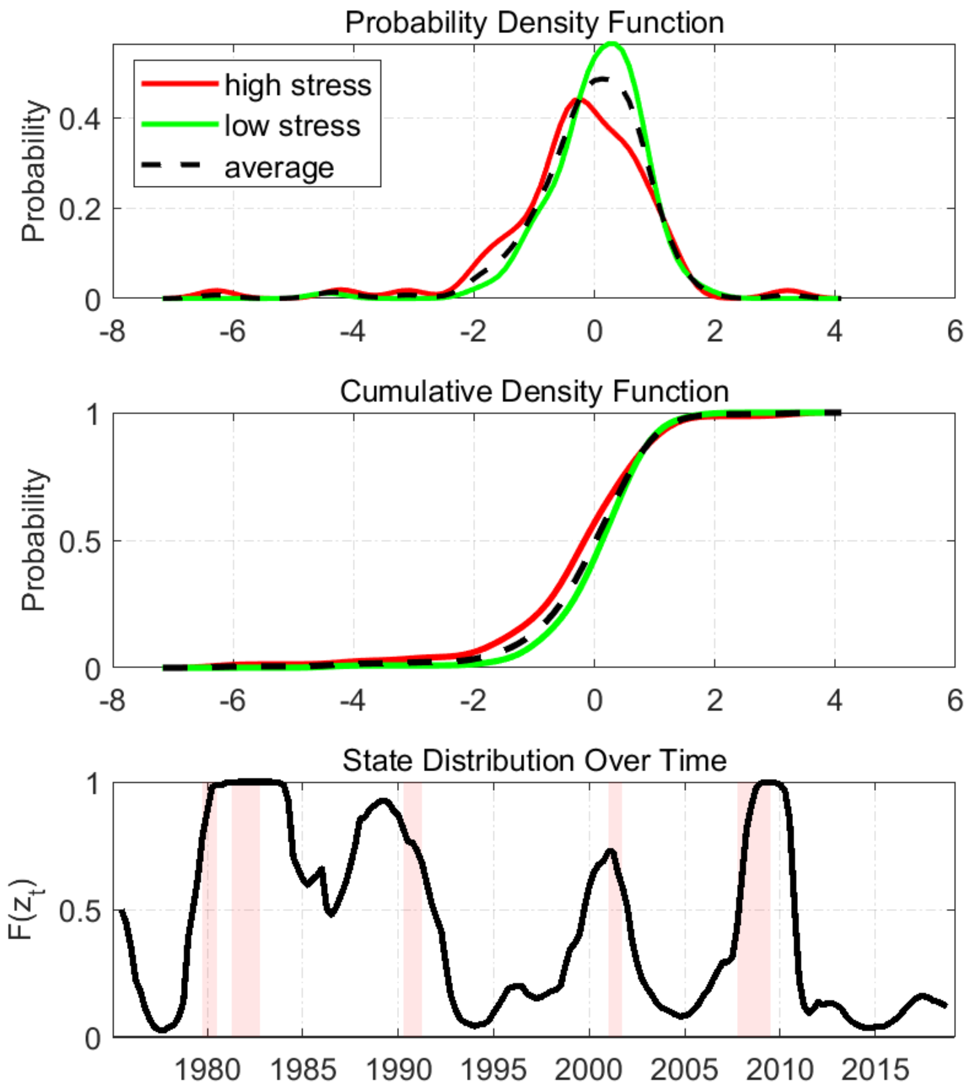
B State-Dependent Distributions of Shocks

Figure B.1: Estimated State-Dependent PDFs and CDFs | z_t : Output Gap



Notes: The state variable z_t is the output gap. The smoothed series relies on seven lags. The calibration is chosen to $\kappa = 3$ and $\mu = 0$. Red-shaded areas in the bottom panel show NBER recession dates.

Figure B.2: Estimated State-Dependent PDFs and CDFs | z_t : Adjusted CFNFCI



Notes: The state variable z_t is the adjusted Chicago Fed National Financial Conditions Index. The smoothed series relies on seven lags. The calibration is chosen to $\kappa = 3$ and $\mu = 0$. Red-shaded areas in the bottom panel show NBER recession dates.

Essay IV:

Loan Supply Shocks, Prudential Regulation, and the Business Cycle

This paper has been published as:

Rudel, Paul, "Loan supply shocks, prudential regulation, and the business cycle," *MAGKS Joint Discussion Paper Series in Economics*, 2024, No. 09-2024.

Acknowledgement

I thank Peter Tillmann and David Finck for fruitful comments and discussion. Katrin Luise Gärtner-Rudel also deserves great thanks in this regard. I would also like to thank David Finck for making his MATLAB toolbox for local projections available. Anisa Tiza-Mimun, Omar Omari, and Justin Berndt have contributed invaluable research assistance to this paper.

Loan Supply Shocks, Prudential Regulation, and the Business Cycle

Paul Rudel[†]

Abstract

How do the business cycle effects of loan supply shocks depend on the state of prudential regulation in the euro area? To address this question, we first identify regulatory cycles from a cumulative prudential policy index that tracks the evolution of the regulatory stance in the euro area. Using sign restrictions in a local projections framework with state-dependency, we identify loan supply shocks and analyse their business cycle effects in regimes with tight and loose prudential regulation. We find that in tight regimes, expansionary shocks trigger a boom-bust cycle. In the loose regime, results appear inconclusive. We also see quite some tendencies toward asymmetry in the responses across regimes. To some extent, however, the results depend strongly on the cycle identified. While our results for the tight regime are very robust across different specifications, the effect of shocks on the business cycle is sensitive to identified loose regimes. The main reason is the historical development of prudential regulation in the euro area, which is primarily characterized by prudential tightening.

Keywords: Prudential regulation, business cycle, loan supply, euro area, state dependence, local projections, sign restrictions.

JEL classification: C54, E32, E50, G28

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1 Introduction

Loan supply shocks unfold significant business cycle effects in the euro area, as documented by Barauskaitė et al. (2022), Mandler and Scharnagl (2020), Altavilla et al. (2019), Gilchrist and Mojon (2018), and Gambetti and Musso (2017), among others.

However, the economic effects of loan supply shocks can turn into a pernicious dynamic if they forge a path of excessive credit growth. The latter poses a serious threat to growth and financial stability, as shown in e.g. Sufi and Taylor (2022), Mian et al. (2017), Jordà et al. (2016), Jordà et al. (2013), and Schularick and Taylor (2012).

Prudential regulation has proven its usefulness in tackling these trends and strengthening the resilience of the financial system. For example, (macro-)prudential instruments can help reduce credit growth (i.a. Kim and Mehrotra, 2022, Jiménez et al., 2017, Akinci and Olmstead-Rumsey, 2018, Cerutti et al., 2017, and Fendoğlu, 2017), house price inflation (e.g. Kuttner and Shim, 2016 or Duca et al., 2021 and the extensive literature therein), or curb the credit cycle (i.a. Jiménez et al., 2017 or Fendoğlu, 2017).[1]

But how does prudential regulation interplay with the business cycle effects of loan supply shocks? Does the regulatory regime determine the economic effects of said disturbances? This paper addresses these questions. To this end, we apply state-dependent local projections which allow the identification of loan supply shocks by means of sign restrictions and analyse their effects on economic activity. In order to examine the role of prudential regulation, we consider different regulatory regimes.

Moreover, this approach allows us to investigate whether there are asymmetric effects with regard to regulatory regimes, as there are a number of factors that could explain possible asymmetry in the propagation of loan supply shocks across the state of prudential regulation.

First, as noted by De Schryder and Opitz (2021), it may be that tightening measures are design generally more restrictive than loosening measures are easing.[2]

Second, even if tight and loose measures are designed and used symmetrically, the

[1] Also the unsystematic elements of (macro-)prudential regulation can help combat undesirable developments by influencing credit growth (Budnik and Rünstler, 2023, Kim and Mehrotra, 2022, De Schryder and Opitz, 2021, Richter et al., 2019), house price inflation (Budnik and Rünstler, 2023, Bachmann and Rüth, 2020, Richter et al., 2019) or promoting financial stability (Fernandez-Gallardo, 2023, Hristov et al., 2021).

[2] Poghosyan (2020) finds asymmetric effects of loosening and tightening measures, with the former having a stronger effect on credit developments. Even though his approach also uses the MaPPED, the results are not necessarily transferable to ours for several reasons. Poghosyan (2020) uses a sample consisting of 28 EU countries, while focusing only on the role of lending restrictions in his analyzes. As a result of this limitation, only five euro area countries with loosening measures and nine euro area member states with tightening measures are represented in his sample. This means that part of the asymmetry may have been caused by country group-specific effects. This is also indicated by the fact that he finds contradictory effects of lending restrictions if he distinguishes between euro area countries and other EU member countries. For the latter, restrictions have the expected effect, while restrictive measures in euro area countries lead to an increase in loans. The author himself also points out that the contradictory results should be taken with a grain of salt and explains the results in particular with the incapability of the euro area member states to conduct individual monetary and exchange rate policies. We circumvent this problem by looking at the euro area as a whole.

timing and thus the existing regulatory environment at which they are implemented can lead to asymmetries if the marginal effects of prudential measures themselves are non-linear. Assume that the regulatory authority implements a tight measure at time t in the face of expansionary credit developments.[3] Irrespective of whether the general regulatory stance is loose or tight at that time, it will be relatively more restrictive in $t + 1$. However, if there are non-linear marginal effects of prudential policy measures, the additional tightening will have bigger consequences in an already tight regime than the same measure if it is introduced in a loose regime.

The banks' lending behaviour is another potential source of asymmetry. Rodano et al. (2018) examine how lending to small and medium enterprises (SME) changes over the credit cycle and, in particular, the role played by the credit ranking of the enterprises in Italy. The authors do not find any indications of a different allocation of loans to performing SME (i.e. SME with a good credit ranking) as against enterprises that are ranked sub-standard by banks in phases of a credit expansion. More specifically, both groups receive roughly the same amount of loans volumes. Credit terms also differ only marginally, as the interest rate differential for loans to sub-standard SME is only 20 basis points above the interest performing SME have to pay on their loans. However, this equal treatment changes in bust periods as banks' funding costs for wholesale funds deteriorate, thus rationing loans and excluding sub-standard SME. This adjusted allocation behaviour has real effects. In crises, the output of performing SME is just over 50% above the output of SME rated sub-standard. This is primarily due to the fact that performing SME can invest more in crises, as they are still able to get loans. Furthermore, downgrades of enterprises in the bust phase can also lead to a self-reinforcing downward spiral, as downgraded SME receive 39% less loans than SME, that have not been downgraded. This asymmetric lending behaviour can be triggered or may be further exacerbated by regulatory restrictions imposed on banks.

We find that loan supply shocks lead to boom-bust phases. In the first year after the shock materialises, there is an expanding business cycle. This effect is reversed in the following years. So far, this is nothing new. What is new, however, is that the boom-bust cycle is more pronounced in a tighter regulatory regime than in a comparatively looser regime. What's more, the bust-phase lasts longer in the loose regime. We observe that credit growth can follow a sustained positive growth path as a result of an expansionary loan supply shock. However, this effect is largely dependent on the underlying regulatory cycle, which distinguishes between loose and tight phases.

Furthermore, we do not find any clear patterns of asymmetry in the responses to the

[3] Kim and Mehrotra (2022) show in their panel analysis considering 32 advanced economies, that expansionary shocks to credit are in general met with macroprudential tightening measures. Boar et al. (2017) also report a strong response of macro-prudential policy to credit and output growth for 64 advanced and emerging economies.

shocks across regimes. This is also due to the fact that the impulse responses vary considerably depending on how the regulatory regime is identified. This is because loose regimes are more difficult to identify, as prudential regulation has followed a clear trajectory of tightening in the past. Consequently, the results for the tight regime turn out to be extremely robust.

The remainder of this paper is as follows. In Section 2, we calculate the cumulative prudential policy index, which quantifies the development of the regulatory stance in the euro area. The econometric model is described in Section 3. Section 4 is dedicated to the determination of regulatory regimes. In Section 5, we analyse the role of regulatory regimes on the effects of loan supply shocks on the business cycle and assess possible asymmetric effects. We run a number of robustness checks Section 6 before Section 7 concludes.

2 Prudential Policy in the Euro Area

We derive the evolution of prudential policy in the euro area from the Macroprudential Policy Evaluation Database.[4] It is the outcome of a standardized questionnaire that was completed by the national central banks and supervisory authorities and contains information about prudential policy actions taken in the European Union. Information concerning the character of a policy were categorized by the respondents as either i) *Macroprudential*, ii) *Macroprudential, Microprudential* or iii) *Macroprudential, Microprudential, Other*. For our analysis, we incorporate all responses from all three categories given by Eurozone member countries. This gives us a total of 370 prudential measures.[5]

In order to translate the 370 reported measures into an index that captures the stance of prudential policy in the euro area, we adopt the approach of Akinci and Olmstead-Rumsey (2018), among others, and proceed as follows.[6]

First, we code every reported measure into a balanced ternary on a country-quarter basis. The information on the effect of a measure stem from the MaPPED questionnaire, as the respondents were asked to indicate whether the reported policy was (intended as) a *policy tightening*, *policy loosening*, or something *other and with ambiguous impact*.[7] Consequently, measure m of category k in country i at time t is coded as +1 (−1) if it is a policy tightening

[4] As the detailed description of the MaPPED is out of scope of this paper, we refer the interested reader to Budnik and Kleibl (2018).

[5] The 370 observations break down by category as follows: 316 instances *Macroprudential*, one instance *Macroprudential, Microprudential*, and 53 instances *Macroprudential, Microprudential, Other*.

[6] This approach is also used by Kim and Mehrotra (2022), Hristov et al. (2021), and Cizel et al. (2019), for example.

[7] It should be noted that the response option *other and with ambiguous impact* itself introduces some degree of uncertainty into the index.

(loosening). Measures with an ambiguous effect are coded as zero, i.e.

$$m_{i,t}^{k} = \begin{cases} +1, \text{ if } & \textit{tightening} \\ -1, \text{ if } & \textit{loosening} \\ \ \ 0, \text{ if } & \textit{ambiguous}\ . \end{cases} \tag{2.1}$$

In the MaPPED, some measures are accompanied by information concerning their announcement period. In that cases, t refers to the announcement period. In all other cases, t relates to the period the measures came into force.

The inevitable flaw of this procedure, with which the existing literature has also to cope, is that all measures are weighted equally across both, instruments and time and thus have an identical impact on the index. This is because in most cases, information concerning prudential measures are stated in qualities, rather than quantities.

As a consequence, it is impossible to adequately weight measures not only within and across instruments, but also across time.[8] In addition, if non-linear effects arise from the use of different measures, they would not be accounted for by the approach here.

Summing the measures across categories $k = 1, \ldots, K$ results in the *country-specific prudential policy indicator*, which indicates prudential policy changes in country i and quarter t.[9] Formally,

$$PPI_{i,t} = \sum_{k=1}^{K} m_{i,t}^{k}\ . \tag{2.2}$$

Note that with this procedure, tightenings and loosenings which are introduced within the same quarter in a given country ultimately cancel out. Thus, an index of, say two, connotes that there have been *net* two more tightening measures introduced than loosening measures, no matter how many measures have been introduced in total.

In the second step, we weight the country-specific prudential policy indicators by the relative contribution that a member country has made to total GDP of the euro area at a

[8] However, there exists literature that quantifies prudential measures, yet incorporates loan-to-value (LTV) ratios only. See Richter et al. (2019) or Bachmann and Rüth (2020). Meuleman and Vander Vennet (2020) map the life cycle of a measure with weightings depending on the extent to which the measure is adapted (activation or deactivation of a tool, change in scope or level of an existing tool, maintenance of the existing scope or level of a tool). However, the weights are arbitrary. Also, the different measures are not contrasted with corresponding weights.

[9] Our sample includes a total of $K = 10$ categories reaching from capital-based measures such as capital buffers or risk weights, to borrower-based measures such as caps on LTV or DTI ratios, as well as liquidity-based measures such as asset-based reserve requirements or caps on short- and long-term maturity.

given quarter t in order to get the *GDP-weighted euro area prudential policy indicator*, i.e.

$$PPI_{EA,t} = \sum_{i=1}^{N} \omega_{i,t} PPI_{i,t} \ . \tag{2.3}$$

The constructed indicator shows net changes in the regulatory environment in the euro area.[10]

In the last step, we cumulate the prudential policy indicator across time, i.e.

$$cPP_t = \sum_{s=0}^{s=t} PPI_{EA,t} \ . \tag{2.4}$$

The resulting *cumulative Prudential Policy-Index* is a proxy for the prudential policy stance and captures prudential effects, which impact can extend far beyond the period in which they were introduced. However, as will be shown in the later part of the paper, we are eventually interested in the trend component of the index, so its level plays a minor role for our purposes.

Figure 1 illustrates the GDP-weighted euro area prudential policy indicator PPI_{EA} (bottom panel) as well as the resulting cumulative Prudential Policy-Index cPP (upper panel). Between 1995 and 2018, prudential policy in the euro area became substantially tight, which can be divided into three phases. Firstly, the prudential policy stance became tighter before the millennium. This was partly due to spillover effects of the Russian and Asian crisis in 1997/1998, which led to prudential tightening. Secondly, in the years before the outbreak of the Great Financial Crisis, prudential policy in the euro area remained on a constant level. Finally, the outburst of the Financial Crisis in 2007, however, ushered in a period of steady tightening, which lasted until the end of 2014. After some loosening measures in mid-2015 and early 2016, the prudential policy stance in the euro area moved at a stable, but historically high level.[11]

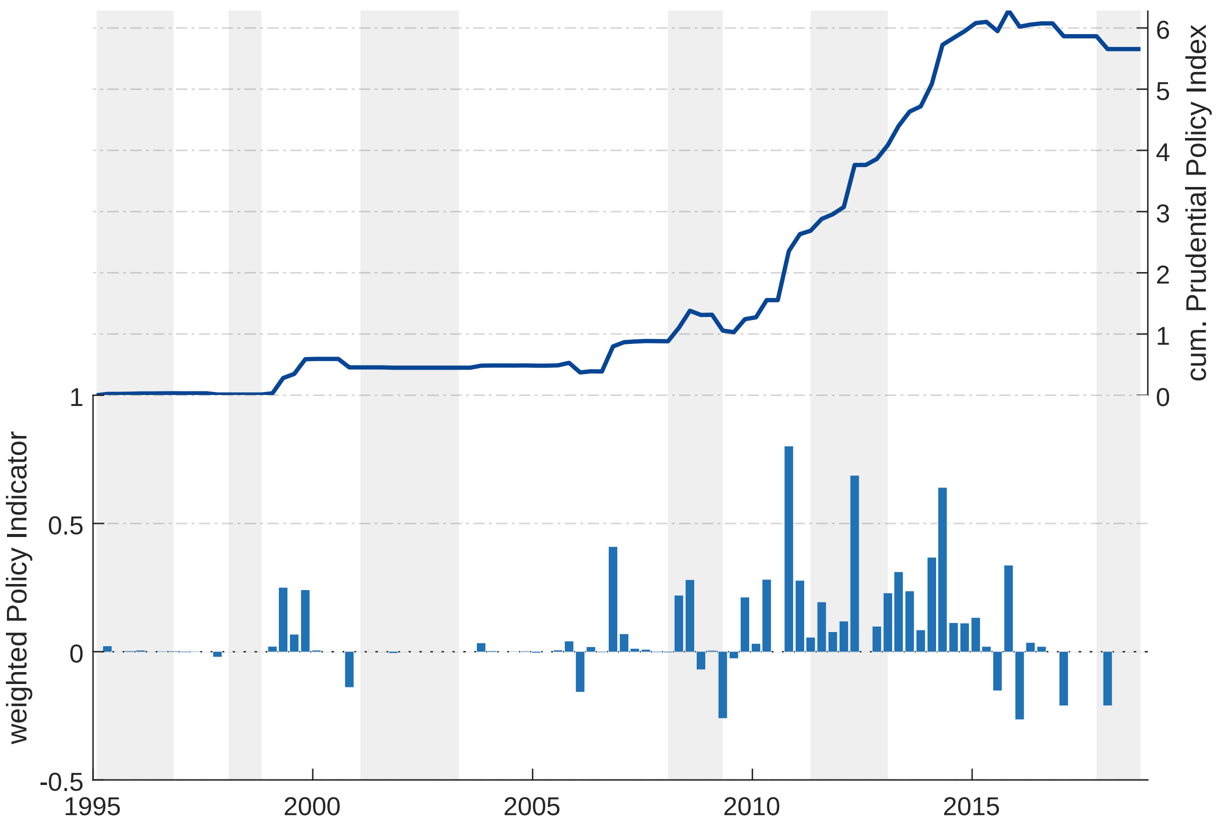
3 Econometric Methodology

Local projections (LPs), as proposed by Jordà (2005), are a widely used and highly flexible analysis tool. For example, they are more robust against misspecification at finite lag lengths, since possible errors are not carried along over the entire projection horizon as is

[10] In robustness Section 6.2, we use the weighting on the basis of the relative amount of nominal outstanding loans. The biggest obstacle here is that the data is generally only starts from 2003 at the earliest. Reliable figures are thus available for a much shorter observation period. Therefore, we use weights based on GDP as our baseline specification. However, this may lead to changes in the index solely as a result of changes in the relative country weights. In another robustness exercise in Section 6.3 we therefore examine whether our results change when we use an unweighted index. As will be seen later, this does not alter our results.

[11] For a extensive description of macroprudential policy in Europe, see Budnik and Kleibl (2018).

Figure 1: GDP-weighted Prudential Policy



Note: Evolution of the policy stance (upper panel) and its quarterly net changes (lower panel). Negative values indicate net loosenings, while positive values show net tightenings. Grey bars mark OECD based recession indicators.

the case within VARs, where impulse responses are generated iteratively. In LPs, on the other hand, the reduced-form coefficients are estimated separately. In the end, however, they are merely different projection techniques. Plagborg-Møller and Wolf (2021) show that in an infinite sample with unrestricted lag structure, VARs and LPs estimate identical impulse responses. Thus, they allow identification of structural shocks i.a. by means of sign restrictions. Moreover, they are suitable for analyses of non-linear effects, as used by Tenreyro and Thwaites (2016), Ramey and Zubairy (2018) or Finck and Rudel (2022), or a combination of both, as applied by Alpanda et al. (2021) or Finck et al. (2023).[12]

In general, the idea of local projections is to perform a series of regressions for each horizon, h, and each variable of interest, i, from a set of variables, y_t, on a set of controls. The linear model can be formulated as

$$y_{i,t+h} = \alpha_{i,h} + \boldsymbol{\beta}_{i,h} y_t' + \boldsymbol{\gamma}_{i,h} x_t' + u_{i,h,t} \ , \tag{3.1}$$

[12]Methodologically, we follow Finck et al. (2023), who examine the role of a flexible exchange rate for the propagation of negative domestic demand shocks between different monetary regimes. Hence, we mainly rely on their notation in the following.

where $y_{i,t+h}$ denotes the i-th endogenous variable in the $n \times 1$ vector y_t at time $t+h$. The constants are collected in $\boldsymbol{\alpha}_h$, while $\boldsymbol{\beta}_{i,h}$ and $\boldsymbol{\gamma}_{i,h}$ capture the projection coefficients for the controls in y_t and x_t, respectively. Impulse responses are constructed as a sequence of the coefficients $\boldsymbol{\beta}_{i,h}$ for horizons $h = 0, \dots, H$. The result is the response of y_i at time $t+h$ to a structural shock that hits the economy at time t. The $n \times p$ vector $\boldsymbol{\gamma}_{i,h} = \left[\phi_{i,h,1}, \dots, \phi_{n,h,1}, \phi_{i,h,2}, \dots, \phi_{n,h,2}, \dots, \delta_{n,h,p}\right]$ collects the coefficients for the covariates in $x_t = \left[y_{t-1}, \dots, y_{t-p}, 1\right]$, i.e. the p lags of y_t. Finally, the projection residual of the i-th variable at horizon h in t is denoted by $u_{i,h,t}$ and has a (strictly) positive variance.

A. *Specification of State-Dependent Local Projections with Sign Restrictions*

The non-linear, state-dependent extension of the linear model can be written as

$$\begin{aligned} y_{i,t+h} = (1 - S_t)\left[\alpha_{i,h}^{tight} + \beta_{i,h}^{tight} y_t' + \gamma_{i,h}^{tight} x_t'\right] \\ + S_t\left[\alpha_{i,h}^{loose} + \beta_{i,h}^{loose} y_t' + \gamma_{i,h}^{loose} x_t'\right] + u_{i,h,t}\ , \end{aligned} \tag{3.2}$$

where S_t is a state variable which will be introduced in Section 4.

In this exercise, $\beta_{i,h}^{R}$ captures the average effect of a structural shock across regimes $R = \{tight, loose\}$. It not only captures the effect within a specific regime at the time the shock hits the economy, but also takes into account the effects of regimes changes, which may occur across the projections horizons, since the effects of a shock in period $h = 0, \dots, H$ are estimated sequentially.

B. *Inference*

Plagborg-Møller and Wolf (2021) show that the local projections coefficients correspond to the reduced-form impulse responses of y_t to the Wold innovations $e_t = y_t - E\left(y_t | \{y_\tau\}_{\tau<t}\right)$ from a VAR for horizon h. Moreover, the LP residuals $(u_{1,1,t}, ... u_{n,1,t})$ correspond to those same innovations. Consequently, the variance-covariance matrix estimated by local projections contains the same information as the variance-covariance matrix from a VAR. Thus, sign and zero restrictions can be implemented within local projections.[13]

Sign and zero restrictions are implemented by first, estimating the model for each $h = 0, \dots, H$ and storing the resulting, state-dependent coefficients in $C_h^R = \left[\beta_{1,h}^R, \beta_{2,h}^R, \dots, \beta_{n,h}^R\right]$. We perform bias correction on the (bootstrapped) estimators, as LP estimates in small samples can be severely biased, as Kilian and Kim (2011) and Herbst and Johannsen (2024) show. Plagborg-Møller and Wolf (2021) demonstrate that structural

[13] Further feasible identification schemes are long-rung restrictions a la Blanchard and Quah (1989) or narrative sign restrictions as in Antolín-Díaz and Rubio-Ramírez (2018).

impulse responses for horizon h can be computed as

$$\Theta_h^R\left(Q, C_h^R, f(\Sigma)\right) = C_h^R f(\Sigma) Q \; .$$

That is, they are a function of the stored LP coefficients as well as $f(\Sigma)$, the lower triangular Cholesky factor of Σ, which denotes the variance-covariance matrix of the one step ahead projection residuals, where $Var\left(u_{1,1,t}, \ldots u_{n,1,t}\right) = f(\Sigma) f(\Sigma)'$. The remaining ingredient is an orthogonal matrix Q, where $QQ' = Q'Q = I_n$.

Sign and zero restrictions on the impulse response of variable i at horizon h then can be implemented by randomly drawing Q as in Arias et al. (2018). Permissible draws must meet

$$\mathbf{S_k} \boldsymbol{\Theta}^R\left(Q, C^R, f(\Sigma)\right) e_k \geq 0$$
$$\mathbf{Z_k} \boldsymbol{\Theta}^R\left(Q, C^R, f(\Sigma)\right) e_k = 0 \; .$$

Note that Q is retained only if it meets the restrictions in both regimes. For example, if all restrictions are met in one regime, but at least one is not satisfied in the other, Q is discarded. The $n(H+1) \times n$ matrices $\boldsymbol{\Theta}^R = \left[\Theta_0'^R \, \Theta_1'^R \, \ldots \, \Theta_H'^R\right]$ contain the stacked state-dependent impulse response coefficients. The $n(H+1) \times n(H+1)$ matrices $\mathbf{S_k}$ and $\mathbf{Z_k}$ are constructed as in Rubio-Ramirez et al. (2010) with e_k being the k-th column of the identity matrix I_n.[14]

Finally, inference on the impulse responses is based on percentiles of the permissible draws. Note that the resulting confidence bands do not display estimation uncertainty of the individual draws, but rather describe the distribution of the models, that satisfy the sign and zero restrictions.

C. *Data*

Our sample spans from 1995Q1 to 2018Q4, the period for which detailed information on prudential policies in Europe is available in the MaPPED. We consider the euro area as a single entity. This is helpful for our analyses in that we can more conveniently take into account the common monetary policy in our estimates.

In the baseline case, we estimate a model with $p = 2$ lags. The vector y_t consists of $n = 5$ variables, namely, real GDP growth, annual growth of nominal loan volumes, the inflation rate, a shadow short rate, as well as a composite lending rate.

We compute year-on-year growth rates of real GDP, nominal loans, and the Harmonized Index of Consumer Prices (HICP), all taken from the ECB data portal. As the HICP is only available from 1997Q1, we extend it backwards to 1995Q1 using the `HICP` time series from

[14] Although we do not use equality restrictions in our model, we nevertheless present their computation for the sake of completeness.

the area wide model (AWM) database. Loan volumes are constructed as the sum of nominal outstanding amounts of banks' loans to households and non-financial corporations.

The short-term interest and the composite lending rate enter the model in levels. In order to account for the unconventional policy measures taken by the European Central Bank in the aftermath of the Great Financial Crisis and European debt crisis, we rely on the shadow short rate as proposed in and provided by Wu and Xia (2016) from 2004Q4 onward. The shadow rate is extended backwards to 1995Q1 by using the change in the EONIA.

Finally, the lending rate is derived as the weighted average of interest rates claimed on loans to households and non-financial corporations with weights based on the respective outstanding amounts. As data on bank interest rates are only available from 2003Q1 onward, we backward extend the series with changes in the composite lending rate from Gambetti and Musso (2017).[15]

D. *Identification of Loan Supply Shocks*

As our analyses focus on the propagation of loan supply shocks across regulatory regimes in the euro area, we require a well established procedure to identify appropriate loan supply shocks. Thus, we rely on the identification scheme proposed by Gambetti and Musso (2017), which has been also applied by, e.g. Barauskaitė et al. (2022), Mandler and Scharnagl (2020), or Bijsterbosch and Falagiarda (2015), among others. The identification scheme is based on the dynamics observed in well-established DSGE models. The underlying causes of the disruptions can have a variety of reasons, such as shocks to bank's reserve demand, bank's loss rate or bank's net worth.[16] In short, loan supply shocks cause real GDP growth, inflation, the short-term interest rate, and growth in loan volumes to move in the same direction while the lending rate has an opposite sign.

The identification scheme is shown in Table 1.

Table 1: Sign Restrictions of a Loan Supply Shock

Shock	GDP Growth	Inflation	(Shadow) Short Rate	Lending Rate	Loan Growth
Loan Supply	+	+	+	–	+

Notes: Identification scheme for expansionary loan supply shocks. The identifying assumptions are imposed on impact, where '+' means an increase and '–' a decrease in the underlying variable.

We now have most of the ingredients for our analysis. What is left is an indicator S_t, which determines the regulatory regime.

[15] For an extensive description of their composition of the lending rate as well as the respective sources, we refer the interested reader to the supplementary material (jae2537-sup-0002-Supplementary2.pdf) accompanying Gambetti and Musso (2017).

[16] For a detailed overview of the models considered, see Table II in Gambetti and Musso (2017).

4 Determining Regulatory Regimes

The cumulative prudential policy index derived and described in Section 2 contains information on the regulatory stance. That is, it tells us about the regulatory package that is in effect at a given time. In this form, however, no conclusions can be drawn from this as to whether the existing regulatory regime is above or below average.

We therefore decompose the *cPP*-Index into its regulatory trend and cycle using the Hodrick-Prescott filter. This approach requires the choice of a smoothing parameter λ^{HP} that determines the penalization of deviations from the trend. When the smoothness penalty goes to 0, the extracted trend becomes the actual time series. At the other end of the scale, a linear time trend is extracted.[17] While apt values to identify the business cycle have been extensively studied and discussed, there is a lack of an appropriate value to extract a faithful prudential cycle. In order to overcome this gap, we rely on the literature concerning financial cycles.

A. *Prudential Policy and Financial Cycles*

Macroprudential regulation is closely linked to financial cycles. The goal of macroprudential policies is to prevent the build-up of financial imbalances and financial risk. Borio (2014) argues that, in doing so, macroprudential policy should focus on limiting the potential for damage caused by financial instability and hereby address the pro-cyclicality of the financial system head-on. The reason is that peaks in the financial cycle are closely associated with systemic banking crises (e.g. Drehmann et al., 2012; Aikman et al., 2015; Bauer and Granziera, 2017) or financial crisis recessions (e.g. Gourinchas and Obstfeld, 2012; Schularick and Taylor, 2012, among others).

However, a clear value for the smoothing parameter λ^{HP} to extract the financial cycle does not exist and differs depending on the point of view. From a regulatory perspective, the Basel Committee on Banking Supervision (BCBS) recommends in its 2010 "Guidance for national authorities operating the countercyclical capital buffer" to tie the counter-cyclical capital buffer to the credit:GDP-gap, which in turn serves as an indicator for the financial cycle. In order to compute the credit:GDP-gap, the BCBS applies a real-time (one-sided) Hodrick-Prescott filter with smoothing parameter $\lambda^{HP} = 400,000$ on the credit:GDP-ratio. Moreover, the credit:GDP-gap derived in this way has proven to be a reliable leading indicator for financial crises, as Drehmann et al. (2011), Detken et al. (2014), Drehmann and Yetman (2018), or Galán (2019) show.

On the other hand, this value implies a duration of the financial cycle of 30 years, which

[17] Hamilton (2018) discusses the shortcomings of the HP-Filter and offers a much-noticed alternative which is not suitable for our application due to a lack of observations.

turns out not to be valid for the euro area. For example, Galati et al. (2016) find the financial cycle for the euro area big-five to vary between ten (Germany and Netherlands), 14 (Italy) and 15 (France and Spain) years. Schüler et al. (2020) and Rünstler and Vlekke (2018) report similar durations for some selected member countries. Taking 17 euro area countries into account, Rünstler et al. (2018) also point to rather medium-term cycles of 13 years, on average. The empirical literature on the duration of financial cycles in the euro area thus implies much lower values for the smoothing parameter. Following Ravn and Uhlig (2002), the smoothing parameter for the financial cycle can be expressed as a function of the length of the business cycle according to

$$\lambda^{HP} = \mathrm{m}^4 \times 1600\,,$$

where m is the multiple of the business cycle duration. Given quarterly data, a standard value of $\lambda = 1,600$ implies a business cycle duration of 7.5 years, which is reasonable for many advanced economies. The financial cycle in the euro area is estimated to be approximately twice as long. Thus, $m = 2$ and the smoothing parameter becomes

$$\lambda^{HP} = 2^4 \times 1600 = 25,600\,.$$

Taken together, a variety of plausible values thus come into question for determining the financial cycle. We take an agnostic approach and extract different regulatory cycles setting the smoothing parameter to

$$\lambda^{RC} = \{25.6, 100, 200, 300, 400\} \times 1000\,.$$

This also serves as a robustness analysis, as it allows us to determine the sensitivity of our results to the choice of the parameter value.

Since regulators make their decisions on the information available at the time of the decision, applying the two-sided HP filter, which uses the entire sample — including future observations — would be corrupted. We therefore use the real-time version of the Hodrick-Prescott filter.

Simply applying λ^{RC} from a two-sided HP filter on the the real-time version harbors distortions. Wolf et al. (2020) show that for a given value of the smoothing parameter, the one-sided HP filter dampens high frequency fluctuations to a greater extend than the two-sided version. That is, it increasingly filters the desired fluctuations with lower values of λ^{RC} and thus, higher frequencies of the cycle. We therefore apply their proposed adjusted one-sided HP filter that overcomes this issue.[18]

Figure 2 shows the resulting regulatory cycles, depending on the underlying value of the smoothing parameter.[19]

A positive value implies that the actual regulatory stance is above its long-term trend. This means that prudential regulation is tighter than average in a historical context, and vice versa.

Up to 2011, the different λ^{RC} identify an almost identical cycle. From 2011 onward, however, three differences emerge, depending on the assumed frequency for the regulatory cycle. First, the higher the frequency, and thus the lower the value of λ^{RC}, the shorter the phase of comparatively tight regulation that begins in 2011. Secondly, the historical extent of the tightening is assessed differently. When the frequency of the regulatory cycle is high, the GDP-weighted cPP-Index is at most one point above its long-term trend in the years between 2011 and 2015. If the frequency is slowed down, the difference rises to more than two points. This means that the historical extent of tightening changes noticeably. Third, with higher frequency, a phase of relative easing is reached sooner.

The extracted cycles form the basis for analysing state-dependent effects, as they are the indicator variable for calculating a transition function.

B. *Smooth Regime Transition*

In order to allow for smooth transitions between the regulatory regimes, we follow Granger and Teräsvirta (1993) and compute the state variable S as a logistic transition function of the form

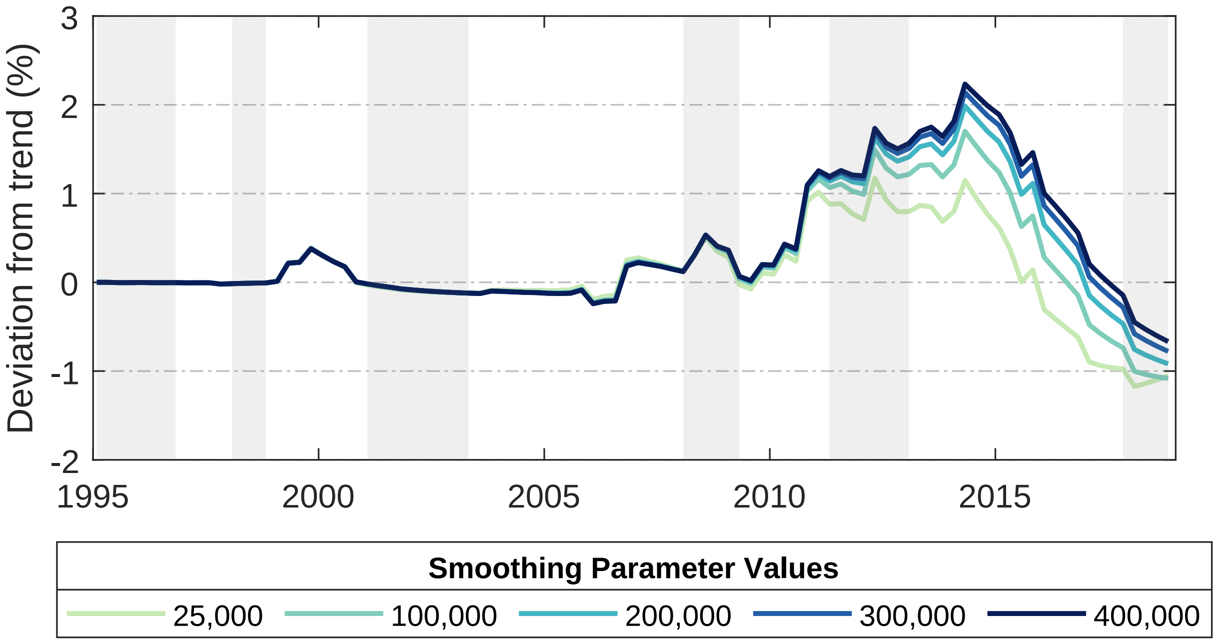
$$S\left(rc_{t-1}\right) = \frac{\exp\left(\kappa \frac{rc_{t-1}-\mu}{\sigma_{rc}}\right)}{1+\exp\left(\kappa \frac{rc_{t-1}-\mu}{\sigma_{rc}}\right)} \in [0,1]\,. \tag{4.1}$$

Thus, S is a smooth increasing function of the indicator variable rc, the regulatory cycle with underlying parameter value $\{25.6, 100, 200, 300, 400\} \times 1000$. We use the lagged value of the indicator variable in order to avoid endogeneity between the loan supply shock and the regulatory regime. The main reason is that a loan supply shock can alter the prudential

[18] For example, a desired cycle from $\lambda = 25{,}600$ corresponds in their approach to set $\lambda = 10{,}427.7$ and additionally scale the extracted cyclical component by a factor of 1.073.

[19] In order to validate our statement mentioned at the beginning regarding the relationship between prudential policy making and the financial cycle, we also looked at the leading and lagging properties of the regulatory cycle and the financial cycle in relation to each other. We calculated the latter as the cyclical component of the debt:GDP-ratio using a HP filter with $\lambda = 400{,}000$. Our analyses show that the regulatory cycle and the financial cycle interact as expected. We measure a high positive correlation between the current state of the financial cycle and future realizations of the regulatory cycle. That is, if the economy is in a state of credit expansion (debt:GDP-ratio is above its long-term trend), prudential regulation in the future will also be disproportionately tight, i.e. above its long-term trend. We also find a high negative correlation between the current regulatory cycle and the future debt:GDP-gap.

Figure 2: Regulatory Cycles



Notes: Cycles from the GDP-weighted cumulative Prudential Policy-Index extracted using the one-sided HP-filter. The cycles vary depending on the value of the underlying smoothing parameter. Grey bars mark OECD based recession indicators for the euro area.

landscape. For example, if the dynamics caused by the loan supply shock lead to changes to capital requirements or the loan-to-value ratios applicable to enterprises and households. Such regulatory adjustments would clearly be captured by the state variable which, in turn, inevitably results in endogeneity problems.[20]

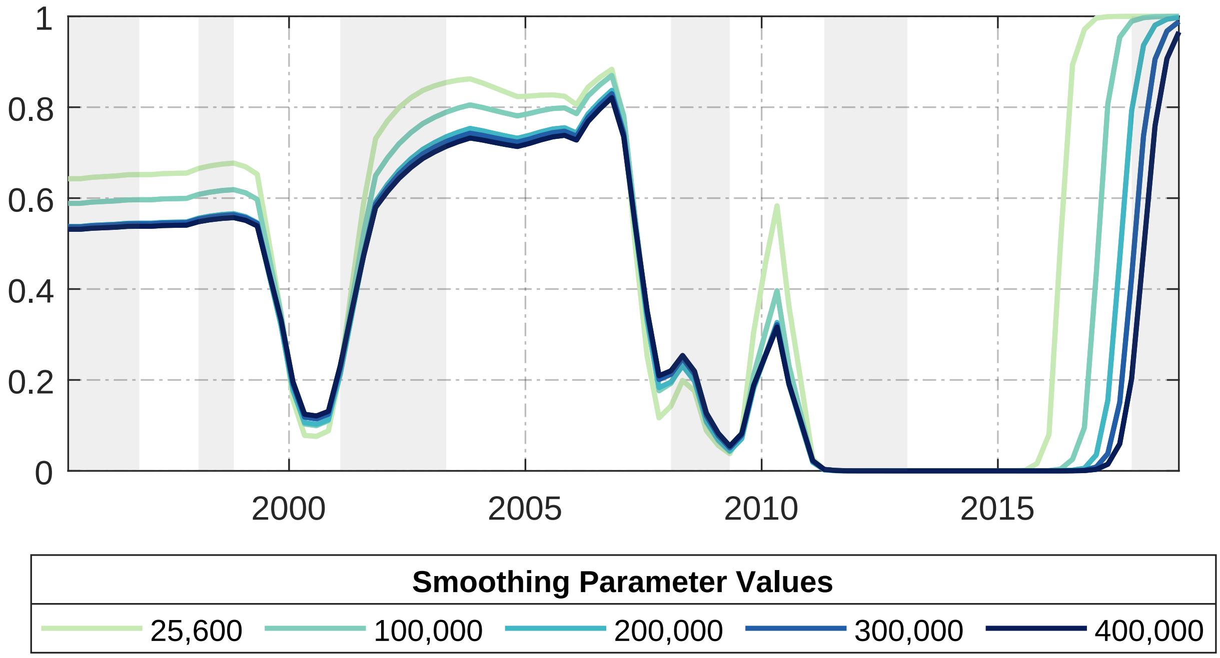
The share that the economy is in a particular regime is determined by μ. In our case, μ is specified by the share that the economy spends in a loose regime and varies depending on the smoothing parameter.[21] σ_{rc} is the sample standard deviation of the indicator variable. The vehemence of the regime change is determined by κ: the higher the selected value for κ, the more abrupt the change. We follow the standard literature and set $\kappa = 5$ to generate an intermediate intensity of regime changes.

The resulting state variables are depicted in Figure 3. They reflect the weights of the regimes that are assigned to the economy in the corresponding periods. A value close to one implies that the economy is in a relatively loose regime, and vice versa. Accordingly, prudential regulation in the euro area was comparatively tight shortly after the turn of the millennium and in the years following the financial crisis and the subsequent crisis years. Depending on the frequency assumed for the regulatory cycle, prudential regulation becomes comparatively loose sooner (relatively high frequency) or later (relatively low

[20] This is also another reason why we consider the announcement date of the policy measures when setting $m^k_{i,t}$.

[21] The parameter takes the values 56 when $\lambda^{RC} = 25,000$, 51 when $\lambda^{RC} = 100,000$, 48 when $\lambda^{RC} = 200,000$, 47 when $\lambda^{RC} = 300,000$, and 46 when $\lambda^{RC} = 400,000$.

Figure 3: State Variables



Notes: Transitions functions based on the regulatory cycles derived from the GDP-weighted cumulative Prudential Policy-Index. Grey bars mark OECD based recession indicators.

frequency).

Given that the time at which the economy is once again in a loose regime varies at the end of the sample depending on λ^{RC}, and that at the same time there is no unique value for lambda that extracts a regulatory cycle beyond doubt, we conduct our analysis below as follows: We first estimate a model for the period 1995Q1 to 2015Q1. The latter corresponds to the point in time up to which no change in trend towards a looser regime is identified across all values for λ^{RC}. These results represent our baseline results. We then estimate our model for the entire sample. This adds observations for both regimes. However, as λ^{RC} increases, the tighter regime gets disproportionately more observations and vice versa.

5 Loan Supply Shocks, Prudential Regulation, and the Business Cycle

This section discusses the role of the regulatory regime for the business cycle effects of expansionary loan supply shocks. Furthermore, we analyze possible asymmetries in the propagation.

A. *Baseline Results*

What role does the prudential regime play in the business cycle effects of loan supply shocks? Figure 4 shows the state-dependent impulse responses to an expansionary loan supply shock across regulatory regimes. Solid lines represent the baseline median responses. The surrounding dark (light) areas demarcate the space between the 16th (5th) and the 84th (95th) percentiles.[22]

First, we examine the effects in the tight regime given the short sample, which covers the period 1995Q1 until 2015Q1. The responses to be considered are depicted in red.

Accordingly, expansionary loan supply shocks lead to significant effects in the first year after they occur. After an initial increase of 0.2 percentage points, output grows at about the same rate in the following two quarters. This is also true for inflation and credit growth, which increase at a similar rate and over roughly the same period of time. As a consequence, the central bank increases the short-term interest rate in order to curb the business cycle. This induces the lending rate, after an initial fall, to turn positive. This immediate reversal effect is also found in Mandler and Scharnagl (2020), Gambetti and Musso (2017) or Bijsterbosch and Falagiarda (2015), among others. For all variables, the peak of the expansionary effect is measured within the first year after the shock hits the economy.

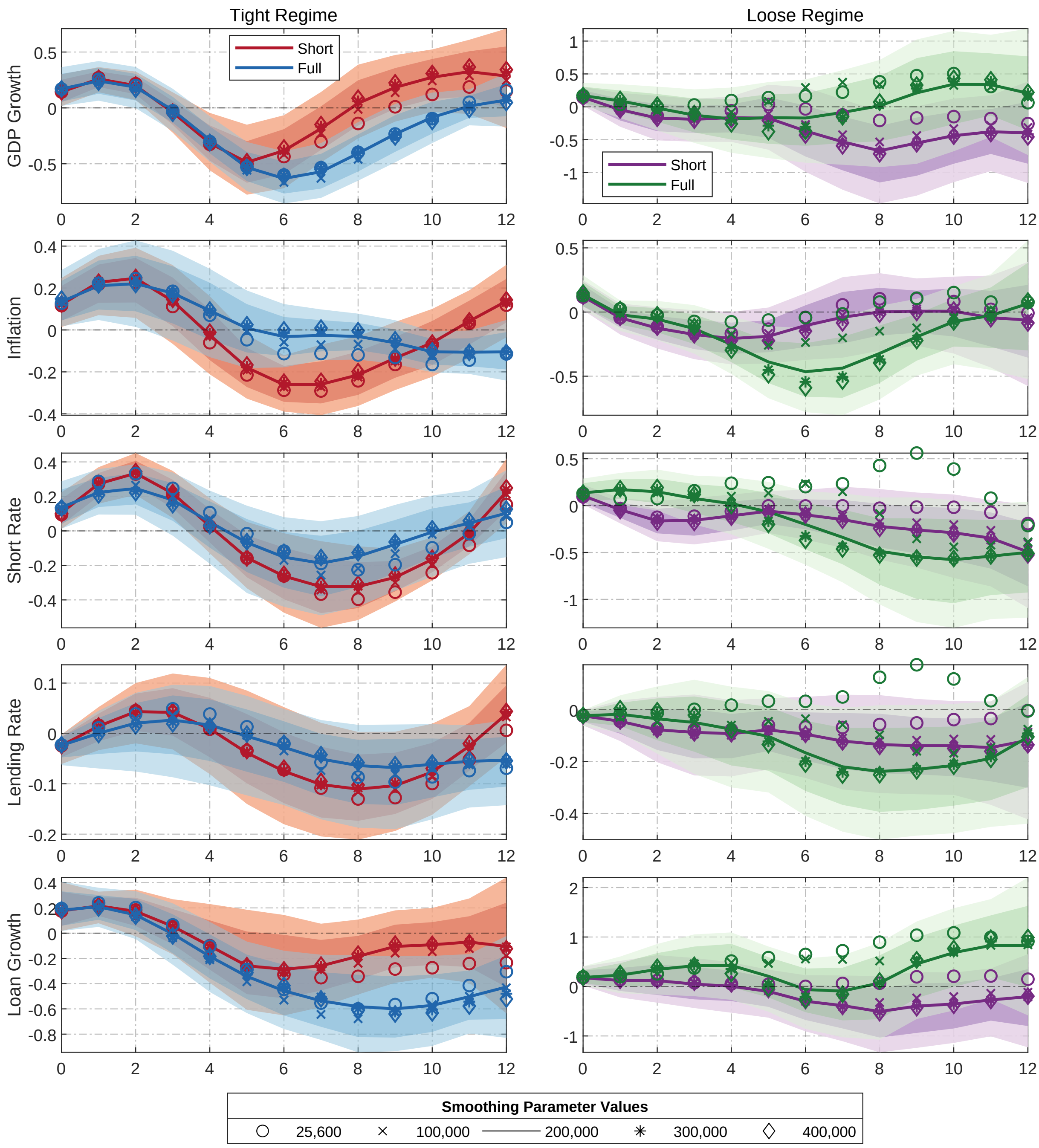
The expansionary effect turns into a bust phase after about one year. All the variables considered show negative growth or changes, which are significant at least at the 68 percent level. All quantities reach their trough within the second year. The pattern is found regardless of the choice of the value for the smoothing parameter used in order to extract the regulatory cycle.

Extending the time frame to the entire sample (blue) confirms the central finding that expansionary loan supply shocks lead to a business cycle characterised by a boom-bust swing. What is striking is that, with the exception of the impulse responses of inflation, the remaining median impulse responses are very similar for the first four to six quarters after the shock hits the economy.

A closer look at the impulse responses from the varying samples reveals that the most pronounced differences are found in the response of output, inflation and loan growth. The deviations in the median responses between the samples is up to 0.5 percentage points, with the negative effect being stronger in the full sample. Inflation, on the other hand, does not exhibit the pronounced bust cycle, but returns to and remains at the zero line. Loan growth, a key factor for prudential activities, follows the same pattern as output. This is in line with Jordà et al. (2016), who show that private borrowing is strongly pro-cyclical in advanced economies. In the first 1.5 years after the shock, we find a pronounced boom-bust phase. Looking at the entire sample, however, the bust phase lasts longer. Loan growth now reaches its trough at -0.6 percentage points at $h = 9$, i.e. after

[22]For the sake of comparability, the median responses from the linear model are shown in Section B of the appendix. In the linear specification, we estimate equation 3.1 with the lag structure as well as the choice of variables as in the state-dependent case. The results are shown in Figure B.1.

Figure 4: Impulse Responses Across Regimes, Short Vs. Full Sample



Notes: State-dependent impulse responses to an expansionary loan supply shock. Identifying assumptions are impose on impact. Lines and markers depict median responses in tight (left panel) and loose (right panel) regulatory regimes. Red (blue) lines and markers depict median responses in the tight regime from the short (full) sample spanning the period 1995Q1 until 2015Q1 (2018Q4). Purple (green) lines and markers depict median responses in the loose regime from the short (full) sample spanning the period 1995Q1 until 2015Q1 (2018Q4). Smoothing parameter values relate to the smoothing parameter λ^{RC} used in order to extract regulatory cycles, as described in the main text. Dark (light) areas depict corresponding 68% (90%) probability masses.

more than two years. And negative loan growth in the tight regime can also be observed in the periods thereafter. As with GDP growth, the difference in median responses across the samples is up to 0.5 percentage points (for $h = 9$).

Looking at the effects of expansionary loan supply shocks in a loose regulatory regime, the responses do not provide such a consistent pattern. The responses from the short sample (purple) indicate very short-lived effects of the shock. All variables except for the lending rate are already insignificant in the first quarter after the shock occurs.[23] That is, a clear boom phase cannot be observed. Rather, the economy tends to move directly into a recessionary phase. Even if the median responses are significant in the fewest cases, this tendency is counter-intuitive. The impulse responses show this pattern regardless of the λ-value used to determine the underlying regulatory cycle. However, it is striking that the responses produced by a setup with $\lambda^{RC} = 25,600$ (purple circle) are always above the other responses. While this discrepancy is barely noticeable in the short sample, it becomes striking when all observations are taken into account. Depending on which variable is considered, the responses from the full sample differ to a greater or lesser extent. Output, inflation, the lending rate, and credit growth are confirmed at least for the first four to six periods after the shock. After that, they tell a different story, especially in the case of output, inflation, and loan growth.

For instance, output is on a positive growth path in the third year after the shock. This development is similar to the response of output from the short sample in the tight regime. The same applies to the reaction of inflation. More decisive from a prudential perspective is the reaction of loan growth in the loose regime when looking at the entire sample. The responses from the models with $\lambda^{RC} \geq 200,000$ already indicate a moderately positive path of loan growth. However, this is insignificant in all but the third year, which is consistent with the positive output growth path, rising inflation and negative interest rates over the projection horizon. However, assuming a higher frequency for the regulatory cycle i.e. a lower value for λ^{RC}, loan growth moves along a noticeably positive growth path over the entire projection horizon. Thus, unlike in the tight regime, the results are sensitive to some extent to the choice of the smoothing parameter. From a regulatory perspective, this is particularly problematic in the case of loan growth (and output), as prudential regulation is closely linked to its development.

With this limitation in mind, we now examine whether asymmetric effects can be detected.

B. *Are the Responses Asymmetric?*

Have loan supply shocks similar business cycle effects across regulatory regimes? To answer this question, we estimate $\beta_{i,h}^{tight} - \beta_{i,h}^{loose}$ for each variable i and horizontal h as well as the

[23]Per construction, the initial responses are identical in both regimes.

corresponding percentiles.[24] Figure 5 shows the results. The magenta (cyan) lines represent the median differences from the model with the short (full) sample. For ease of reading, we add a filled dot for each difference that is significant at the five percent level. The vertical blue lines highlight the periods where both models indicate significant state dependence.[25]

If a rather high frequency, i.e. $\lambda^{RC} = \{25.6, 100, 200\} \times 1,000$, is assumed for the regulatory cycle (columns 1 – 3), significant differences in the responses of inflation appear in both samples, as shown by the blue lines. The lower the value of λ^{RC} — and therefore the higher the frequency of the regulatory cycle — the more periods within the first year after the onset of the shock show significant differences. More precisely, in the tight regime inflation reacts more strongly. This finding is interesting from a monetary policy perspective, as it implies that the central bank would also have to react state-dependently to the developments triggered by the loan supply shock — which she does, as can be seen from the reactions of the short-term interest rate. However, the difference in the responses also comes about because inflation in the loose regime becomes deflationary from $h = 2$, as already seen in Figure 4. Since this development seems rather counter-intuitive, the findings must be taken with a grain of salt.

In the case of the truncated sample, we also find significantly state-dependent responses of output within the first year after the occurrence of the shock. This finding holds across all calculated regulatory cycles. Taken in isolation, this suggests that the loan supply shock is stronger in the tight regime. We find no significant state dependence in the response of loan growth.

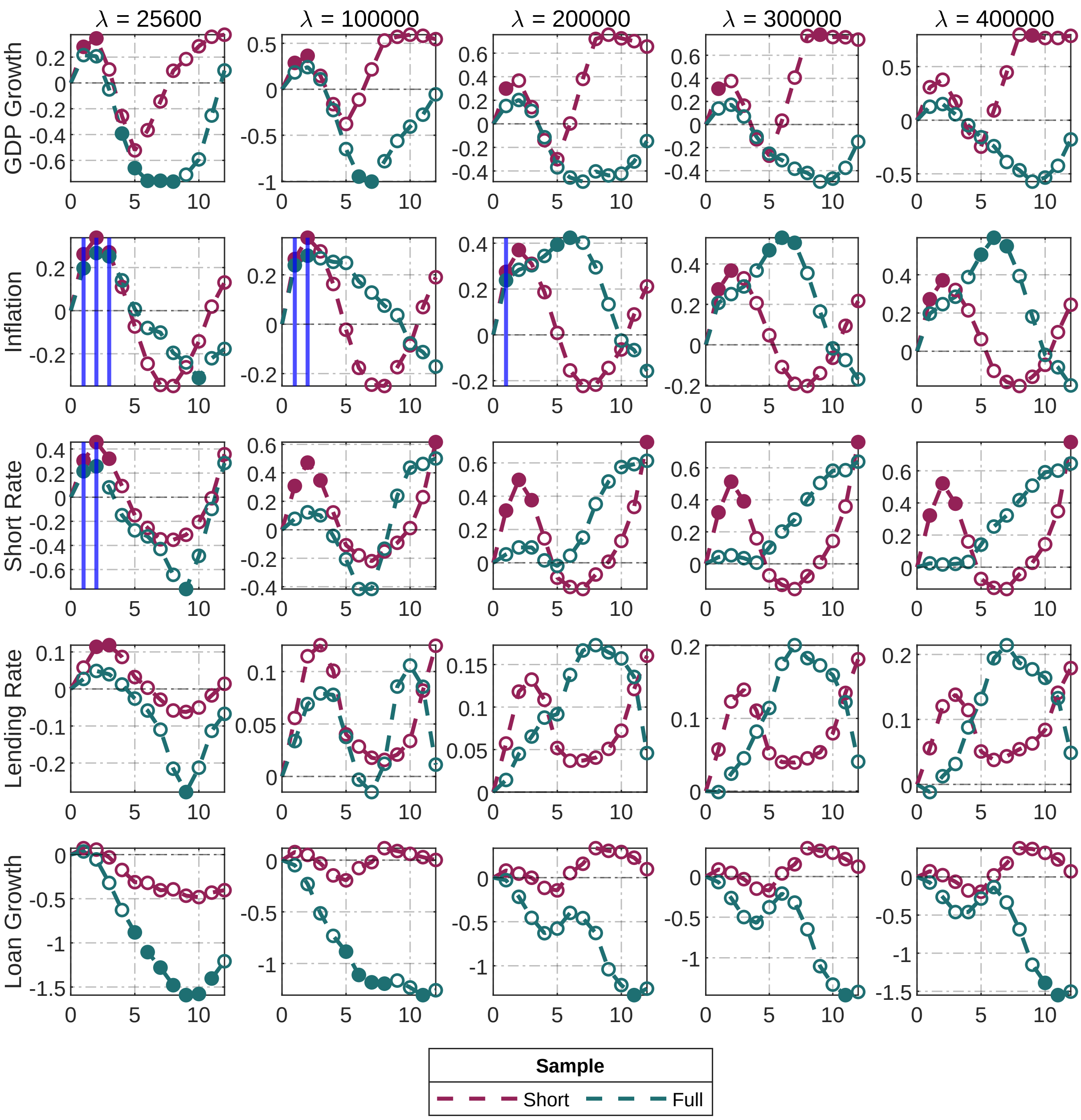
Looking at the entire sample, we find significant state dependence for models with low values of the smoothing parameter λ^{RC}, especially for GDP and loan growth rates in the course of the second year. Figure 4 reveals that the state dependence arises because (i) in the tight regime, the economy is in a recessionary phase during that projection horizon, while (ii) in the loose regime, at the same projection horizon, the loan supply shocks cause output and loans to take a positive growth path. For high values of λ^{RC}, which correspond to slow moving regulatory cycles, we cannot identify any significant state dependencies, except for the already mentioned state dependencies of inflation.

To summarise, the reactions in the tight regime are independent of the choice of the

[24] It is quite conceivable that in a tight regime, expansionary loan supply shocks have more muted effects than contractionary loan supply shocks – and vice versa in the case of loose regulatory regimes. In order to investigate this possibility, expansionary and contractionary shocks would have to be analysed separately. One possibility would be to decompose an identified loan supply shock into its positive (expansionary) and negative (contractionary) components and compare their effects for given states, e.g. as in Finck and Rudel (2022) or Tenreyro and Thwaites (2016). However, this approach leads to inconsistency, as asymmetry is being imposed on a shock from a linear model. We also have too few observations to divide our sample accordingly. Therefore, when we talk about asymmetry in the following, this refers exclusively to the differences in the effects between the regulatory regimes. Since we are dealing with a linear model, asymmetric responses to an expansionary loan supply shock are the mirror image of the responses to a contractionary shock.

[25] The corresponding full results are shown in Figures C.3 and C.4 in the appendix.

Figure 5: Difference in Responses



Notes: Difference between the impulse responses from the tight and loose regime ($\beta_{i,h}^{tight} - \beta_{i,h}^{loose}$). The magenta (cyan) dotted lines represent the median differences from the short (full) sample. Filled dots indicate projection horizons with significant asymmetry at the 5% level. Blue bars emphasise horizons in which there is significant asymmetry in both samples.

smoothing parameter λ^{RC} for determining the regulatory cycle. That is, here we find quite robust results concerning the effects of expansionary loan supply shocks on the business cycle. All reactions are characterised by a considerable boom-bust cycle. In the full sample, the bust cycle lasts longer. In the loose regime, on the other hand, we find different responses depending on the frequency of the prudential cycle as well as the observation period considered. While all responses are relatively similar in the first year after the onset of the shock, we find some considerable contrasts in the subsequent projection horizons.

Against the background of the relevance of credit developments for prudential regulation, we want to discuss the reactions of loan growth in more detail. In the short sample, loan growth responds only marginally to the expansionary loan supply shocks. This applies to both regimes and all smoothing parameters, resulting in no asymmetry whatsoever, as can be seen in Figure C.3. This changes when all observations are taken into account. In the tight regime, a short period of loan expansion is followed by a phase of negative credit growth. The result applies regardless of the cycle frequency assumed. In the loose regime on the other hand, the basic tenor across all regulatory cycles frequencies is that an expansionary loan supply shock tends to causes persistent loan growth. Particularly when the regulatory cycle has a high frequency, an expansionary loan supply shock triggers sustained positive credit growth. As output shows no notable reaction, we measure a positive growth differential between loans and output, which increases in the course of the projection horizon. Thus, in such a regime, credit-driven growth — originating from the private sector — occurs. Thus, we find evidence that loose prudential regulation is more likely to foster an enduring build-up of private borrower's credit after an expansionary credit supply shock as against a tight regulatory regime. Jordà et al. (2016) report that such credit booms have the potential to make recessions and recoveries worse and increase the probability of financial crisis.

This result should, however, be treated with caution. Our approach yields robust results on the effects of expansionary loan supply shocks on the business cycle when prudential regulation is relatively tight. But not if the regulatory stance is below its trend. Why is that?

C. *The Impasses of Determining Loose Regimes*

The historical development of prudential regulation plays an integral role in this. With a few exceptions, prudential regulation has followed a path over the entire sample that is mainly characterised by tightening, as can be seen in Figure 1. This rather unidirectional development is also reflected in the course of the cumulated Prudential Policy index. The consequence is, on the one hand, that the regulatory trend, no matter by which means one determines it, is rising over almost the entire sample. This ensures that we have a good understanding of what a relatively tight regime is, i.e. when prudential regulation is above its long-term trend. However, since this trend is ascending the majority of the time, even loose periods are tighter by historical standards than past periods of loose regulation. Therefore, the extracted loose regimes cannot be clearly distinguished as such. They are merely to be understood as less tight regimes rather than actually looser regulatory conditions.

Another difficulty concerns the choice of the smoothing parameter λ^{RC}. As can be seen in Figure 3, there are different assignments of when the economy turns into a state of relatively loose regulation, especially towards the end of the observation period. With increasing values of λ^{RC}, the point in time, at which $S(rc_{t-1}) > 0.5$, shifts to the end of the observation period. As a result, with increasingly low frequency of the regulatory cycle, more and more observations are assigned to the tight regime.[26] In our case, this leads to more robust results of the responses in the corresponding regime. In combination with the already described difficulty to separate loose regimes as well as our relatively short observation period, this leads to our results being more dependent on the choice of the smoothing parameter in the loose regime.

Therefore, additional observations of periods of persistent prudential loosening are needed to allow us to make more accurate conclusions about the role of a loose regulatory regime for the business cycle effects of expansionary loan supply shocks.

6 Robustness

In this section we put our results to the tests by performing a number of sanity checks. First, we estimate our model using a purified regulatory cycle in order to rule out that our regulatory cycle is driven by the business cycle. Next, we use the unweighted version of the cumulative prudential policy index in our empirical model. Finally, we incorporate state variables that are derived from the empirical cumulative density function of the underlying indicator variable. In all exercises, we utilise the full sample to take into account all available observations.

A. *Purified Regulatory Cycle*

Especially for low values of the smoothing parameter λ, it may be that the identified regulatory cycle is heavily driven by the business cycle. The reason is that we use a high-pass filter to extract the cycles. This allows fluctuations in the high frequency range to pass into the identified cycle almost without dampening. The business cycle is such a (relatively) high-frequency cycle. Therefore, one could argue that our impulse responses represent the reactions to an expansionary loan supply shock over the business cycle in the euro area, rather than over the regulatory cycle. To avoid this bias, we cleanse our regulatory cycle from the business cycle. To do this, we regress each of the regulatory cycles, rc, derived in Section 4 on the business cycle, bc, as well as a trend τ, and a constant

[26] Recall how the share the economy spends in the loose regime, μ, decreases with the increase in the smoothing parameter value λ^{RC}.

c, i.e.

$$rc_t = c + \delta * bc_t + \tau + u_t \; .$$

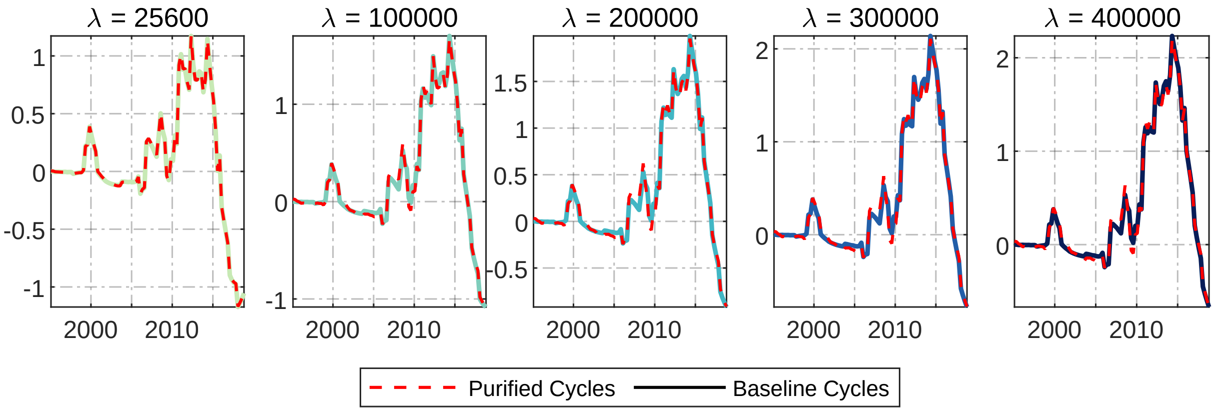
To calculate the business cycle, we rely on an established method and filter the natural log of real GDP by means of a two-sided HP filter with smoothing parameter $\lambda = 1,600$.[27] The purified regulatory cycle, $\tilde{rc}$, is then the difference between the original regulatory cycle and the estimated contribution of the business cycle, i.e.

$$\tilde{rc}_t = rc_t - \hat{b} * bc_t \; ,$$

which then represents our state indicator.[28]

The purification process only slightly alters the development of the regulatory cycle, as can be seen in Figure 6. If any, deviations from the baseline cycles (solid lines) are only detectable in homeopathic doses for cycles extracted by a high smoothing parameter. That is, our regulatory cycles are not driven by the business cycle in the euro area. Consequently,

Figure 6: Purified Regulatory Cycles



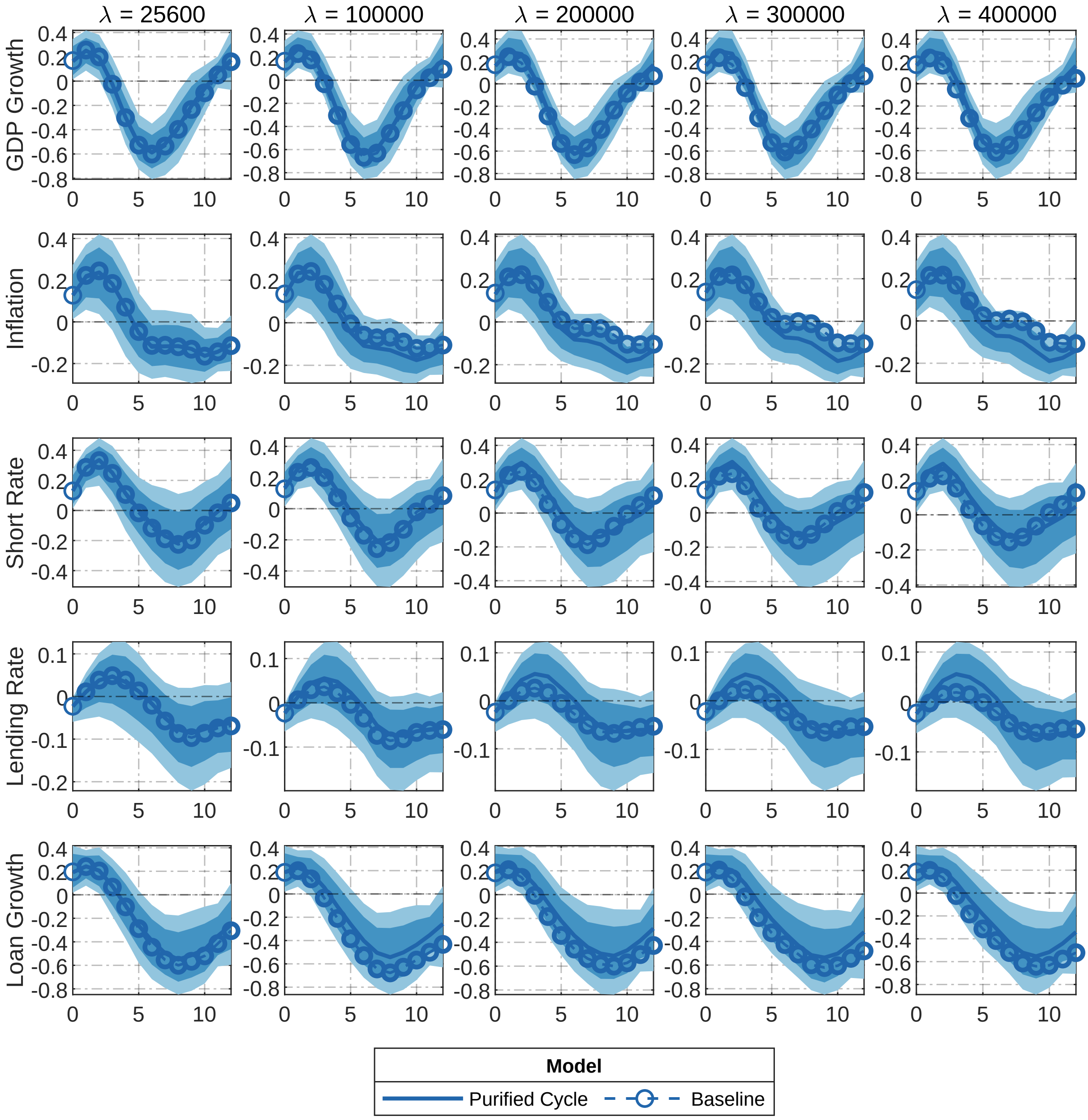
Notes: Regulatory cycles purified from the business cycle. Smoothing parameter values λ correspond to the frequency of the regulatory cycle. In all cases, the business cycle is extracted by applying the two-sided HP-filter with smoothing parameter value 1,600 on the natural log of real GDP.

the impulse responses from this robustness exercise are consistent with the results found so far, both in the tight (Figure 7) and loose (Figure 8) regimes.

[27] Hamilton (2018) discusses the shortcomings of the HP-Filter and offers a much-noticed alternative which is not suitable for our application due to a lack of observations.
However, Schüler (2019) shows that Hamilton's approach comes with similar flaws as the HP-filter.

[28] It should be noted that this approach introduces uncertainty on three dimensions. Firstly, there is some level of uncertainty in the computation of the regulatory cycle, as the true smoothing parameter is latent. The same is true for the computation of the business cycle, which is the second source of uncertainty. Lastly, there is estimation uncertainty in the regression of the regulatory cycle on the business cycle.

Figure 7: Purified Regulatory Cycle (Tight Regime)

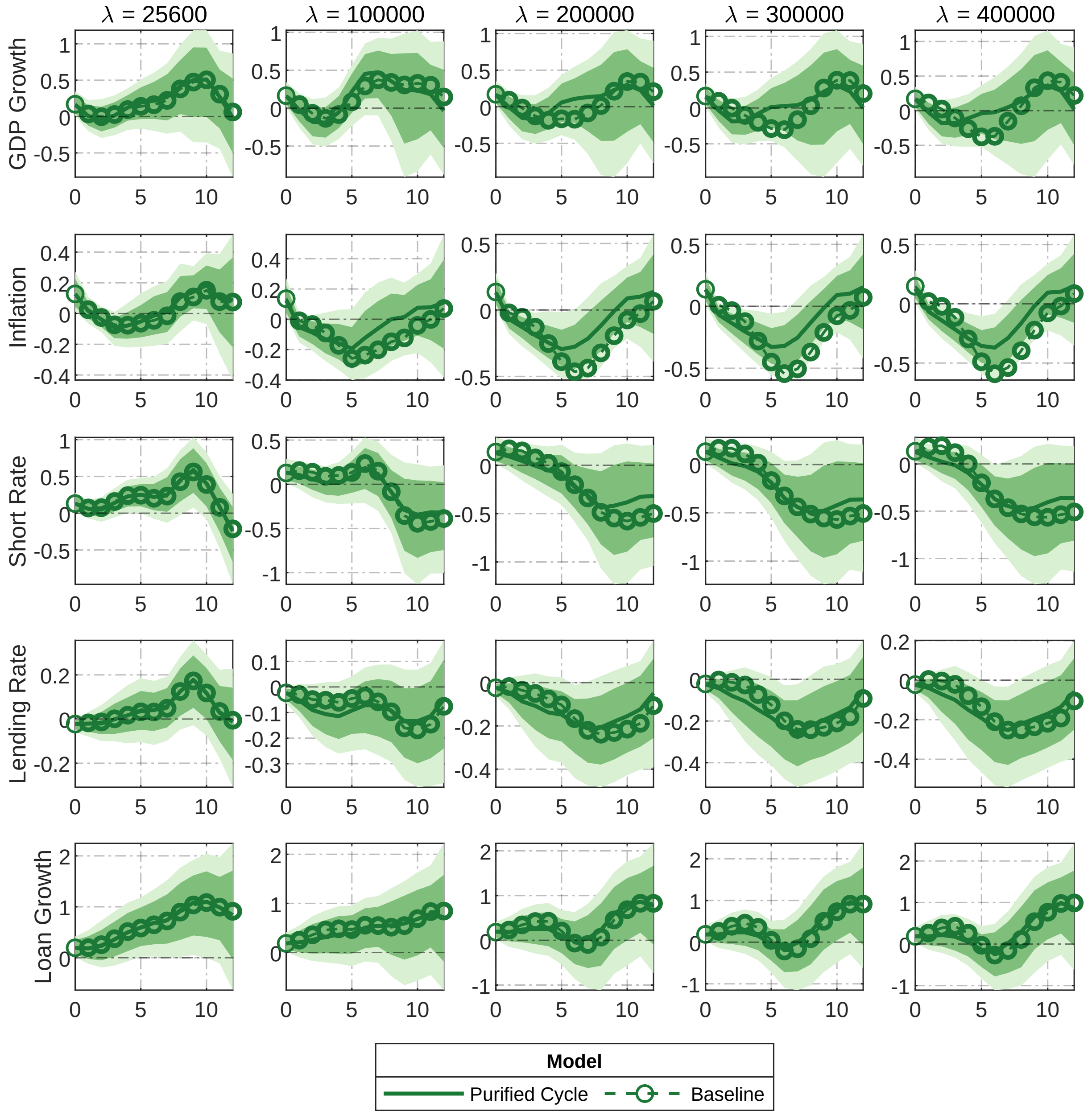


Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with purified regulatory cycle. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

B. *Re-weighting: Loan Volumes*

In our baseline model, we compute the cumulative prudential policy index for the euro area based on GDP-weighted country-specific prudential policy indexes, *iPPI*. The rationale behind this is to assure that our cumulative index is not driven by prudential policies introduced by rather small countries to the same extent as, say, one of the four large member states.

Figure 8: Purified Regulatory Cycle (Loose Regime)

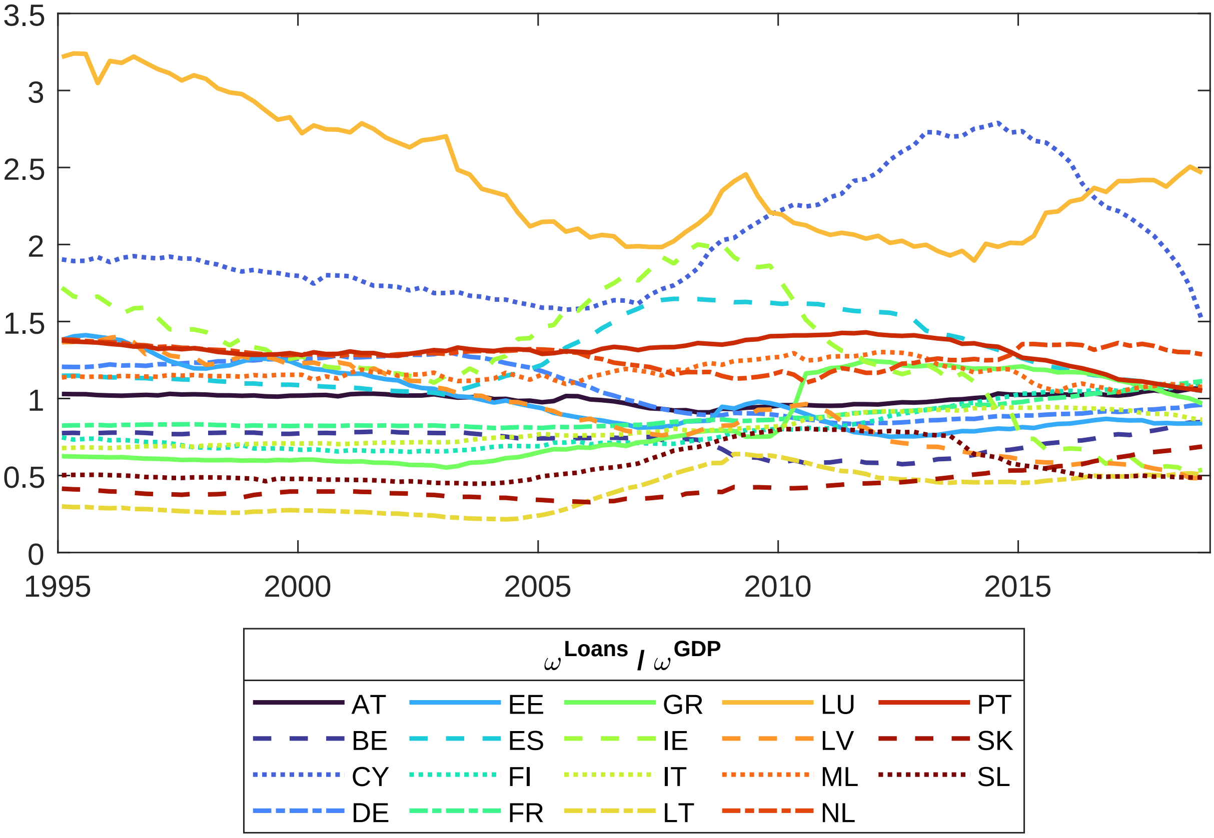


Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory loose regime. Solid lines represent median responses from the models with purified regulatory cycle. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

However, there are countries that are relatively small economically but have a sizeable financial sector. Their regulatory measures are therefore likely more relevant than prudential measures in countries where the financial sector is not as prominent.

To take this into account, we re-weight the country-specific measures with the share of the total nominal loan volume that the country has at the given time. The changes in the country's influence are indicated in Figure 9. It depicts the ratio between the loans-weight and GDP-weight for each country. A ratio above one implies that the weighting based on loan volume is higher than the country's GDP weighting. Values below one indicate that the country loses leverage in the corresponding periods with the new weighting. Hence, regulatory measures taken by Luxembourg, Cyprus, and Ireland are now much more weighty, while Lithuania, Slovakia, and Slovenia are contributing less to the euro area cumulative prudential policy index.

Figure 9: Loans-weight over GDP-weight

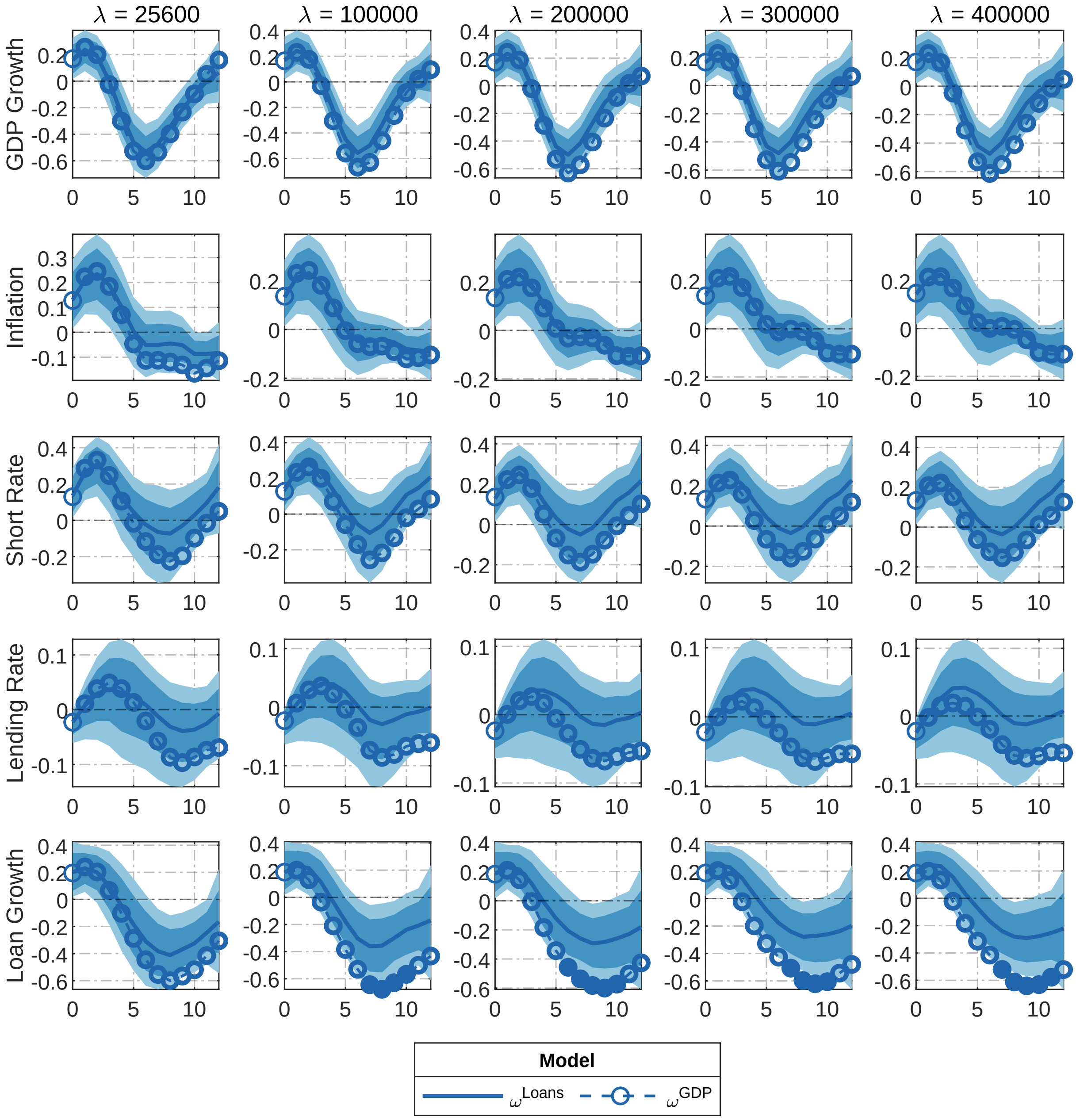


Notes: Ratio between country's loans weight and GDP-weight.

The business cycle effects of a loan supply shock in this setup barely differ from our baseline results, as Figure 10 shows. The most obvious deviation is the more muted reaction of loan growth. In particular, if a low frequency is assumed for the regulatory cycle ($\lambda^{RC} \geq 100,000$), the deviation from the base model is significant, as indicated by the colored dots. The bust phase of output is also more muted. However, the differences are not significant. Overall, we again see robust results for the tight regime.

Again, in the loose regime, we find the most apparent divergence from the baseline model in the response of loan growth, especially when a slower moving regulatory cycle is assumed. As can be seen from Figure 11, in this constellation loan growth follows a boom-bust cycle, similar to the response of output. In this exercise, we cannot confirm that expansionary loan supply shocks lead to sustained loan growth.

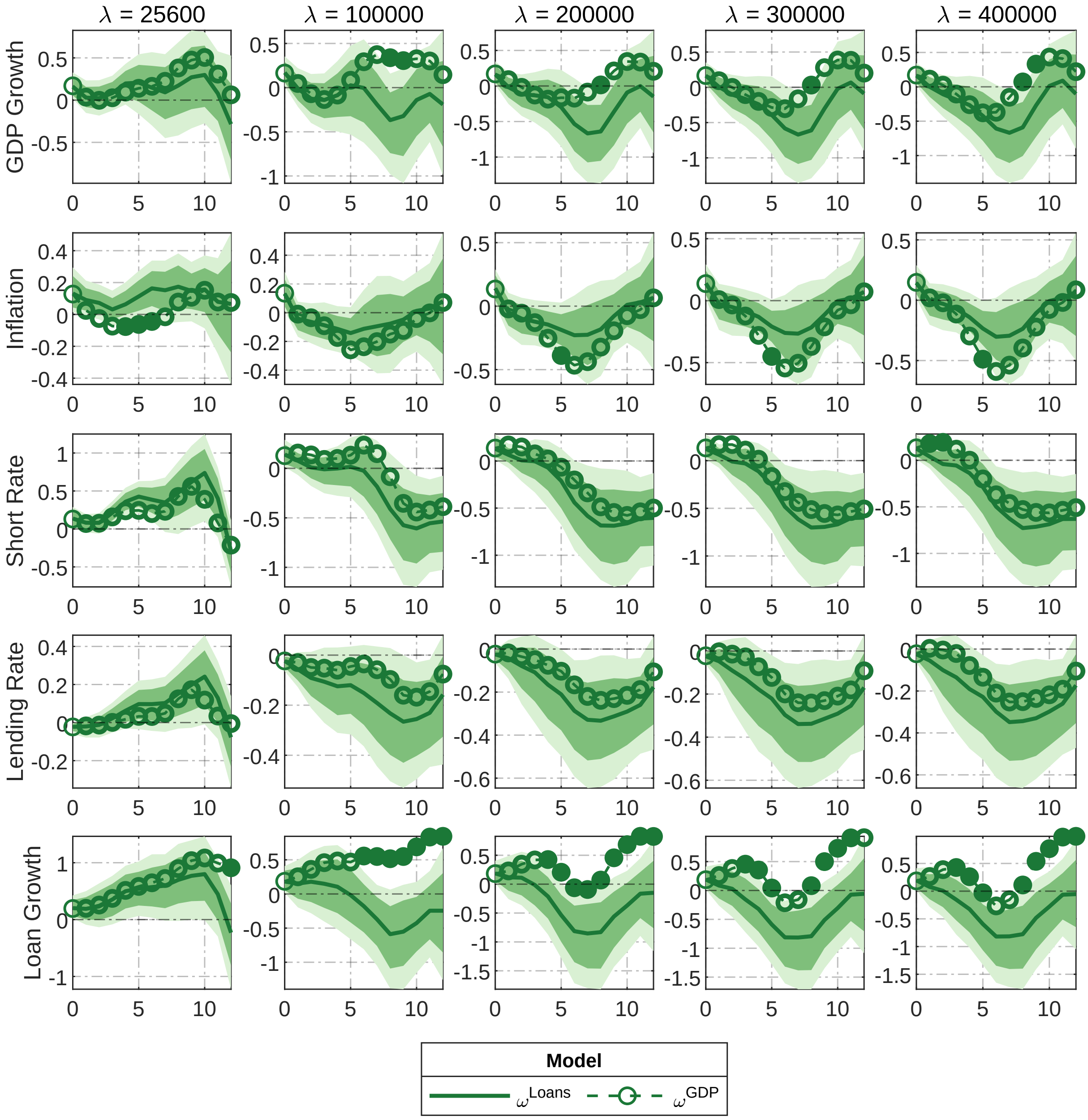
Figure 10: Loans-weighted cPPI (Tight Regime)



Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with regulatory cycles based on the loans-weighted cPP-index. Dashed lines depict median responses from the corresponding baseline model with weights based on a country's GDP. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

However, it must be said that analysis suffers from data availability. Reliable data on national credit volumes are available for most countries from 2003Q1 at the earliest. With so few observations, we would not have been able to meaningfully estimate the number of unknown parameters. In order to backwards extend the data to 1995Q1, we have used the weights from the first quarter for which data was available for the missing periods.

Figure 11: Loans-weighted cPPI (Loose Regime)



Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with regulatory cycles based on the loans-weighted cPP-index. Dashed lines depict median responses from the corresponding baseline model with weights based on a country's GDP. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

To further investigate the robustness of our results with regard to the cumulative prudential policy index, we estimated our model with an unweighted index as the next stress test.

C. *Unweighted Cumulative Prudential Policy Index*

The cumulative prudential policy index is the basis for identifying regulatory cycles and is therefore essential for our results. In order to avoid distortions due to the choice of country weightings, we derive our regulatory cycles from an unweighted index in the following. At the same time, this means that each country and each measure contributes equally to the cPPI. All other settings remain unchanged.

Figure 12 shows the state-dependent median impulse responses from this exercise. The solid lines depict the median responses from the setup with unweighted policy indexes. Dashed lines are the median responses from the baseline model.

In both regimes, our results are overwhelmingly confirmed with the use of the unweighted index. As before, our results from the tight regime are strongly confirmed. Here, for a given value of λ^{RC}, the median response from the baseline model tends to be below the median response from the alternative specification. As Figure 13 shows, the median responses from the baseline model are within the range of the variation in $\beta_{i,h}^{tight}$ from the alternative specification. However, the general dynamics that expansionary loan supply shocks in the euro area cause remain unchanged.

In this analysis, too, the responses in the loose regime give a diffuse picture, as they differ in part significantly with the choice of the smoothing parameter value used to determine the regulatory cycle. In particular, the responses of inflation in the loose regime deviate from the results of the baseline model as the value of the smoothing parameter increases, as Figure 14 shows. Nevertheless, for the vast majority of projection horizons, the results from our baseline model lie within the confidence range of the alternative specifications.

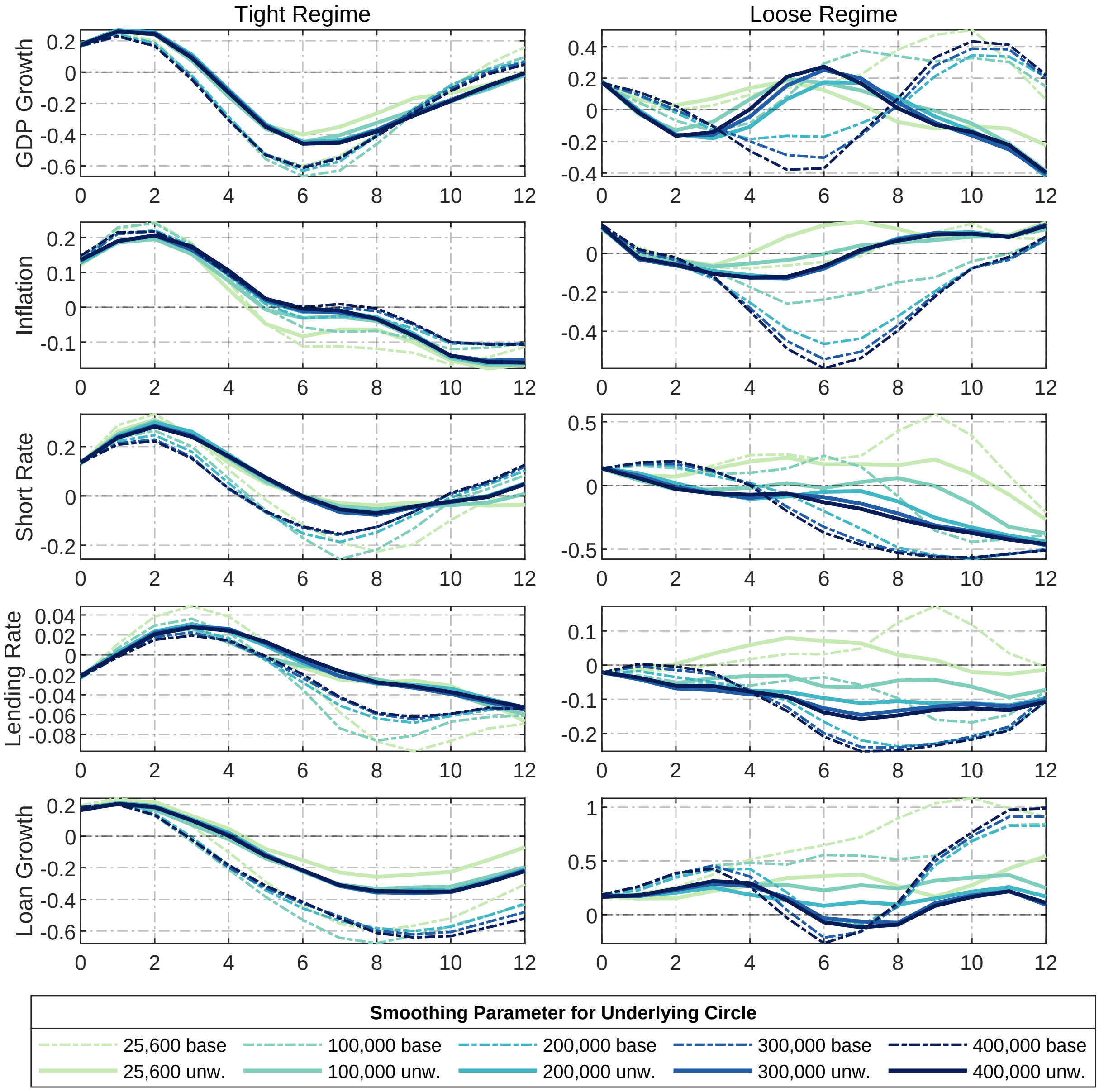
D. *Regime Determination via Empirical Cumulative Density Function*

In our baseline model, we generate an intermediate intensity of regime changes by setting $\kappa = 5$ in the logistic transition function equation (4.1). Although this value is standard in the literature (e.g. Ascari and Haber, 2022), we test our results for robustness by replacing the logistic function with an transition function based on the empirical cumulative density function (ecdf) of the regulatory cycle. Following Born et al. (2020), the ecdf is calculated as

$$F(rc_{t-1}) = \frac{1}{T}\sum_{t=2}^{T} 1_{rc_j<rc_{t-1}} \,, \tag{6.1}$$

with T being the sample size. The term $1_{rc_j<rc_{t-1}} = 1$ if $rc_j < rc_{t-1}$ and 0, else. That is, the transition function equals 1 if the regulatory cycle is at the maximum of the sample. If the regulatory regime is unprecedented loose, on the other hand, $F(rc_{t-1})$ equals 0.

Figure 12: Unweighted vs. GDP-weighted cPP



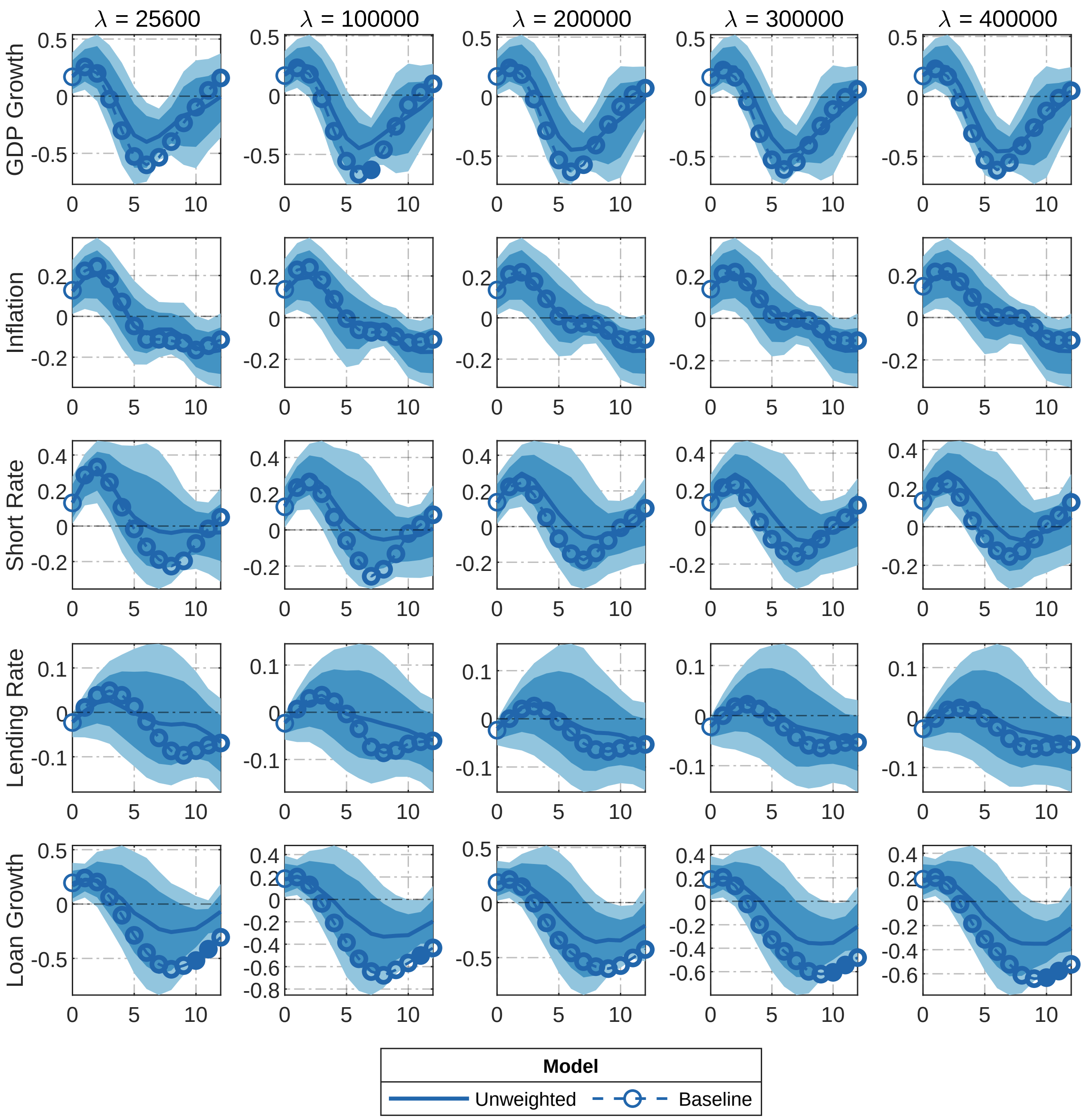
Notes: State-dependent impulse responses to an expansionary loan supply shock. Regulatory regimes are derived from the unweighted cumulative Prudential Policy (cPP) Index. Resulting median impulse responses are depicted by solid lines. Dashed lines report the median responses from the baseline model with states derived from the GDP-weighed cumulative prudential policy index.

Again, we compute the regulatory cycle applying the one-sided HP-filter with values $\lambda^{RC} = \{25.6, 100, 200, 300, 400\} \times 1,000$ on the GDP-weighted cumulative Prudential Policy-index as the indicator variable rc. As in the baseline case, we use the lagged value of the regulatory cycle.

Figure 15 shows the resulting indicator functions. For comparison, the transition function from the baseline specification with $\lambda^{RC} = 100,000$ is also shown, as these are in the middle of the other transition functions from the baseline model.[29] In principle, both approaches

[29] We could have used any other transition function, as the correlation between those and the ecdf-based

Figure 13: Weighted vs. Unweighted cPP (Tight Regime)

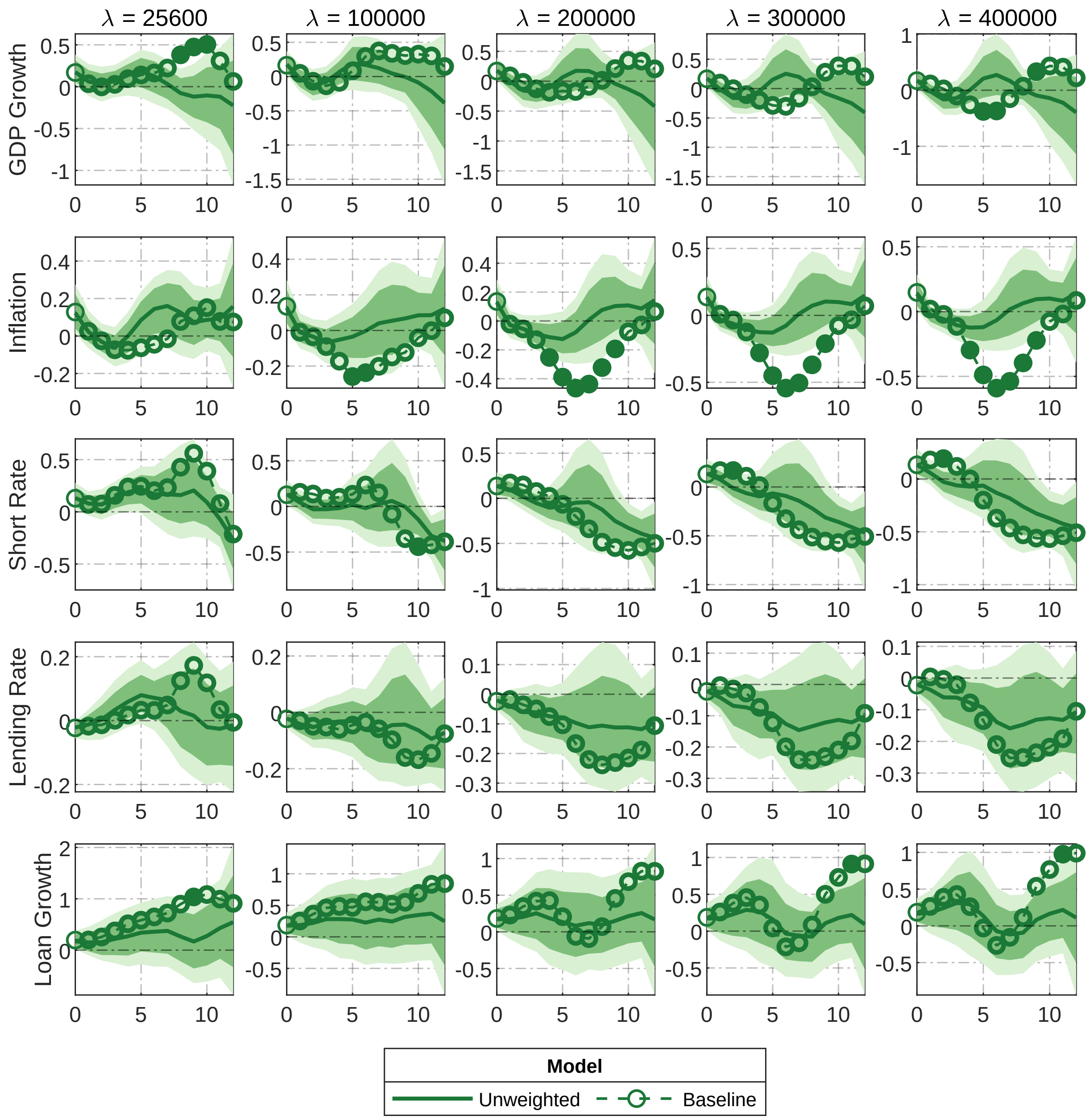


Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with regulatory cycles based on the unweighted cPP-index. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

qualify the time periods of the respective states identically (compare, for example, the course of the dashed line and the light turquoise line belonging to the specification with $\lambda^{RC} = 100,000$). The essential difference lies in the weightings that are attributed to the respective regimes at each point in time. The approach using the ecdf tends to assign relatively higher weights in the loose regime (> 0.5) and lower weights in the tight regime compared to the

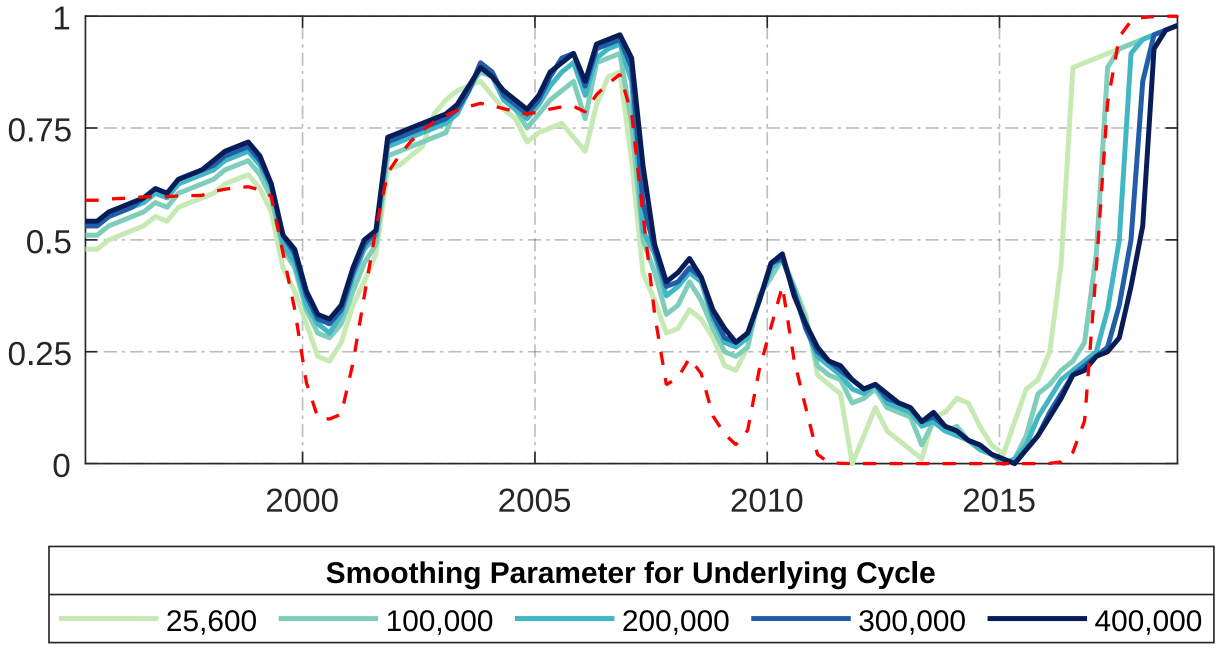
transition functions, for a given λ^{RC}, is a very high 0.97.

Figure 14: Weighted vs. Unweighted cPP (Loose Regime)



Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory loose regime. Solid lines represent median responses from the models with regulatory cycles based on the unweighted cPP-index. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

Figure 15: Transition Functions from ECDF



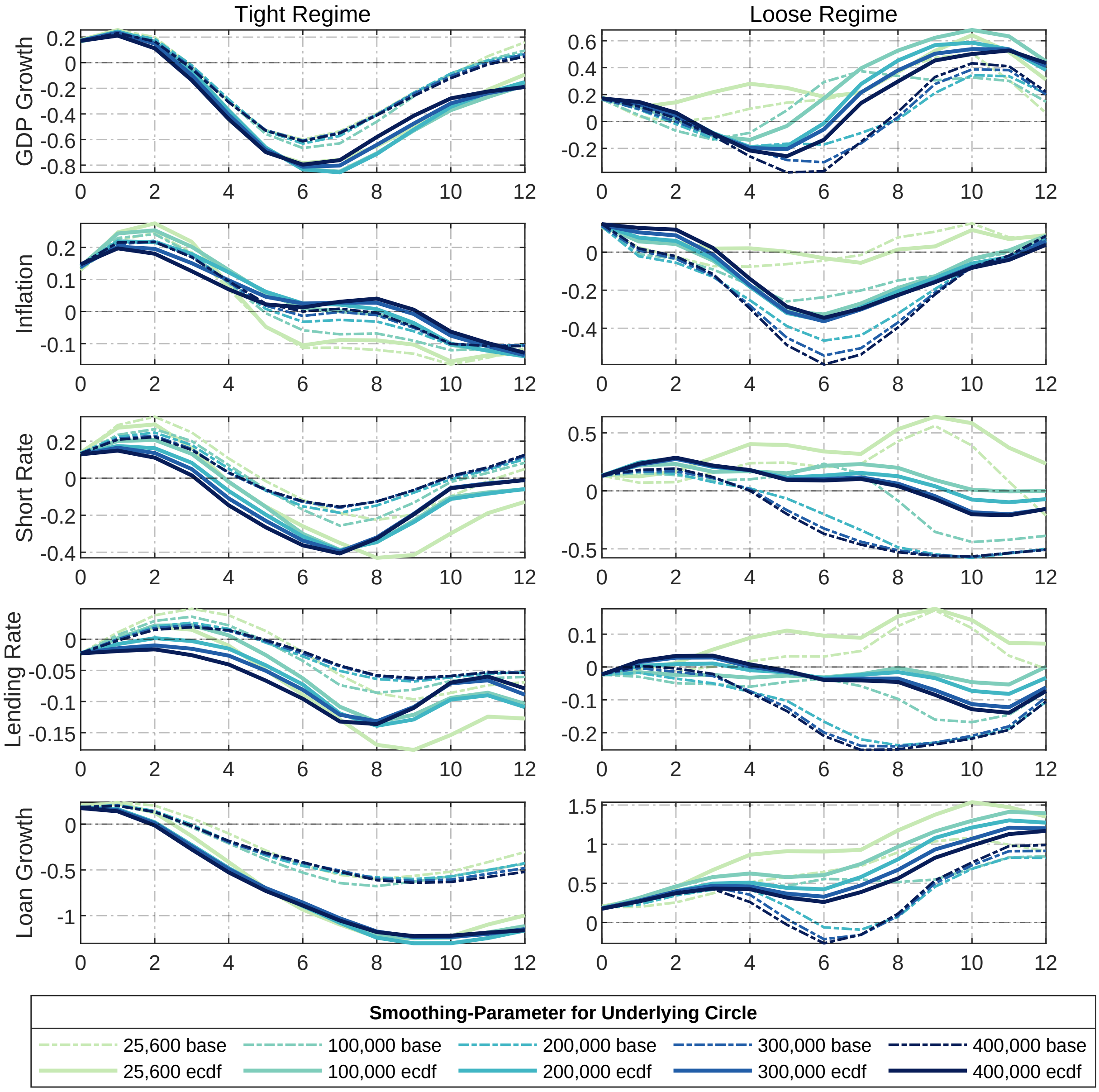
Notes: Transitions functions based on the empirical cumulative density function of the various regulatory cycles. The red dashed line depicts the transition function from the baseline model with $\lambda = 100,000$ for comparison.

approach in the baseline specification, as the baseline transition functions is predominantly below the alternatives.

The resulting state-dependent median responses are depicted in Figure 16. In the tight regime, the median responses from our robustness exercise (solid lines) confirm the pattern observed in the baseline models (dashed lines). It is striking that the responses from the alternative specification tend to measure stronger effects of an expansionary loan supply shock. Compared to the baseline specification, output falls by roughly 0.2 percentage points more in the bust phase (-0.6 vs. -0.8). Loan growth even declines twice as much: -1.2 percentage points compared to -0.6 from the baseline model. With the exception of loan growth, the median responses from the baseline model are part of the variation in the alternative models, as illustrated by the unfilled circles in Figure 17. A filled circle highlights that the value of the median impulse response from the baseline model at projection horizon h is outside the 90 percent interval of the alternative specification. For loan growth, the discrepancy in the responses just mentioned becomes apparent. In particular, in specifications where a relatively high frequency is assumed for the regulatory cycle, the median response from the baseline model is in part clearly outside the 90 percent levels of the respective alternative specification.

The robustness analysis confirms our baseline results for the loose regime in that, in this state, the results are more dependent on the choice of the smoothing parameter λ^{RC}. Again,

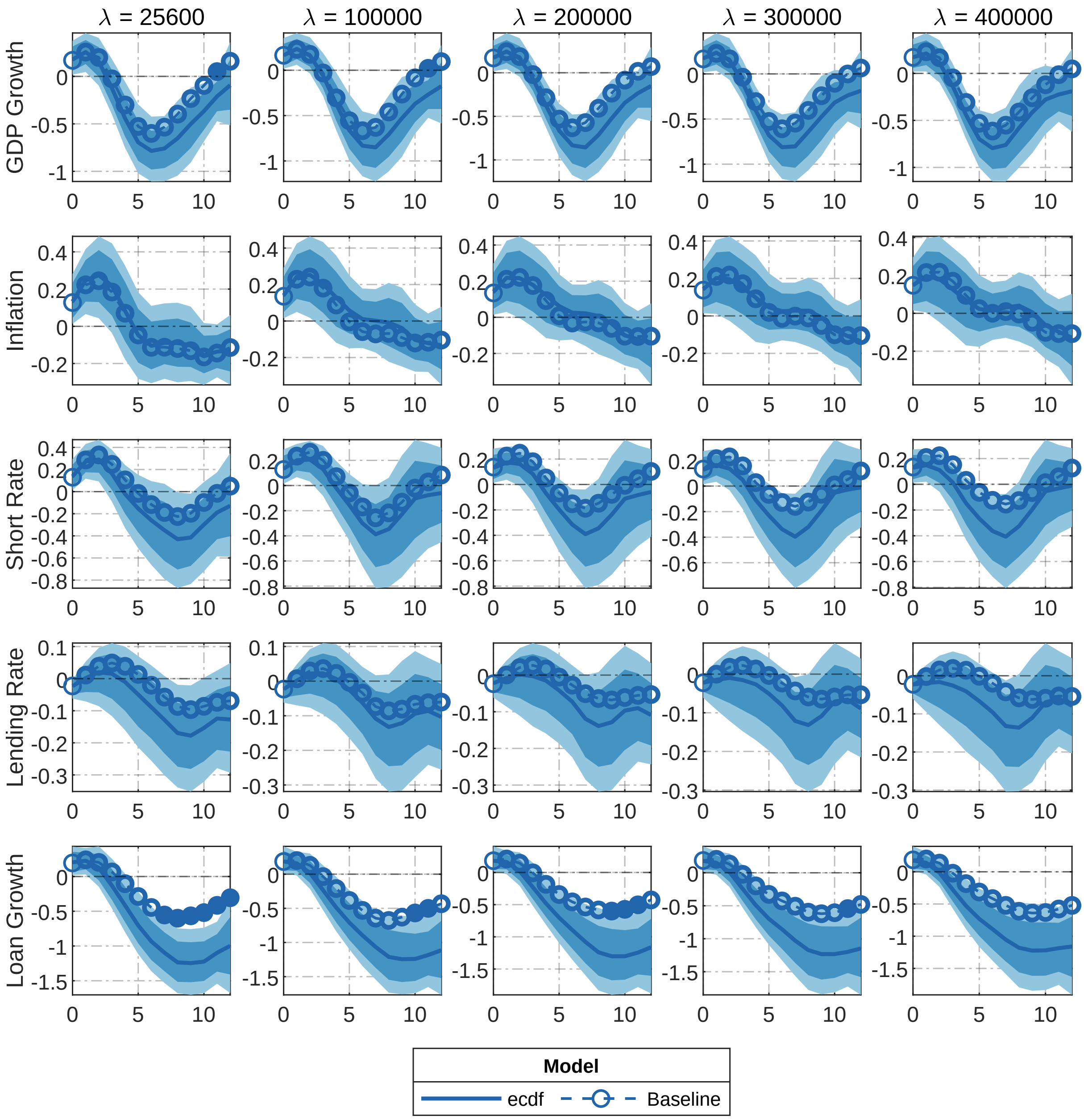
Figure 16: Comparison of Median Responses



Notes: State-dependent impulse responses to an expansionary loan supply shock. Alternative regulatory regimes are derived from the empirical cumulative density function of the GDP-weighted cumulative Prudential Policy Index. Resulting median impulse responses are depicted by solid lines. Dashed lines report the median responses.

the patterns of the impulse responses are similar for a given value of λ^{RC}. While the baseline median responses in the tight regime were more at the upper end of the distribution of $\beta_{i,h}^{tight}$ in the alternative specification, as shown in Figure 17, the baseline median responses in the loose regime are more likely to be at the lower end of the distribution of $\beta_{i,h}^{loose}$, as Figure 18 shows. In the case of loans, this means that an expansionary loan supply shock triggers a sustained positive growth of nominal loans in a model with an alternative specification of the transition function. Together with the corresponding responses in the tight regime, we find much more pronounced asymmetric effects here.

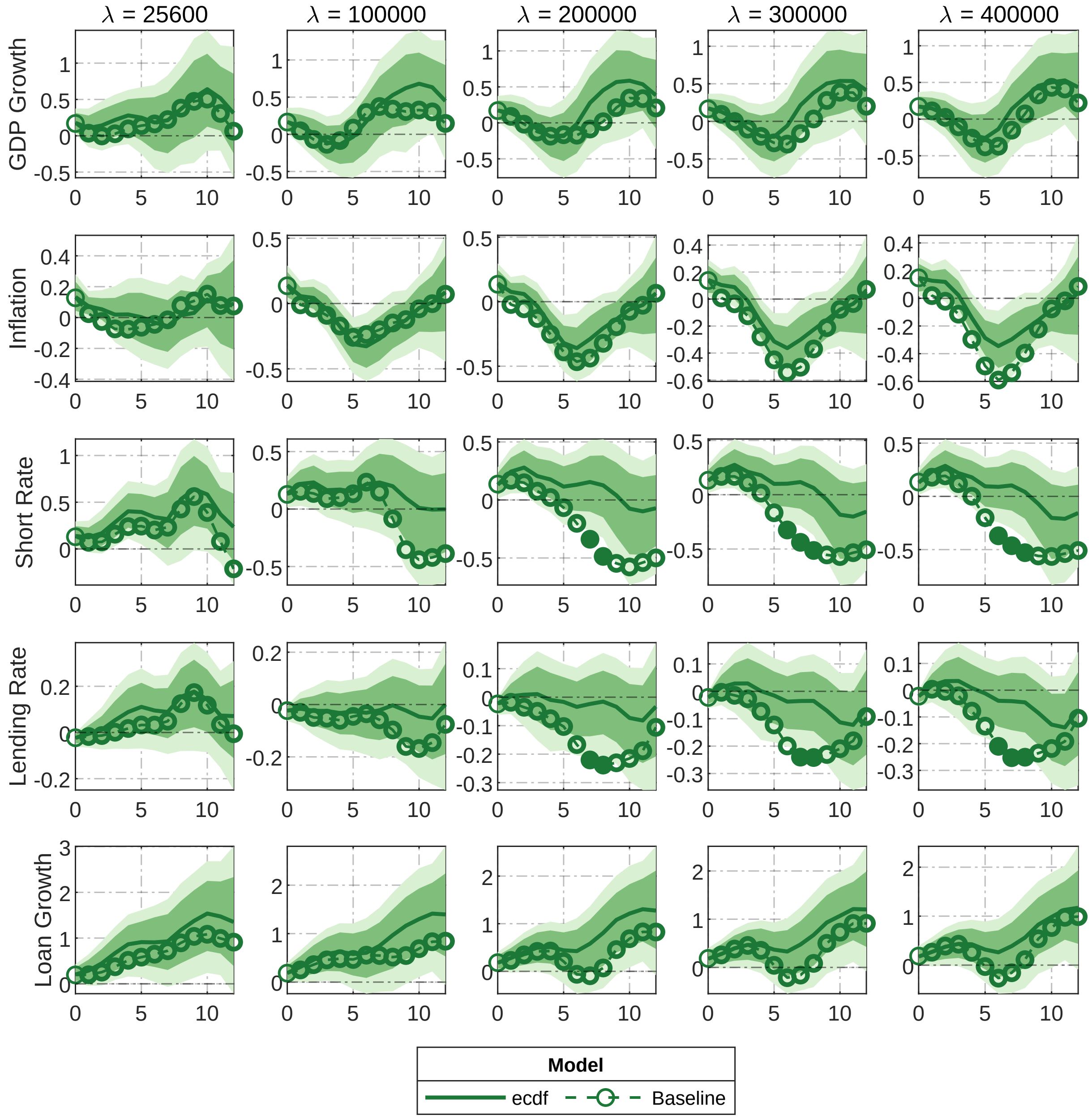
Figure 17: ecdf vs. Baseline Median Response (Tight Regime)



Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with regime determination by means of an empirical cumulative density function. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

In principle, this robustness exercise confirms our previous results. Here, too, we find the unclear results in the loose regime. However, there is a potential flaw when using the ecdf. Given our relatively short sample, we cannot rule out the possibility that the ecdf derived from our observations incorrectly represents the true ecdf of the population.

Figure 18: ECDF VS. BASELINE MEDIAN RESPONSE (LOOSE REGIME)



Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory loose regime. Solid lines represent median responses from the models with regime determination by means of an empirical cumulative density function. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

7 Conclusion

Over the past decade or so, credit developments have increasingly become the focus of attention. One key aspect of this is that misguided dynamics harbour great potential to trigger economic turmoil. Analyses of expansive loan supply shocks in particular have intensified, as credit-driven private sector debt has been a key factor in past crises, especially in the euro area.

Prudential measures have proven their worth in counteracting misguided credit developments. This set of instruments has proven to be particularly effective in keeping credit developments on track. Accordingly, this toolbox is being used more and more frequently.

When implementing prudential measures, decision-makers have to resolve a conflict of objectives. If they apply the brakes too hard on expansive credit development, there is a risk that favourable investments will not be made and economic growth will be weakened. On the other hand, if they do not counter such developments vigorously enough, there is a risk that these developments will foster a harmful debt dynamic.

In analysing the role of prudential regulation on economic factors, the empirical literature has so far focused on the effects of the systematic and non-systematic components of prudential measures. We add a further dimension to the existing literature by analysing the role of the regulatory regime for the business cycle effects of expansionary loan supply shocks.

In doing so, we uncover two main results. First, we find that expansionary loan supply shocks in a tight regime cause a noticeable boom-bust cycle. These results hold regardless of the frequency of the chosen regulatory cycle. Comparing the business cycle effects between the regimes, we see asymmetric responses. Loan growth in particular responds noticeably differently. In the tight regime, expansionary loan supply shocks do not sustainably increase credit growth. In contrast, we see that in the loose regime, lending follows a sustained growth path as a result of the shock. However, the responses found in a loose regulatory regime are not as robust. A key reason for this is that it is difficult to identify loose regimes, as prudential measures have so far mainly taken only one form: tighter.

Even if we cannot draw any definite conclusions, the tendencies for asymmetric effects should not be completely ignored in light of the importance of credit development for prudential regulation.

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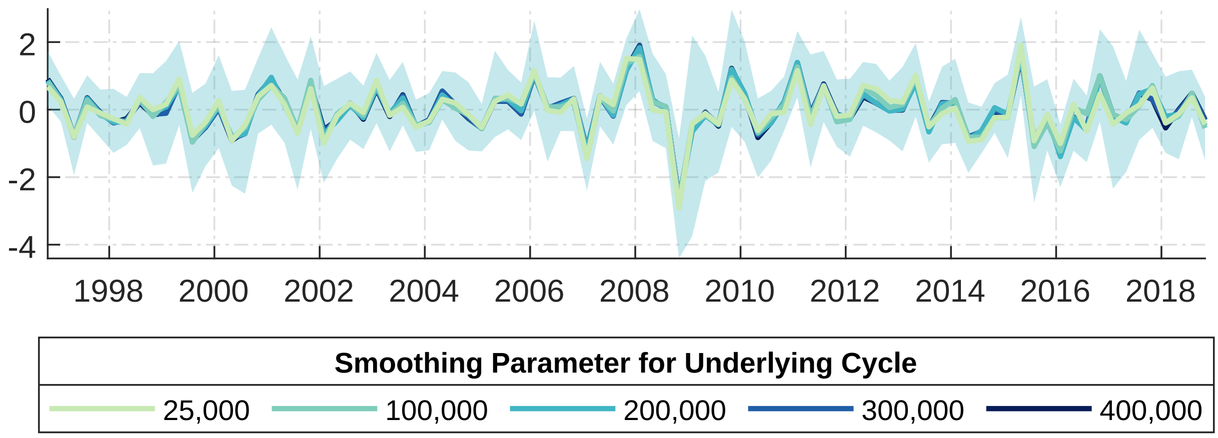
A Identified Shocks

The identified median loan supply shocks are depicted in Figure A.1. The 90% probability band from the model with smoothing parameter value $\lambda^{RC} = 200,000$ is shown for reference. The median shocks are basically indistinguishable, indicating that the shocks are well identified independent from the underlying regulatory cycle. The shocks show noticeable negative oscillations in the first half of 1999, in early 2002, and in the first quarter of 2007, with the negative shock at the end of 2008 being the most obvious. Noticeable positive impacts are identified in the first quarters of 2008 and 2011. The identified shocks can hardly be distinguished from each other, regardless of the choice of the smoothing parameter λ^{RC}.

Figure A.1: Loan Supply Shocks

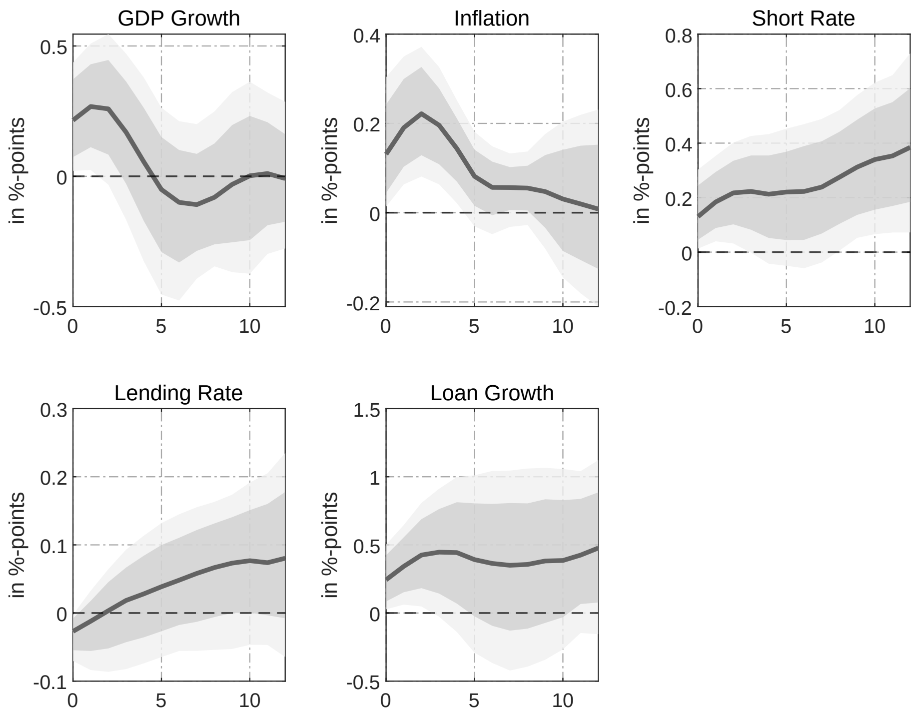


Notes: Solid lines show median shocks. Light area denotes 90 % probability band of the shocks from the model with smoothing parameter $\lambda^{RC} = 200,000$.

B Baseline Linear Model

As far as the linear model is concerned, the responses shown in Figure B.1 match the findings for the euro area in, i.a. Barauskaitė et al. (2022), Mandler and Scharnagl (2020), Altavilla et al. (2019), Gilchrist and Mojon (2018), Gambetti and Musso (2017), or Bijsterbosch and Falagiarda (2015). Concerning the effect on output, loan supply shocks have a notable, yet rather short-lived effect. When the expansionary shock hits the economy, output increases by 0.2 percentage points on impact and peaks at 0.4 percentage points within the first year after the shock hits the economy. Thereafter, the effect gradually decays. Inflation shows a similar but more persistent response. Interest rates follow the rise in inflation. They appear to be more persistent than the developments of inflation. The lending rate initially falls, thereafter permanently reverses to positive rates, which is explained by the development of the short-term interest rate.Finally, an expansionary loan supply shock leads to a sizeable and lasting credit expansion.

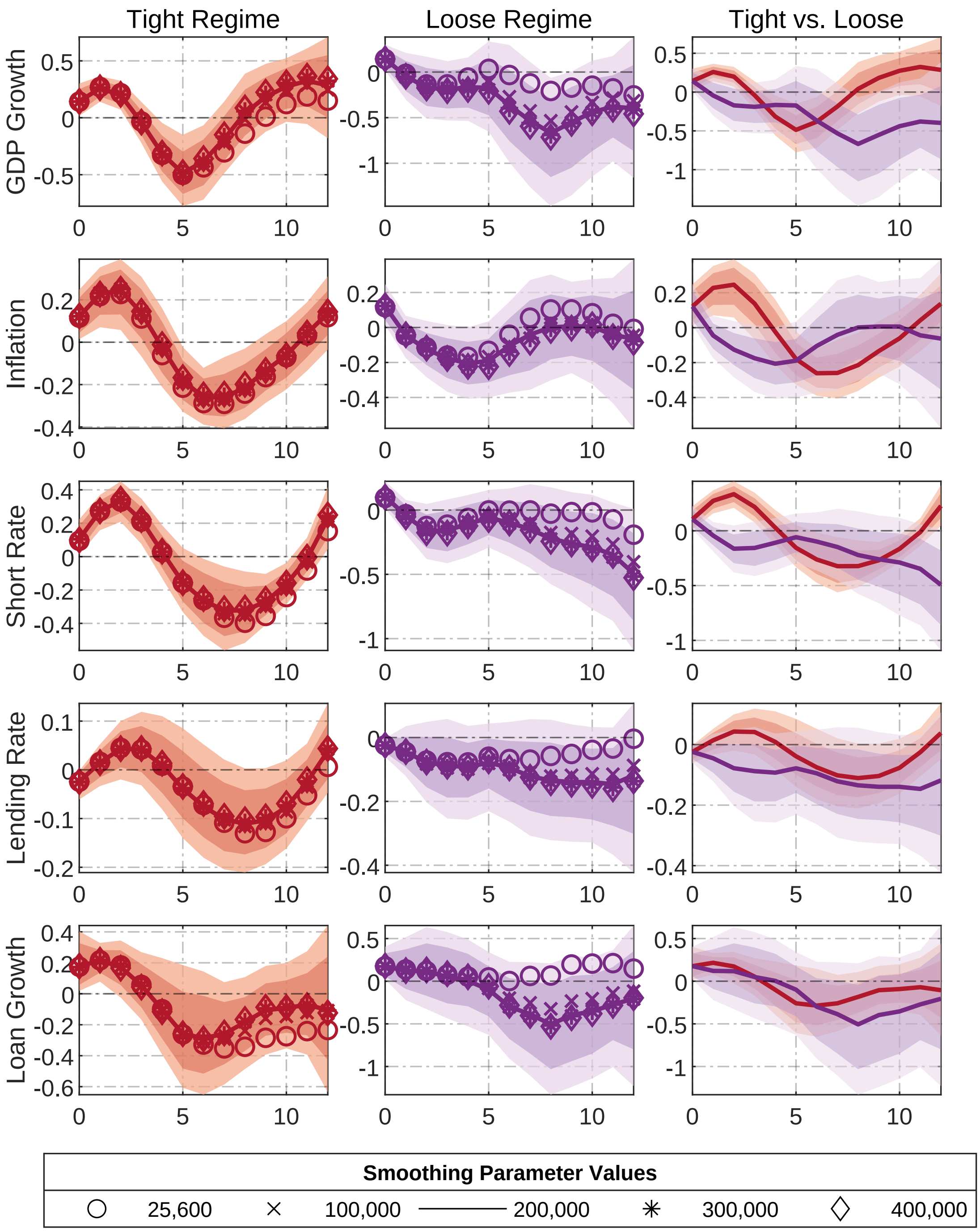
Figure B.1: Linear Model



Notes: Impulse responses to an expansionary loan supply shock from a linear LP model with model specified as described in Section 3. Identifying assumptions are impose on impact. Solid lines depict median responses, accompanied by 68% (dark grey) and 90% probability masses (light grey).

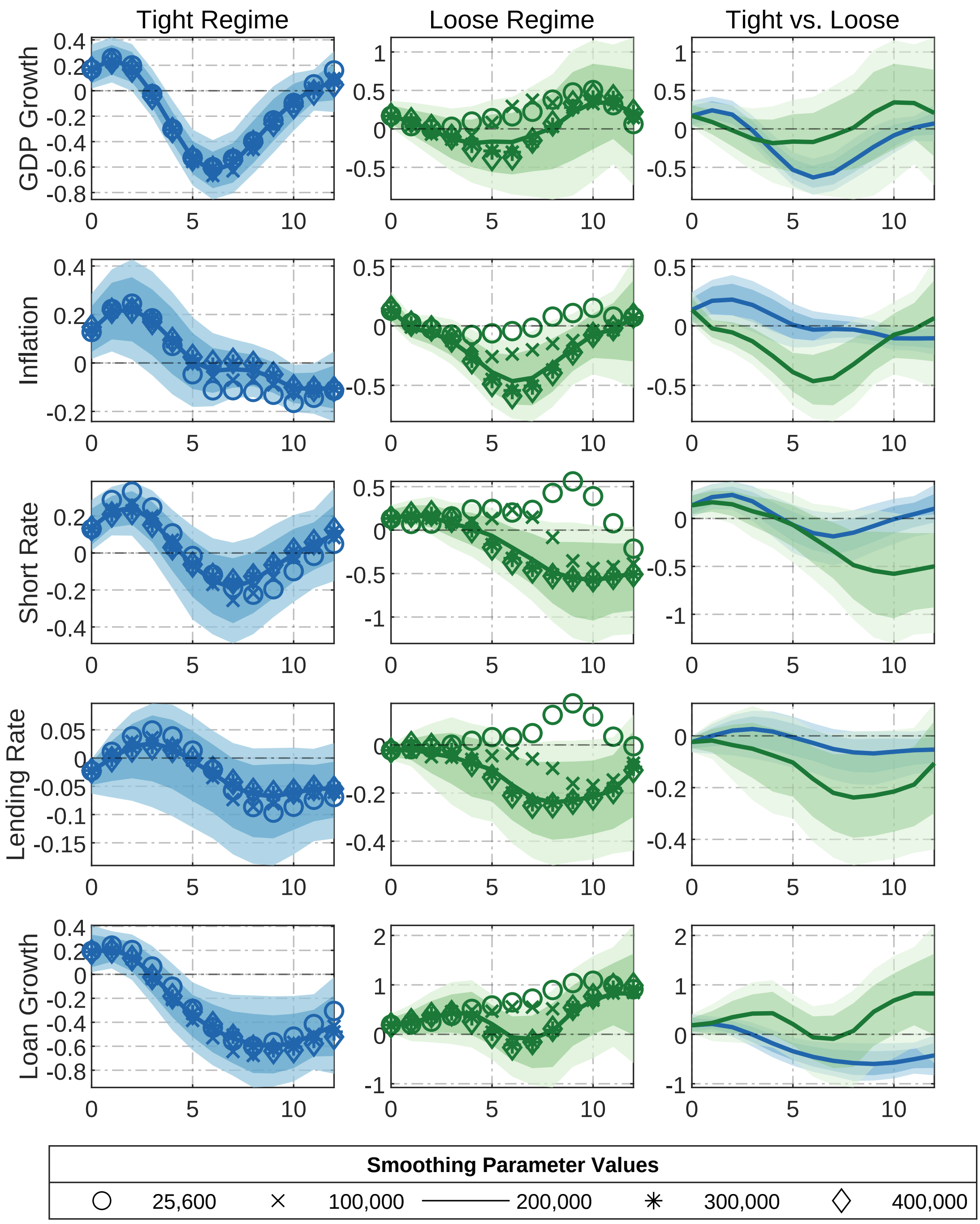
C Supplementary Figures

Figure C.1: Impulse Responses from Short Sample



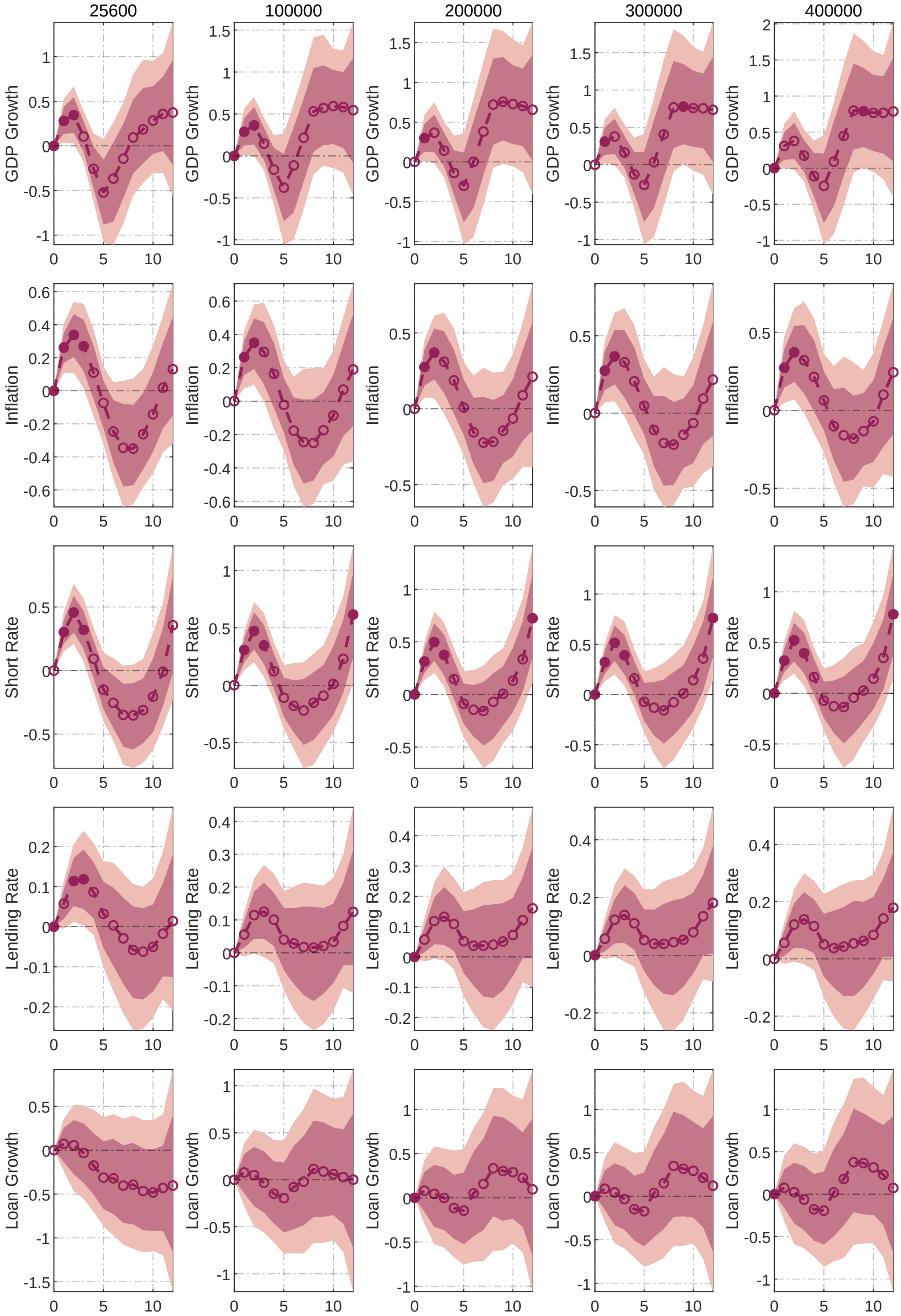
Notes: State-dependent impulse responses to an expansionary loan supply shock in the short sample spanning the period 1995Q1 until 2015Q1. Identifying assumptions are impose on impact. Lines and markers depict median responses in tight (left panel) and loose (center panel) regulatory regimes. Lines and markers depict median responses. For ease of comparison, median responses and probability band from the model with smoothing parameter value 200,000 are shown in the right panel. Smoothing parameter values relate to the smoothing parameter λ^{RC} used in order to extract regulatory cycles, as described in the main text. Dark (light) areas depict corresponding 68% (90%) probability masses.

Figure C.2: Impulse Responses from Full Sample



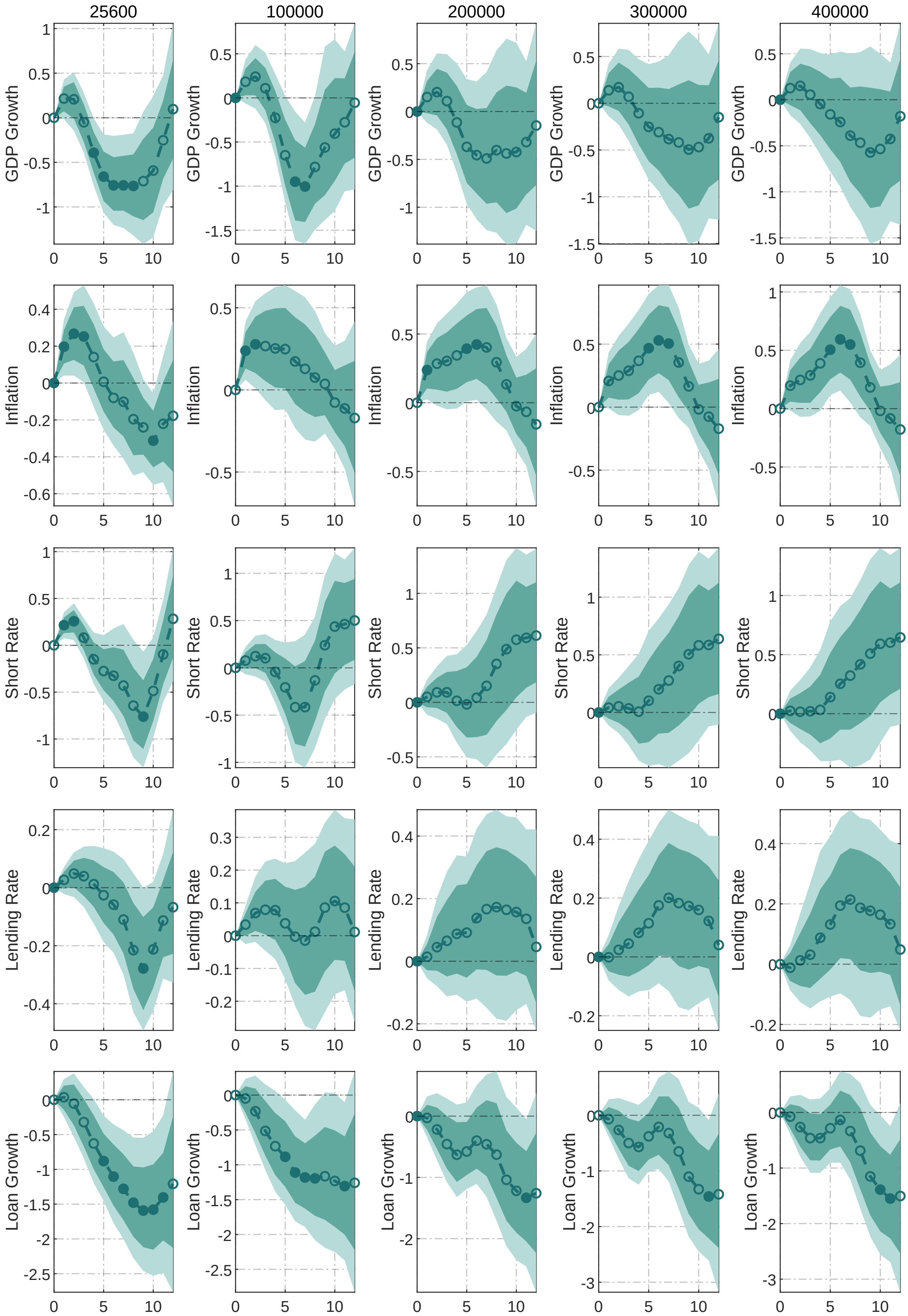
Notes: State-dependent impulse responses to an expansionary loan supply shock in the full sample spanning the period 1995Q1 until 2018Q1. Identifying assumptions are impose on impact. Lines and markers depict median responses in tight (left panel) and loose (center panel) regulatory regimes. Lines and markers depict median responses. For ease of comparison, median responses and probability band from the model with smoothing parameter value 200,000 are shown in the right panel. Smoothing parameter values relate to the smoothing parameter λ^{RC} used in order to extract regulatory cycles, as described in the main text. Dark (light) areas depict corresponding 68% (90%) probability masses.

Figure C.3: Difference in Responses from Short Sample



Notes: Difference between the impulse responses from the tight and loose regime ($\beta_{i,h}^{tight} - \beta_{i,h}^{loose}$) based on the short sample. The dotted lines represent the median responses which are also shown in Figure 5 in the main text. Filled dots indicate projection horizons significant asymmetry at the 5% level. Dark (light) areas depict 68% (90%) probability masses.

Figure C.4: Difference in Responses from Full Sample



Notes: Difference between the impulse responses from the tight and loose regime ($\beta_{i,h}^{tight} - \beta_{i,h}^{loose}$) based on the full sample. The dotted lines represent the median responses which are also shown in Figure 5 in the main text. Filled dots indicate projection horizons with significant asymmetry at the 5% level. Dark (light) areas depict 68% (90%) probability masses.

Affidavit

Ich erkläre hiermit, dass ich die vorgelegten und nachfolgend aufgelisteten Aufsätze selbstständig und nur mit den Hilfen angefertigt habe, die im jeweiligen Aufsatz angegeben oder zusätzlich in der nachfolgenden Liste aufgeführt sind. In der Zusammenarbeit mit den angeführten Koautoren war ich mindestens anteilig beteiligt. Bei den von mir durchgeführten und in den Aufsätzen erwähnten Untersuchungen habe ich die Grundsätze guter wissenschaftlicher Praxis, wie sie in der Satzung der Justus-Liebig-Universität Gießen zur Sicherung guter wissenschaftlicher Praxis niedergelegt sind, eingehalten.

Paul Rudel
02. August 2024

I hereby declare that I completed the papers submitted and listed hereafter independently and only with those forms of support mentioned in the relevant paper. When working with the authors listed, I contributed no less than a proportionate share of the work. In the analyses that I have conducted and to which I refer in the papers, I have followed the principles of good academic practice, as stated in the Statute of Justus Liebig University Giessen for ensuring good scientific practice.

Paul Rudel
August 2, 2024

Submitted Papers

i. Hafemann, Lucas, Paul Rudel, and Jörg Schmidt, "Moving closer or drifting apart: Distributional effects of monetary policy," *The Manchester School*, 2018, *86*, 110–136.

ii. Rudel, Paul and Peter Tillmann, "News shock spillovers: How the euro area responds to expected Fed policy," *MAGKS Joint Discussion Paper Series in Economics*, 2024, No. 13-2024.

iii. Finck, David and Paul Rudel, "Do credit supply shocks have asymmetric effects?," *Empirical Economics*, 2023, *64*(4), 1559–1597.

iv. Rudel, Paul, "Loan supply shocks, prudential regulation, and the business cycle," *MAGKS Joint Discussion Paper Series in Economics*, 2024, No. 09-2024.