A non-linear analysis of fiscal multipliers and consumption drivers

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Abstract

This thesis explores the non-linear features of fiscal multipliers in the US economy and of consumption drivers in the euro area. In Chapter 1 we examine a Smooth Transition implementation of a VAR model by Auerbach and Gorodnichenko (2012). We show how the difference in the fiscal multiplier disappears when the design matrix is not augmented with business cycle lags and the model is estimated in first differences. Furthermore, we build on this original approach by using generalized impulse analysis to produce authentic non-linear impulse responses. Our results highlight the Great Recession as a significant turning point, the inclusion of which in the sample enables us to reverse the sign of the effect on GDP of a fiscal shock and endorse the expansionary budget cuts narrative.

Chapter 2 presents the use of the same STVAR and generalized impulse response analysis to examine the non-linear effects of unanticipated government expenditure shocks on US GDP, controlling for private credit and public debt. We also perform a scenario analysis exercise to investigate shock responses during recessions and expansions, while making explicit the effect of the shock on public debt. We find that (i) the results support the inclusion of a measure of fiscal burden in the model; (ii) the GDP response to fiscal shocks is asymmetric in sign and magnitude; (iii) there exists a phenomenon of diminishing returns to expansionary shocks, which limits counter-cyclical fiscal policy; (iv) scenario analysis shows stronger multipliers on average in typical recessions.

We investigate the combined effect of business and financial cycles on a non-linearly fluctuating economy in Chapter 3, designing and estimating a joint economic cycle. A STVAR model and generalized impulse response analysis enable us to examine the non-linear effect on GDP of unanticipated government expenditure shocks, which we complement by performing scenario analysis. The main findings are that (i) every specification shows concordance between signs of shock and GDP response; (ii) the inclusion of an indicator of fiscal capacity in the model leaves the baseline key findings unchanged; (iii) the main results show diminishing returns to increasing expansionary stimuli; (iv) public debt and private credit generally behave pro-cyclically; (v) scenario analysis suggests higher yield to shocks during recessions.

Chapter 4 studies the cyclical dynamics of consumption in the euro area (EA) and the large EA countries by distinguishing between durable and nondurable expenditures. We adopt a theoretical partial equilibrium framework to justify the identification strategy of our empirical model, a time-varying parameter structural vector autoregression (TVP-SVAR). Following the main insight from the theoretical model – that liquidity constraints induce important interactions between durables and nondurables – we distinguish durable-specific demand and supply shocks, while taking into account monetary and credit conditions. Our main findings are: (i) durables react faster and more strongly than nondurables after monetary shocks in the euro area and in the largest EA countries; (ii) there is large degree of cross-country heterogeneity in the factors that drive consumption; (iii) strength of spillovers from durables to nondurables is empirically correlated with the likelihood of being liquidity-constrained across countries.

List of Contents

List of Tables

List of Figures

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Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References. Chapter 4 was co-authored, as specified below. This research was financially supported by the Economic and Social Research Council, grant number ES/J500215/1.

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Introduction

Every social scientist approaching the practice of research is bound to quickly learn a fundamental lesson: models, irrespective of how complex or well-designed they might be, are but a vast simplification of the intricacies we experience on a daily basis in the real world. This holds true even more so in the field of empirical economic research, as we try to find quantitative answers to questions too complex to be treated in their original form. One of the most apparent shortcomings of a large part of our models is to assume that responses hold constant over time and are, more generally, linear. As pointed out by Alan Greenspan in his opening remarks of the 2003 symposium sponsored by the Kansas City Federal Reserve,

> An assumption of linearity may be adequate for estimating average relationships, but few expect that an economy will respond linearly to every aberration [...] Recent history has also reinforced the perception that the relationships underlying the economy's structure change over time in ways that are difficult to anticipate.[1]

The effort to consider non-linearities in the analysis of different phenomena will be the *fil rouge* throughout this dissertation.

We focus on two different phenomena in which a non-linear perspective can produce new results and greatly impact the narrative: Government expenditure fiscal multipliers in the US economy, that is how much the GDP reacts to a fiscal government expenditure shock, and cyclical dynamics of consumption in the euro area (EA), as well as in the EA member states. Regarding fiscal multipliers, we model a state-contingent economy using an a-theoretical model which lets the economy free to fluctuate on a continuum of states between the extreme phases of the cycle. We build on previous studies and expand the focus from the business cycle to an economy led by a financial cycle. Furthermore, we build and estimate a comprehensive economic cycle, carrying information on both real economy and financial variables, and we present a selection of meaningful results yielded by its use in conditioning the model.

In chapter 4 we shift our focus to consumption dynamics in the EA and large EA countries, distinguishing durable and nondurable expenditures. Modelling consumption in a non-trivial and insightful way becomes substantially more challenging when the task includes consumer durables like cars, furniture, and electronics, which provide utility over multiple periods and depreciate over time. Furthermore, since they can be financed with credit (as well as used as collateral), these durables are often sensible to interest rate dynamics and can exhibit some important adjustment costs. These features have led expenditures on consumer durables to account for a much more than proportionate part of overall economic fluctuations.

Several studies have been produced on fiscal multipliers, a topic which cyclically dominates even the public non-specialistic debate, given its policy relevance and centrality. The question of how much and how well the economy will react to a given fiscal shock via government expenditure is a central pillar of the discussion surrounding the

[1] Greenspan, A. (2003). Monetary policy under uncertainty. In *Opening remarks – Economic Policy Symposium: "Monetary Policy and Uncertainty: Adapting to a Changing Economy" – Jackson Hole*, pages 1–7. Federal Reserve Bank of Kansas City

cost and efficiency of any public intervention on the economy. This holds particularly true during periods of crisis, when a counter-cyclical government intervention is often a key part of the damage control and recovery strategy. Typical research questions in this strand of literature include the exact size of the multiplier and the optimal structure of intervention to apply in order to achieve the maximum effect. Typical answers are that the multipliers are around one in size, slightly larger during recessions, depending on which model and sample are used to compute them. We make an effort to go beyond such questions. In a non-linear setup the dynamic and the evolution path of the response to a shock become much more relevant than its peak size, since the behaviour of the economy is contingent on its own state and on the characteristics of the shock. At the same time, we do not overlook how central it is, under a policy perspective, to know whether a recession can be counteracted with a fiscal stimulus package. To this end, the question is translated in non-linear terms and the model is calibrated so that the economy is in a state of average representative recession (or expansion) when the shock hits, but it is then left free to evolve naturally according to its own non-linear mechanics.

There are few studies in the literature which feature a distinction between durable and nondurable consumption. Data limitations have severely restricted any model-based investigation of structural factors behind expenditures on consumer durable goods in the euro area, as well as their interaction with the other components of consumption. Since such studies are, to our knowledge, virtually non-existent at the time of writing, one of our main contributions can be considered an in-depth investigation into this crucial demand component.

To explore the interactions between US fiscal policies and the broad economy, imposing as few theoretical assumptions as possible and, at the same time, preserving a certain degree of comparability with the literature, our model of choice is a Smooth Transition VAR, as introduced by Auerbach and Gorodnichenko (2012). This model allows the shocks to propagate via two channels: a dynamic one, through the lag polynomials, and a contemporaneous one, via the state-contingent shock variance-covariance matrix. Our estimation strategy exploits the fact that the model linearises for a given guess of the variance-covariance matrix, whose non-standard distribution needs, however, to be numerically estimated. To this aim, we use a Markov Chain Monte Carlo Bayesian technique, adopting the Metropolis-Hastings sampling algorithm with flat priors, a well established choice in the literature. To keep the non-linear transition dynamics intact we use generalized impulse response functions (GIRF), which are defined as the expectation of the realization conditional on the history and the shock, over a baseline conditional expectation on just the history. As the differences between two conditional expectations are random variables, the value of the impulse response is itself a random variable. Since our model is known, we are able to use a Monte Carlo approach to estimate the distribution of the conditional expectations and, therefore, to obtain the empirical distribution of the realizations of the generalized impulse response. This enables us to conveniently estimate any preferred measure of centrality of distribution, as well as the confidence bands. We adopt short-run recursive restrictions implied by Cholesky decomposition to identify fiscal shocks from the vector of reduced form residuals. Scenario analysis experiments rely on the flexibility provided by the GIRF approach to keep the exercise simple, while still meaningful. After picking a criterion to build a chronology of recessions and expansions, we select the quarters falling in a given regime, as well as their lags, to put together a history of regime-specific realizations. The median of such series gives a typical, representative scenario history, which we use to augment our sample effectively feeding the lag mechanics of the model with synthetic values reflecting a given state of the economy. This allows us to explicitly define the history on which the expectation is conditional. A further extension of this exercise, limited to the specifications including public debt, is to explicitly assume what impact the government expenditure variation will have on public debt. That is, to simulate either debt-financed fiscal expansions, or budget cuts aimed at restructuring the stock of public debt.

Chapter 3 is centred around the concept of a synthetic measure for both the real activity and the financial environment. We name this index the *economic cycle*, as it includes informative power on the economy as a whole. In order to build such a cycle, we start from a large monthly database of economic and financial variables: the Fred-MD database put together by McCracken and Ng (2016) as an extension of Stock and Watson (1996). We straightforwardly follow a factor analysis reasoning and go for a dimension-reduction strategy: we use an information criterion to identify the optimal number of factors and adopt the well known EM algorithm to estimate them. Factors are interpreted as informative about real production and activity, employment, interest rates, forward looking, prices, or the stock market according to which series they are able to explain the most. Consequently, we filter them with a passband filter to extract either the short-term business cycle-related components of the larger and broader financial cycle frequencies. Finally, we project GDP onto the filtered factors to estimate an index rich in information and animated by fundamental drivers spanning the whole economy – financial side included.

When approaching the structural factors of consumption in the EA, we start by setting up a simple theoretical model distinguishing between durable and nondurable consumption, in which we embed non-linear dynamics and occasionally binding borrowing constraints. The model does not aim to represent the whole economy, but rather it focuses on a very specific class of agents – the quasi-constrained ones – as they are unable to fully adjust to their preferences due to a non-linear liquidity constraint kicking in. A key model-based prediction is that such agents will experience a shift in consumption after a durable-specific shock, from durable to nondurable expenditures, which we dub a spillover. We take this result as a confirmation that durable and nondurable consumption need to be modelled separately and in a time-contingent manner, to allow for asynchronous and non-linear adjustments in the presence of borrowing constraints. Following this intuition, we step into the empirical investigation, using a time-varying parameter structural vector autoregressive model (TVP-SVAR) which explicitly allows for non-linearities both via its coefficient matrix and via its stochastic volatility features. We use country-level data on 19 EA member states to build the series for the euro area as a whole, and estimate the model over a sample from 1997Q1 to 2018Q3. We compare results for the EA, the four largest EA countries – Germany, France, Italy, and Spain – as well as the US. Our identification strategy relies on a mix of short-term zero and sign restrictions and it is able to account for broad monetary and credit conditions (considering together continent-wide monetary policy and country-level idiosyncratic credit environment), while distinguishing between durable-specific and aggregate consumption supply and demand shocks.

Overall, we find merit in an econometric framework allowing for non-linear features, as it better fits complex real-world phenomena. Concerning fiscal multipliers and the econometric strategy used to investigate them, in Chapter 1 we show that including the whole Great Recession in the sample dramatically changes the dynamics of the response to a shock, as well as some of its key features, notably including the sign of the response. This raises crucial caveats over the stability of non-linear findings and advocates for caution when evaluating policy measures enacted in a peri-crisis period, where two different dynamics merge. Conclusions of Chapter 2 are that (i) the results support the inclusion of a measure of fiscal burden in the model; (ii) once allowing for non-linear features in the model, the GDP response to fiscal shocks is asymmetric in sign and magnitude; (iii) there exists a phenomenon of diminishing returns to increasing expansionary shocks, which calls into question the efficiency of counter-cyclical fiscal policies during a crisis; (iv) scenario analysis shows on average stronger multipliers in typical recessions. We confirm these findings in Chapter 3, showing that (i) every specification shows a concordance between the sign of the shock and GDP response; (ii) the inclusion of fiscal burden and fiscal space in the model does not alter the key findings of the baseline, proving that the economic cycle is informative enough; (iii) main results show diminishing returns to larger expansionary stimuli; (iv) public debt and private credit generally behaves pro-cyclically; (v) scenario analysis suggests that on average fiscal multipliers are stronger in a typical recession.

Our main results on consumption dynamics in the euro area can be summarised as follows: (i) durables react faster and stronger than nondurables after monetary shocks in the euro area and in the largest euro area countries, confirming an outcome commonly reported for the United States; (ii) there is a large degree of cross-country heterogeneity in how different factors (including durable-specific ones) explain consumption; (iii) the strength of spillovers from durable to nondurable consumption, as predicted by theory, is empirically correlated with the extent to which households across countries are likely to be liquidity constrained. In particular, countries with a larger share of constrained households, like Italy and Spain, experience larger spillovers from durable-specific factors on nondurable consumption.

This thesis develops as follows. Chapter 1 revisits a measure of output response to fiscal policy, it explores some technical features of the STVAR model, it shows how modelling choices can steer the results, and it substantiates the claim that a GIRF approach yields richer findings than a linear one. In Chapter 2 we assume that the economy is fluctuating along a purely financial cycle and we show how the GDP reacts to government expenditure shocks. Chapter 3 delves into an economy contingent on a novel economic cycle, encompassing real economy and financial environment information. We show how this new measure of economic and financial activity can produce richer results with more parsimonious specifications. The dynamics and structural drivers of consumption are explored in Chapter 4.

Chapter 1

Revisiting the measure of output response to fiscal policy

1.1 Introduction

Be it either in the midst of a recession or in times of prosperity, when policy makers are faced with the choice to use fiscal policy to influence the economy, the underlying question is often simply *How large is the multiplier?* That is, how much the fiscal intervention will affect the broad economy, measured by the means of GDP. Such an answer is made less straightforward by the state of the economy itself: the way the economy – a complex system made of a plethora of parts interacting with each other in what is often a non-linear fashion – will react to a shock will depend on its status. In other words, the same fiscal shock will bring forth different outcomes depending on when and how it is delivered.

Auerbach and Gorodnichenko (2012, henceforth AG) find large differences in the size of fiscal multipliers in recessions and expansions, with the spending multiplier being considerably larger in recessions. Their research can be taken as a seminal contribution in the field of empirical investigation on state-contingent multipliers, and it has inspired a number of other works exploring non-linearities and state contingency. Callegari et al. (2012) use a somewhat simpler non-linear econometric framework, a threshold VAR, to estimate the effect of several budget consolidation programs following the 2009 financial crisis (the so called austerity period). Their results endorse fiscal consolidations operated via spending cuts rather than tax increases and estimate that a spending cut initiated during a period of economic expansion will be contractionary only in the short-term, as opposed to the longer lasting effect of a spending cut initiated during a recession.

Galvão and Owyang (2018) augment the AG smooth transition model with financial factors, acknowledging the crucial role of the financial environment, in the same spirit as our Chapter 2, albeit with an approach closer to the setup in Chapter 3. They find evidence of the existence of important non-linear dynamics occurring between the financial conditions and macroeconomic variables measuring production and price stability, thus advocating for the adoption of models able to allow for such non-linearities. Bolboaca and Fischer (2019) look into the non-linear effect that news shock about technological innovation brings forth adopting the same econometric framework as AG. They find important differences in the effect of a news shock hitting the economy in different times. A shock can initiate a boom and make the economy transition from a recession to an expansionary phase, but the reaction will be slower that in normal times, albeit larger. They identify a state variable in the amount of uncertainty, which is negatively correlated with the business cycle and can impair the positive effect of a shock. Tenreyro and Thwaites (2016) investigate the business cycle conditionality of monetary policy shocks in the US economy. Using a different modelling strategy centred on a smooth transition local projection framework, they find similar results: non-linearities do exist and the timing of a shock in terms of business cycle phase is crucial to determine its overall effect. Berger and Vavra (2014) look at consumption of durable goods under different government purchase behaviours. They adopt the very same AG econometric specification and famously find that the expenditure on durables reacts strongly procyclically to government expenditure shocks.

AG use a non-linear Smooth Transition VAR model, a multivariate extension by van Dijk et al. (2002) of the univariate specification already proposed by Granger and Teräsvirta (1993), further extended by allowing the variance-covariance matrix of the innovation shock to be subject to the smooth transition mechanism. The model is estimated using Markov Chain Monte Carlo methods with the Metropolis-Hastings algorithm and flat priors. The choice of variables follows Blanchard and Perotti (2002, henceforth BP): (log real) government expenditure (G), net tax receipts (T), and gross domestic product (Y), for a sample from 1947Q1 to 2008Q4. Multipliers are computed using orthogonalised impulse response functions analysis, adopting the same BP order: $[G,\ T,\ Y]$.

We clarify how much the original results are affected by the augmentation of the model with foreign variables, and by the choice of estimating the model in levels, thus mapping statistical interactions among levels into a cycle. The first issue originates from the model estimation strategy using, at its core, Generalised Least Squares to perform the model parameter estimation, where the design matrix is augmented with lags of the state indicator treated as a foreign variable. Such an approach could inflate the effect of a policy shock and potentially lead to the estimation of large differences in the size of fiscal multipliers between regimes. The second issue spurs from the estimation of the model using non-stationary data in levels. Despite the advantage of a super-consistent estimation of parameters using cointegrated series, this approach still raises a number of questions. Particularly, the Bayesian sampling procedure relies on hypothesis testing to ensure convergence and consequently any form of inference when GLS estimation is applied to cointegrated series becomes fragile.

Building on the original approach of AG we introduce generalized impulse response analysis, as in Koop et al. (1996) and Pesaran and Shin (1998), to overcome the most crucial limitation of the linear orthogonalized IRFs used in the original paper, which is the implicit assumption that the regimen is extreme and does not change over time. However, we improve the methodology to allow for the identification of fiscal shocks, following the spirit of Kilian and Vigfusson (2011) and Pellegrino (2021). The identification is achieved by imposing the conventional short-run recursive structural restrictions implied by Cholesky decomposition on the vector of reduced form residuals. We also complement the original narrative with an updated sample.

The chapter proceeds on as follows. Section 1.2 deals with the inclusion of exogenous variables, and Section 1.3 with the estimation in levels. Section 1.4 show results of generalized impulse response analysis. Section 1.5 concludes.

1.2 Smooth Transition VAR or VARx?

The Smooth Transition VAR model used by AG is given by

$$\begin{gathered}
\mathbf{X}_t = \left[(1 - F(z_{t-1}))\mathbf{\Pi}_E + F(z_{t-1})\mathbf{\Pi}_R\right](L)\mathbf{X}_{t-1} + \mathbf{u}_t \\
\mathbf{u}_t \sim N(\mathbf{0}, \mathbf{\Omega}_t) \\
\mathbf{\Omega}_t = \mathbf{\Omega}_E(1 - F(z_{t-1})) + \mathbf{\Omega}_R F(z_{t-1}) \\
F(z_t) = \frac{e^{-\gamma z_t}}{1 + e^{-\gamma z_t}} \qquad \gamma > 0 \\
\mathrm{Var}(z) = 1 \qquad \mathrm{E}[z] = 0,
\end{gathered}$$

where $\mathbf{X}$ is the data matrix, $\mathbf{\Pi}_E$ and $\mathbf{\Pi}_C$ are the coefficient matrices; z is the switching variable, ruling the transition on the cycle, and computed as the 7-quarters moving average of the GDP growth; and $0 \leq F \leq 1$ is the smoothing function. The subscripts E and R refer respectively to expansion and recession phases of the business cycle.

The estimation strategy, summarized in Appendix A.1, rests on the maximum likelihood approach developed in Chernozhukov and Hong (2003). The model log likelihood is given by

$$\mathcal{L} = a - \frac{1}{2}\sum_{t=1}^{T} \log\left(|\mathbf{\Omega}_t|\right) - \frac{1}{2}\sum_{t=1}^{T} \mathbf{u}_t' \mathbf{\Omega}_t^{-1} \mathbf{u}_t \tag{1.1}$$

where

$$u_t = \mathbf{X}_t - (1 - F(z_{t-1}))\mathbf{\Pi}_E(L)\mathbf{X}_{t-1} - F(z_{t-1})\mathbf{\Pi}_R(L)\mathbf{X}_{t-1}$$

and a is a constant. After defining

$$\begin{aligned} &\mathbf{W}_t = [(1 - F(z_{t-1}))\mathbf{X}_{t-1},\ F(z_{t-1})\mathbf{X}_{t-1} \ldots\ (1 - F(z_{t-1}))\mathbf{X}_{t-p},\ F(z_{t-1})\mathbf{X}_{t-p}] \\ &\mathbf{u}_t = \mathbf{X}_t - \mathbf{\Pi}\mathbf{W}_t' \end{aligned} \tag{1.2}$$

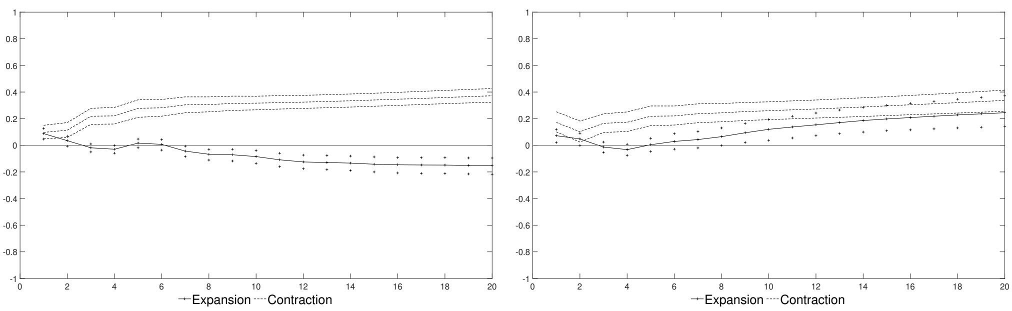
AG proceed to take the first order condition:

$$\text{Vec}\left[\mathbf{\Pi}'\right] = \left(\sum_{t=1}^{T} \left[\mathbf{\Omega}_t^{-1} \otimes \mathbf{W}_t'\mathbf{W}_t\right]\right)^{-1} \text{Vec}\left[\sum_{t=1}^{T} \mathbf{W}_t'\mathbf{X}_t\mathbf{\Omega}_t^{-1}\right] \tag{1.3}$$

For any guess of the model variance-covariance matrix $\mathbf{\Omega}_t$, Equation (1.3) gives the optimal value of $\mathbf{\Pi} = [\mathbf{\Pi}_E, \mathbf{\Pi}_R]$. Crucially, when defining $\mathbf{W}$ in Equation (1.2) AG augment it with lags of the indicator variable z. This amounts to transforming the model into a STVARx, where the foreign variables added are lags of the output growth smoothed by a seventh order moving average – that is, a function of one of the endogenous variables themselves. This results in the estimation of an augmented $\mathbf{\Pi} = [\mathbf{\Pi}_E, \mathbf{\Pi}_R, \mathbf{\Pi}_z]$ matrix, from which only the two submatrices $\mathbf{\Pi}_E$ and $\mathbf{\Pi}_R$ are then extracted and used for computation of the multipliers.

Using the above specification with the original $\mathbf{W}_t$ as per Equation (1.2) critically changes the size of the response to the policy experiment. This can be seen in Figure 1.1, showing linear orthogonalized impulse response functions with (a) or without (b) an augmented design matrix $\mathbf{W}$.

Figure 1.1: Effect of foreign variables



(a) With foreign variables (b) Without foreign variables

Note: GDP response to a unit standard deviation of government expenditure for a model with (a) and without (b) augmentation of the design matrix $\mathbf{W}$. STVAR(x) includes (log real) government expenditure, tax revenues, and GDP. Confidence bands are at 5th and 95th percentile.

While the results still show a disparity in the effects of a policy shock during recessions and expansions, this is smaller than the original results and shorter as well, since any statistically significant difference wanes after ten quarters.

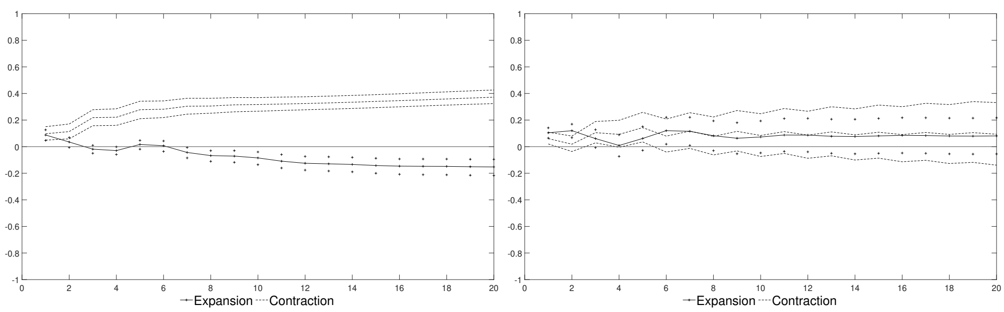
1.3 Estimation in levels

Whether a VAR can be used with non-stationary data is a question sparking controversy since Sims (1980) and his call to move away from artificial constraints used to identify simultaneous equations models. A VAR-specific perspective of the problem can be found in Sims et al. (1990), with the main point always being that differencing variables to achieve stationarity inevitably comes at the cost of disregarding important information on the long-run relationship among the levels. Moreover, estimating a VAR in levels with cointegrated series brings a super-consistent estimation of the parameters, which converge with rate T instead of $\sqrt{T}$.

Notwithstanding the validity of these points, there are some solid reasons compelling us to use stationary data for this and for the following Chapters' specifications. First, the claim by Sims (1980) that Bayesian methods can provide consistency even with non-stationary data does not find application in this specific case. Overall, our procedure possesses Bayesian features, since it makes use of Markov Chain Monte Carlo with the Metropolis-Hastings sampling algorithm. Nevertheless, the proper estimation step of the model is performed via GLS. Furthermore, the Bayesian part relies on hypothesis testing of the parameters matrix to select feasible guesses and, ultimately, to converge. Therefore, even a partial cointegration between series is able to invalidate standard hypothesis testing (Toda and Phillips, 1993). Second, extreme caution is needed specifically when GLS estimation is applied on $I(1)$ series, as highlighted by Kilian and Lütkepohl (2017). Lastly, the model does not include any control for the level of the variables, thus ignoring any possible stock-effect, and mapping non-stationary variables into a business cycle amounts to assuming that the same phase of the cycle will feature the same properties regardless of the relative level of the variables, which is bound to change over time due to different long-run growth rates.

We achieve stationarity by first differencing our variables and then estimating the VAR. We use cumulated responses to retrieve the effect of the shock in levels, as shown in Figure 1.2, which presents orthogonalized impulse response functions for data in levels (a) and in first differences (b).

Figure 1.2: Linear orthogonalized impulse responses in levels and first differences



(a) Estimated in levels (b) Estimated in first differences

Note: GDP response (b is cumulated) to a unit standard deviation of government expenditure. STVAR includes (log real) government expenditure, tax revenues, and GDP. Confidence bands are at 5th and 95th percentile.

Any difference in GDP response to a policy shock between recession and expansion takes place in the first two quarters, after which it becomes virtually non-existent. When the model is estimated in first differences, the effect can be said to be very short-term, to become statistically insignificant after about the fifth quarter.

1.4 Updating methodology and sample

The most striking limitation of the AG linear VAR orthogonalized IRF approach is that the results are no longer state-contingent, as we select one specific value of the smoothing function (and therefore a specific phase of the business cycle). AG present results for the extremes of the cycle, choosing $\mathbf{F} = \{\mathbf{1}; \mathbf{0}\}$, thus assuming that the economy will always be stuck in either a peak or a trough of the cycle.

We use the generalized impulse response functions (GIRF) approach developed by Koop et al. (1996) to capture the smooth transitioning of the economy along the cycle. This technique uses expectation operators conditioned either on the history ($\mathcal{H}$) or on the history *and* the shock (s), averaging out future shocks. The general impulse is defined as the expectation of the realization of $\mathbf{X}_t$ conditional on the history and the shock over a baseline consisting of the conditional expectation given only the history:

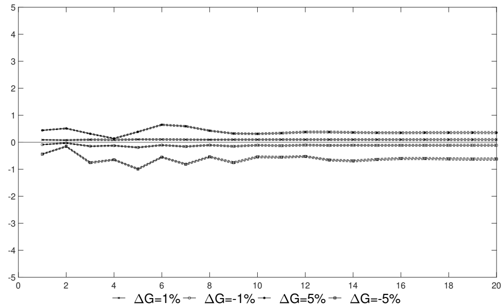
$$\begin{aligned} GI_{\mathbf{X}}(h, s_t, \mathcal{H}_{t-1}) = \mathrm{E}\left[\mathbf{X}_{t+h} \mid \mathcal{H}_{t-1}, s_t\right] - \mathrm{E}\left[\mathbf{X}_{t+h} \mid \mathcal{H}_{t-1}\right], \\ \text{for the horizon } h = 0, 1, \ldots. \end{aligned} \tag{1.4}$$

$GI_{\mathbf{X}}(h, s_t, \mathcal{H}_{t-1})$ represents a realization of the random variable GI, defined in Equation (1.4) as the difference of two conditional expectations being themselves random variables. Since our model is known, we are able to use a Monte Carlo approach to estimate the distribution of the conditional expectations and, therefore, to retrieve the empirical distribution of the realizations of GI allowing for a measure of centrality and for the estimation of the confidence bands. This approach traditionally does not require identification of structural shocks, as detailed in Koop et al. (1996) and Pesaran and Shin (1998), and maps the model dynamics to a government expenditure Equation residual shock, making the order of the variables irrelevant. The question asked by the classical GIRF approach is simply: what happens if we have a unitary shock in the residuals of the government expenditure equation today (since we are conditioning the impulse on the whole history)?

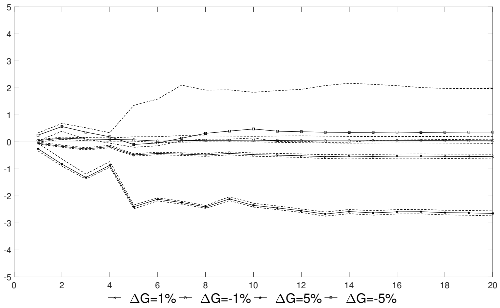
To correctly identify a fiscal shock, we need to adapt the procedure: in the spirit of Kilian and Vigfusson (2011) and Pellegrino (2021), we identify the fiscal shocks from the vector of reduced form residuals adopting the conventional short-run recursive restrictions implied by Cholesky decomposition. This comes with the price of losing the ability of disregarding the order of variables in the STVAR. Moreover, we are also extending the sample up to 2019Q4. This choice allows us to include in the estimation sample the Great Recession, while we deliberately leave out the most recent 2020-2021 recession induced by the global pandemic. Our reasoning is that the former was a recession born out of the financial environment and its origin was embedded in the complex system which is an economy, while the second has been triggered by a purely exogenous policy measure aiming to reduce social interactions.

We consider both positive and negative shocks, namely $\pm 1\%$ and $\pm 5\%$ of the U.S. government expenditure, roughly corresponding to $\pm 0.15\%$ and $\pm 0.8\%$ of GDP. The choice of a $\pm 5\%$ shock is in line with the American Recovery and Reinvestment Act (ARRA) of 2009 (2009) stimulus package, which delivered a combined impact of roughly 2.5% of GDP in the first year of enactment, as clearly shown in The Congress of the United States - Congressional Budget Office (2012). The results, for both the original (a) and the updated sample (b), are shown in Figure 1.3.

Figure 1.3: Cumulative GIRFs, original and longer sample



(a) Original sample



(b) Updated longer sample

Note: Percentage GDP response to a fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, and GDP. The longer sample goes from 1947Q1 to 2019Q4, while the shorter one stops at 2008Q4. Confidence bands are at 5th and 95th percentile.

As expected, the results differ greatly: updating the sample not only means estimating the model on different data, but also triggering the shock in a different phase of the cycle, endowed with a different dynamic (as in a different set of observations fed into the autoregressive lag mechanism). Some general features are, however, maintained: the shock responses are not symmetrical, neither sign- nor size-wise, thus exposing the non-linear properties of the model. In both the samples larger shocks have a more volatile effect than smaller ones and the model manages to identify them well, with the exception of the large negative shock in the longer sample, which appears ill-identified upwards.

The main difference between the two sets of results clearly resides in the sign of the reaction. With an updated sample, we find that positive government expenditure shocks are recessionary, while negative ones are indeed expansionary. Moreover, the magnitudes displayed by the model estimated on the longer sample are on average larger that the ones displayed by the shorter sample. It is easy to spot the crucial difference between samples: the inclusion of the Great Recession. It appears reasonable to impute to the 2009 crisis and subsequent recovery period the results displayed by Figure 1.3(b).

An interesting phenomenon, partially hindered in its interpretation by the large uncertainty associated with the estimation of the effects of the larger negative shock, is what appears to be a sort of diminishing return to increasingly large expansionary (in the effect) shocks. Larger budget cuts are more expansionary than smaller ones, but not proportionally more expansionary.

1.5 Conclusions

AG find large differences in the size of fiscal multipliers, with spending multipliers being sensibly larger in recessions. We suggested that the size of such differences may be inflated by the inclusion of past lags of the indicator variable, that is of past lags of a function of one of the STVAR variables, in the design matrix of the GLS estimation step. In a model without such an addition the difference between regimes as computed by AG becomes considerably smaller.

We also considered whether the model should be estimated in first differences, given the need for clear inference of the Bayesian sampling methodology and the caveats associated with applying GLS estimation on potentially cointegrated series in levels. The results deriving from this correction strongly challenge the original narrative, since the difference between multipliers in the two extreme regimes becomes negligible.

Finally, we built on the original strategy implementing GIRF analysis and we updated the sample to include the Great Recession. The results prove the value of using a non-linear model that allows the economy to fluctuate. Firstly, shock responses are not symmetrical and depend on the size and the sign of the shock. Furthermore, the dynamics shown by the different responses reinforce our choice to use a model able to accommodate for complex dynamics. Secondly, the longer sample yields a negative reaction to positive fiscal expenditure shock, while negative shocks bring a positive effect. This is an expected and even desired result: it proves that including a large scale event such as the 2009-2011 recession can drastically change the dynamics picked up by the model. While we believe it is desirable to have a model incorporating the most recent dynamics displayed by the economy, this limits the generality of the results and calls for great caution if using it to advance policy arguments (such as the existence of expansionary budget cuts á la Alesina and Ardagna (2013)) relating to pre-crisis shocks. Thirdly, there seems to be a diminishing return to the expansionary power of larger budget cuts, where a heavier budget reduction does not yield a proportionally larger GDP response, contrary to what we observed with budget increases.

Chapter 2

Non-linear effects of the financial cycle on fiscal multipliers

2.1 Introduction

The debate about fiscal multipliers, their magnitude, their evolution over time, and their sensitivity to different monetary policy stances or, as more recently explored, to other institutional and macroeconomic environmental variables (unemployment level, labour or goods market openness degree) is endowed with a long history, and yet is far from being concluded. The topic has very recently found a renewed popularity due to the 2020-2021 pandemic crisis, which required massive public relief efforts under the guise of an increase in government expenditure.

The heterogeneity of the related results presented in the recent literature has been extensively surveyed by Favero and Karamysheva (2017). The meta-study looks at the plethora of available empirical estimated, partitioning them between strictly-VAR and narrative approaches. The former group includes the seminal work of Blanchard and Perotti (2002), the sign-restricted version of Mountford and Uhlig (2009), and the expectations-augmented approach of Ramey and Shapiro (1998), and Fisher and Peters (2010). The narrative restrictions family includes the fundamental contribution of Romer and Romer (2010) later extended by Pescatori et al. (2011), the focus on fiscal policy mix of Leeper (2010), the attempt to retrieve better tax multipliers of Favero and Giavazzi (2012), and the focus on tax mix of Mertens and Ravn (2014). Favero and Karamysheva (2017) conclude that a golden fiscal multiplier estimate does not exist, due to the sensitivity of the figures to model specification and identification restrictions, and that much more attention should be paid to the dynamics. Such a remark seems to find a natural answer in the line of inquiry assuming time-varying fiscal multipliers, or rather multipliers contingent on some state variable -usually the business cycle.

This research contributes to the literature on state contingency of fiscal multipliers, with a focus on whether the economy reacts differently in different phases of the financial cycle through expansion or contraction. We consider an economy that fluctuates with the financial cycle, specifically investigating the state contingency of the effects of a fiscal stimulus. Our angle is unlike most studies that we show that fiscal multipliers significantly change between regimes defined by the business cycle, while they appear stable at the extreme stages of the financial cycle. However, they are significantly affected by the cycle dynamic and by the inclusion in the model of a measure of fiscal burden.

We focus on the financial cycle in an effort to take finance seriously, as notably advocated by Jordà et al. (2017). Several phenomena compel us to consider financial fluctuations: the surge of private credit in the second half of the twentieth century, the astonishing growth of the financial sector, and the very recent evidence from the Great Recession, where financial turmoil brought about sizeable output losses. Arcand et al.

(2015) consider whether there is a threshold above which the growth of the financial sector is detrimental to output growth. Complementing their study we investigate the medium-term combined effect of credit fluctuations and fiscal stimuli imparted to the economy. We find a number of interesting results. Government expenditure multipliers are heavily influenced by the cycle and we are able to unambiguously confirm the common notion of stronger multipliers in average recessions. Furthermore, expansionary shocks seem to suffer from diminishing returns, where a larger stimulus is not matched by a proportionally larger GDP reaction. It also appears that the results are strongly sensitive to the choice of including a measure of fiscal space based on public debt into the model specification, to the point where the sign of the response is inverted in this latter case.

The emphasis on public debt is a natural consequence of our approach. While the link between credit and the business cycle was extensively investigated by Gertler and Kiyotaki (2015), the interaction between sovereign debt and the financial cycle has received renewed interest due to the most recent crisis and the subsequent burst of state-owned debt, giving fresh relevance to the discoveries of Reinhart and Rogoff (2010). A recent analysis on such interaction can be found in the work of Poghosyan (2018), whose finding – an asymmetrical relation between financial and debt cycles – complements our own evidence of an asymmetrical and non-proportional output reaction to different magnitudes of fiscal stimulus. Moreover, Ilzetzki et al. (2013) find that public debt acts as a state variable in estimating scale multipliers and where state owned debt is high, fiscal multipliers tend to be low and fiscal policy ineffective.

To reproduce the fluctuating economy we use the approach of Auerbach and Gorodnichenko (2012, henceforth AG), adopting a Smooth Transition VAR able to smoothly change the coefficients between two extreme regimes (a state of absolute contraction/-expansion of the economy). The choice of a non-linear model is deliberate and a growing awareness in the literature supports this path, advocating for representations of phenomena closer to reality: indeed, the reality itself is non-linear.[1] Departing from AG, our focus is on the financial cycle rather than the business cycle, and we include the credit to private non-financial institutions and the public debt among the variables of interest. Furthermore, unlike AG we choose to use the generalized impulse response functions (GIRF) analysis pioneered by Koop et al. (1996) and Pesaran and Shin (1998), modified as in Kilian and Vigfusson (2011) and Pellegrino (2021) to include a structural shock. This powerful tool allows us to use the entire sample history to study the response of a truly fluctuating economy, accounting for the possibility that the shock itself is able to change the way in which the variables interact. We also perform a scenario analysis exercise, investigating which consequences arise if a shock is deliberately delivered in an alternative fixed setting (the so called *scenario*) of typical representative recession or expansion; this amounts to bringing the model to a specific phase of the business cycle and only then triggering the fiscal expenditure shock. The exercise is further expanded to explicitly assume the relationship between a fiscal expenditure shock and the public debt. We establish both an entirely debt-financed expenditure increase and a budget cut aimed to reduce the outstanding stock of public debt.

The evidence drawn from GIRF analysis strongly suggests the importance of taking into account the financial environment and the timing of any fiscal stimulus. Moreover, the existence of diminishing returns to expansionary shocks questions the effectiveness of expansionary fiscal policy measures. Knowing the way in which a specific fiscal operation will affect the economy, given the current macroeconomic conditions, is key in helping policy makers make informed choices.

The rest of this chapter is organized as follows. Section 2.2 details the model and the data, and Section 2.3 presents the empirical results. Section 2.4 concludes.

[1] A more compelling case for a change of perspective in economic modelling can be found in Chiu and Hacioglu Hoke (2016b) and Chiu and Hacioglu Hoke (2016a).

2.2 Methodology

This section presents the model and discusses generalized impulse response analysis that will be used to investigate its dynamics.

2.2.1 The Smooth Transition VAR model

Similar to Chapter 1, our model is a Smooth Transition VAR (henceforth STVAR), as in AG. The STVAR is a multivariate extension by van Dijk et al. (2002) of a univariate specification proposed by Granger and Teräsvirta (1993). AG further extend it by allowing the variance covariance matrix of the innovation process to follow the same smooth transition mechanism. The econometric specification is as follows:

$$\mathbf{X}_t = \left[(1 - F(z_{t-1}))\mathbf{\Pi}_E + F(z_{t-1})\mathbf{\Pi}_C\right](L)\mathbf{X}_{t-1} + \mathbf{u}_t \tag{2.1}$$

$$\mathbf{u}_t \sim N(\mathbf{0}, \mathbf{\Omega}_t) \tag{2.2}$$

$$\mathbf{\Omega}_t = \mathbf{\Omega}_E(1 - F(z_{t-1})) + \mathbf{\Omega}_C F(z_{t-1}) \tag{2.3}$$

$$F(z_t) = \frac{e^{-\gamma z_t}}{1 + e^{-\gamma z_t}} \qquad \gamma > 0$$

$$\mathrm{Var}(z) = 1 \qquad \mathrm{E}[z] = 0,$$

where $\mathbf{\Pi}_E$ and $\mathbf{\Pi}_C$ are again the coefficient matrices corresponding to the extreme expansion and contraction phases of the cycle, respectively, and $\mathbf{X}$ is the data matrix. z is the state variable acting as the input of the exponential transition function $0 \leq F \leq 1$; γ is the parameter controlling the speed of the transition, while the subscripts E and C refer respectively to expansion and contraction phases of the cycle; the order of the lag polynomial p is four.

The model has two different channels of transmission for a shock. The lag polynomials $\mathbf{\Pi}_E(L)$ and $\mathbf{\Pi}_C(L)$ in Equation (2.1) constitute the dynamic element, while the state-contingent shock covariance matrix $\mathbf{\Omega}_t$ in equations (2.2)-(2.3) allows for a contemporaneous propagation. Given the large number of parameters that need to be estimated and the non-linear features of the model, we follow AG and use the Markov Chain Monte Carlo method originally presented in Chernozhukov and Hong (2003) with Metropolis-Hastings algorithm and flat priors. As the first order condition in Equation 2.4 shows, for any guess of the variance-covariance matrix $\mathbf{\Omega}_t$ the model linearises and the optimal value of $\mathbf{\Pi} = [\mathbf{\Pi}_E, \mathbf{\Pi}_R]$ can be immediately computed. The overall estimation approach, detailed in Appendix A.1, is based upon building up a sequence of guesses leading to the highest likelihood via MCMC, while the proper model estimation step is performed via GLS.

$$\mathrm{Vec}\left[\mathbf{\Pi}'\right] = \left(\sum_{t=1}^{T}\left[\mathbf{\Omega}_t^{-1} \otimes \mathbf{W}_t'\mathbf{W}_t\right]\right)^{-1} \mathrm{Vec}\left[\sum_{t=1}^{T}\mathbf{W}_t'\mathbf{X}_t\mathbf{\Omega}_t^{-1}\right] \tag{2.4}$$

Where

$$\mathbf{W}_t = [(1 - F(z_{t-1}))\mathbf{X}_{t-1},\ F(z_{t-1})\mathbf{X}_{t-1} \ldots\ (1 - F(z_{t-1}))\mathbf{X}_{t-p},\ F(z_{t-1})\mathbf{X}_{t-p}]$$

2.2.2 Impulse response functions

As we already discussed in Chapter 1, we need an analysis instrument able to keep the non-linear features of the model intact. The generalized impulse response analysis developed by Koop et al. (1996) serves our purposes, since it allows us to set the economy free to evolve after receiving a shock, a feature critically missing in AG. The generalized impulse response function is defined as the expectation of the realization of $\mathbf{X}_t$ conditional on the history ($\mathcal{H}$) and the shock (s) over a baseline conditional expectation on just the history:

$$GI_{\mathbf{X}}(h, s_t, \mathcal{H}_{t-1}) = \mathrm{E}\left[\mathbf{X}_{t+h} \mid \mathcal{H}_{t-1}, s_t\right] - \mathrm{E}\left[\mathbf{X}_{t+h} \mid \mathcal{H}_{t-1}\right], \quad \text{for the horizon } h = 0, 1, \ldots. \tag{2.5}$$

Since the conditional expectations can be seen as random variables, their difference $GI_{\mathbf{X}}(h, s_t, \mathcal{H}_{t-1})$ defined in Equation (2.5) is itself a realization of the random variable GI. The model is known and explicitly defined, thus we are able to estimate the empirical distribution of its conditional expectations using a Monte Carlo approach, from which a central moment and confidence bands can be easily computed. The identification of fiscal shocks relies on conventional short-run recursive restrictions implied by the Cholesky decomposition imposed on the vector of reduced form residuals, as shown in Kilian and Vigfusson (2011) and Pellegrino (2021).

The GIRF analysis is optimal to account for the non-linearity of our model. For the sake of comparability of results with the general literature on fiscal multipliers, we also include linear impulse response functions computed in the extreme states of the cycle. The most striking limitation of this approach is that the results are no longer state-contingent, as they necessitate selecting one specific value of the transition function (and therefore a specific phase of the cycle). We follow the example of AG and present results for the extremes of the cycle, choosing $F = \{1; 0\}$, thus assuming that the economy will always be stuck in either a peak or a trough of the cycle.

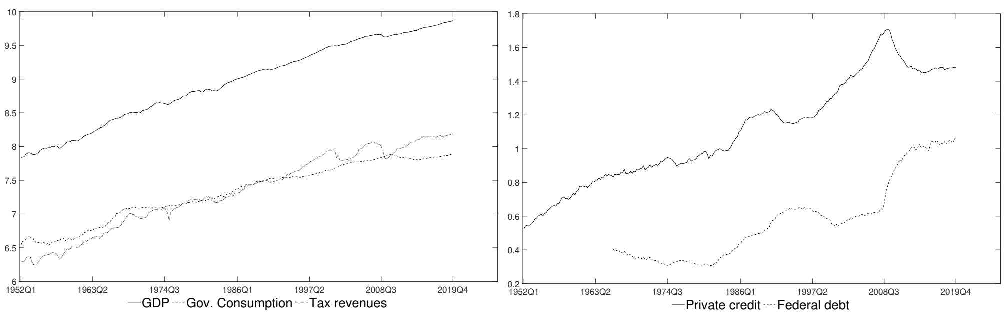
2.3 Empirical analysis

In what follows we present the variables and the data included in the analysis, and discuss our financial cycle estimation strategy. A selection of empirical results is also presented.

2.3.1 Variables and data

We use U.S. quarterly data from 1966Q1 (1952Q2, for the specification not including debt) to 2019Q4. Figure 2.1 shows our variables: government expenditure, tax receipts and GDP are all log real series; public debt and credit to private non-financial institutions (private credit for short) are normalized by GDP.

Figure 2.1: The data: macroeconomic and financial variables



(a) Macroeconomic variables (b) Financial variables

Source: Bureau of Economic Analysis.
Note: Log real data of (a) Government Expenditure, Tax Revenues, GDP, and (b) Public Debt, Private Credit (both normalized by GDP).

The choice of government expenditure, tax revenues, and GDP is standard in the VAR literature related to fiscal multipliers starting with Blanchard and Perotti (2002).

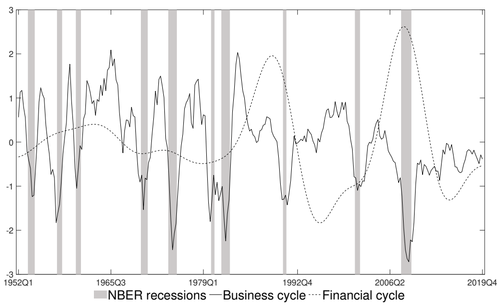
Since our estimation of the financial cycle relies on credit to private non-financial institutions, this is included in the VAR to allow the dynamic computation of non-linear impulse responses. We specifically choose public debt in light of its relationship with fiscal multipliers identified by Perotti (1999) and Ilzetzki et al. (2013), both finding that high levels of fiscal burden (debt-to-gdp ratio) are able to impair fiscal policy, shrinking the size of fiscal multipliers. Furthermore, we believe that controlling for public debt is a natural choice to complement the deficit dynamics. We estimate the model in first differences to ensure stationarity.

2.3.2 The financial cycle

To obtain an estimate of the financial cycle, we adopt the approach of Drehmann et al. (2012) and Borio (2014), relying on frequency analysis. Specifically, we apply the Christiano and Fitzgerald (2003) passband filter to isolate and extract the so called medium-term frequency components of the cycle, that is the components oscillating with a frequency between 32 and 120 quarters (8 and 30 years). The choice of frequency analysis over the longer historied turning-point analysis is dictated by the need to have an explicit value of the cycle for each quarter, instead of an estimate of maximum and minimum points.

Our result is comparable with previous literature estimates, even if we drastically reduce the number of variables considered from five to just one: the credit to private non-financial institutions, normalized by GDP. This choice allows us to base the estimation of the financial cycle on one of the variables included in the model specification, as required for the use of generalized impulse response analysis. To allow a comparison, we also include an estimate of the business cycle obtained as in AG. Figure 2.2 below shows our estimate of the financial cycle. NBER recessions and a simple estimate of the business cycle are also reported for comparison.

Figure 2.2: Business cycle, financial cycle and NBER chronology



Note: The business cycle is the $MA(7)$ of the ouput growth; the financial cycle is obtained via a band pass filter extracting the components fluctuating with frequency 32-120 quarters.

2.3.3 Impulse responses

Our focus is on the response of GDP to a fiscal shock via government expenditure. Together with the non-linear impulse responses presented above in Section 2.2.2, we also provide for comparison linear responses computed using the two extreme regime matrices identified by the model, $\mathbf{\Pi}_E$ and $\mathbf{\Pi}_R$ of Equation (2.1). This amounts to showing the IRFs of two distinct linear models with no interaction with each other.

A baseline and a debt augmented specification are considered for the set of $\mathbf{X}_t$ variables, namely $\mathbf{X}_t = [g_t,\ \tau_t,\ y_t,\ Pc_t]$ and $\mathbf{X}_t = [g_t,\ \tau_t,\ d_t,\ y_t,\ Pc_t]$, where g denotes government expenditure; τ is tax revenues; y represents GDP; Pc is private credit (normalized by GDP); and d denotes public debt (normalized by GDP). All variables are first differences of the log real series. We consider shocks of $\pm 1\%$ and $\pm 5\%$ to U.S.

government expenditure, roughly corresponding to ±0.15% and ±0.8% of GDP. While the larger shock may look *too* large, the American Recovery and Reinvestment Act (ARRA) of 2009 (2009) stimulus package delivered an estimated combined impact of roughly 2.5% of GDP in the first year of enactment, as explained in The Congress of the United States - Congressional Budget Office (2012). Furthermore, the most recent debate on a grand stimulus package encourages us to be confident in using a relatively large shock.

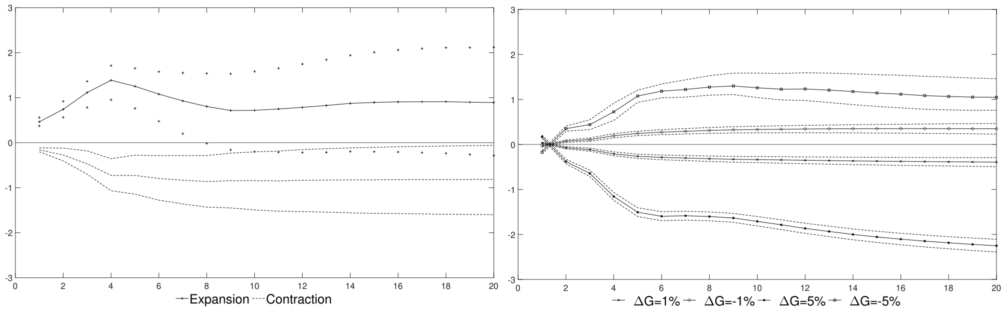
We also perform a scenario analysis considering two different environments in which the fiscal shock is delivered: a typical expansion and a typical recession. This complements the results presented in the main section, where the shock is timed to the most recent phase of the cycle. Our methodology involves building a *typical regime-specific* history of quarters and appending it to the history of realizations, effectively feeding the recursive mechanism of the model with an artificial set of values. This allows us to use the GIRF approach to investigate the effects of a fiscal shock imposed during a specific state of the economy and the cycle without sacrificing the smooth transitioning nature of our model. To build such a history, we use a discriminating criterion – the chronology published by the National Bureau of Economic Research of business cycle dates (as in Figure 2.2) – and we select every quarter in any given regime together with its lags. We then take the median value of the variables, thus obtaining a median representative recessionary or expansionary history. Appendix B.3 shows that the main results still hold when the transition F function is used as a criterion and *recession* and *expansion* are defined as the quarters where the function is, respectively, higher than 0.8 or lower than 0.2.

To further explore the dynamics of fiscal shocks, GDP, and debt reactions of the augmented baseline, we also explicitly assume the relation between a government expenditure shock and the outstanding stock of public debt. We keep our methodology as simple and straightforward as possible and we impart a contemporaneous shock of the same size, and opposite sign, to both government expenditure and the stock of public debt, thus assuming that every expenditure increase is entirely financed via deficit spending and, at the same time, that a budget cut is only aimed to restructuring the stock of debt.

Baseline specification

We start by presenting results for our baseline specification, including the main variables of government expenditure, tax revenues, and GDP, augmented by private credit, that is $\mathbf{X}_t = [g_t,\ \tau_t,\ y_t,\ Pc_t]$. We show results for both the full sample, up to the last quarter of 2019, and for a shorter sample not including the Great Recession. Figure 2.3 presents the GDP responses to a fiscal expenditure shock for the full sample.

Figure 2.3: Baseline specification, GDP reaction



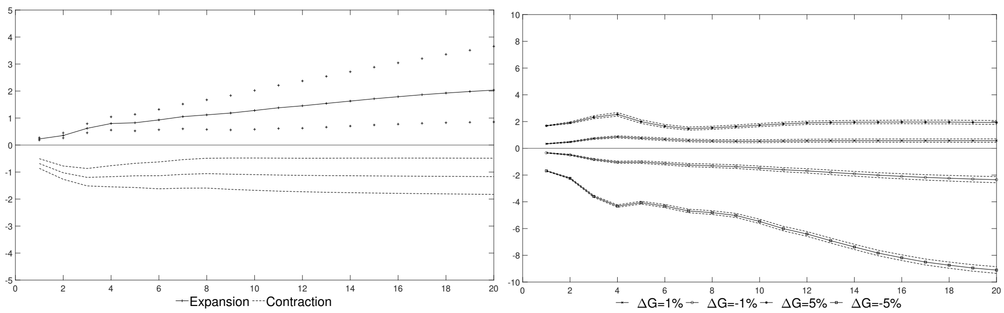
(a) Linear IRF (b) Generalised IRF

Note: Cumulative linear (a) and generalized (b) impulse responses. Percentage GDP response to a unit standard deviation (a) or to percentages of government expenditure (b) fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

The linear model clearly shows that the impact reaction to the same shock is stronger during an expansion period, rather than a contraction. The peak value reached is also higher when the economy is flourishing, despite happening during the same quarter for both the regimes, about a year after the shock. However, the long-run value is similar and in both cases it falls around the unity. The shock response also looks strongly pro-cyclical.

The generalized impulse responses present a number of interesting points. First, the impact and the long-run equilibrium value of the GDP reaction are opposite in sign, drawing a clear line between short, and medium and long-term equilibrium. Moreover, while the shocks are linearly scaled, the responses are not. Evidently there exists a phenomenon of diminishing returns to increasing shocks, where a larger negative shock has a limited, non-proportional, expansionary effect on the economy. The existence of such an asymmetric effect further justifies the choice of a non-linear model. Finally, negative expenditure shocks yield a positive GDP reaction and vice versa, seemingly endorsing austerity-like policies á la Alesina and Ardagna (2013). This is similar to the phenomenon found in Chapter 1, which we imputed to the presence of the Great Recession within the sample. Indeed this seems to be the case again, as results shown in Figure 2.4 suggest.

Figure 2.4: Shorter baseline (not including the Great Recession), GDP reaction



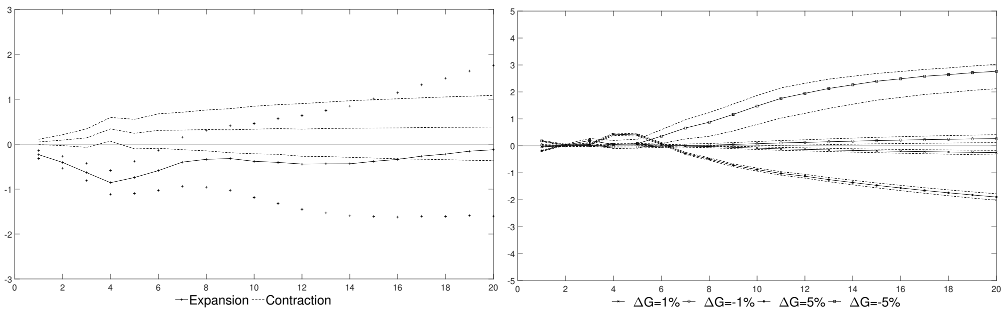
(a) Linear IRF (b) Generalised IRF

Note: Cumulative linear (a) and generalized (b) impulse responses. Percentage GDP response to a unit standard deviation (a) or to percentages of government expenditure (b) fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Setting aside the differences due to a shorter sample (limited to the fourth quarter of 2008), the main divergence from the baseline is the effect of negative (positive) shocks being negative (positive) on the economy, a result already encountered in Chapter 1. A significant commonality, on the other hand, is the persistence of the diminishing returns of expansionary (in their effects) shocks, where there seems to be a limit to how much the economy is boostable via fiscal stimulus.

Figure 2.5 shows instead the response of the ratio of private credit-to-GDP, which we take as an indicator of the financial environment as already shown in Borio (2014). Two features are worth mentioning: the difference between a more dynamic short-run and a stabler long-run, and the marked difference between smaller and larger stimuli. Since the GDP reaction in Figure 2.3 looks smooth at every horizon, the overall conclusion we can draw is that the private credit reacts robustly pro-cyclically only after the short-period, pushing the ratio in the same direction as the GDP.

Figure 2.5: Baseline specification, credit-to-GDP response



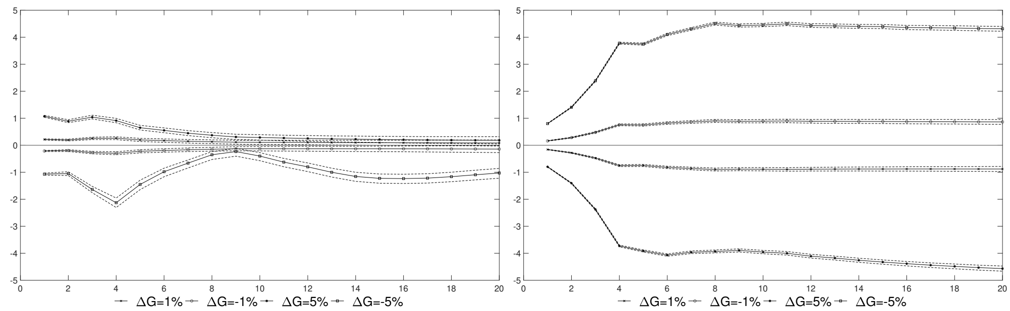
(a) Linear IRF (b) Generalised IRF

Note: Cumulative linear (a) and generalized (b) impulse responses. Percentage private credit response to a unit standard deviation (a) or to percentages of government expenditure (b) fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Scenario analysis, baseline specification

State-contingent IRFs computed in what we defined as *typical expansions* and *typical recessions*, and presented in Figure 2.6, feature a number of striking differences, aside from the general dynamic of the GDP response. In a typical expansion the fiscal stimulus is pro-cyclical and smaller in absolute value than in a typical recession. Moreover, the phenomenon of diminishing returns to larger shocks appears only during typical expansion, to the point where the long-term expansionary effect of a larger fiscal shock is almost identical to the response of the smaller one and very close to zero.

Figure 2.6: Baseline specification, scenario analysis



(a) Typical expansion (b) Typical recession

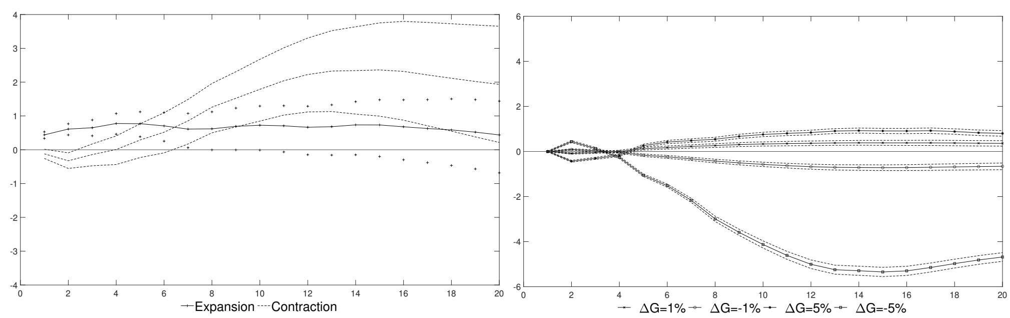
Note: Cumulative generalized impulse responses to a fiscal shock delivered in a median representative recession or expansion. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Augmented specification

Next we change the model specification to $\mathbf{X}_t = [g_t,\ \tau_t,\ d_t,\ y_t,\ Pc_t]$, augmenting the previous one with public debt. Rather than including it as it is, we choose to normalize it by GDP to obtain not a measure of the debt stock as such, but rather an indicator of fiscal burden relative to the size of the economy.

Due to data availability our sample is now shorter, starting in 1966Q1. Appendix B.1 shows that estimating the baseline specification over the same shorter sample does not change the key empirical evidence presented. Figure 2.7 illustrates GDP reaction to a fiscal shock under the new specification.

Figure 2.7: Augmented specification, GDP response



(a) Linear IRF (b) Generalised IRF

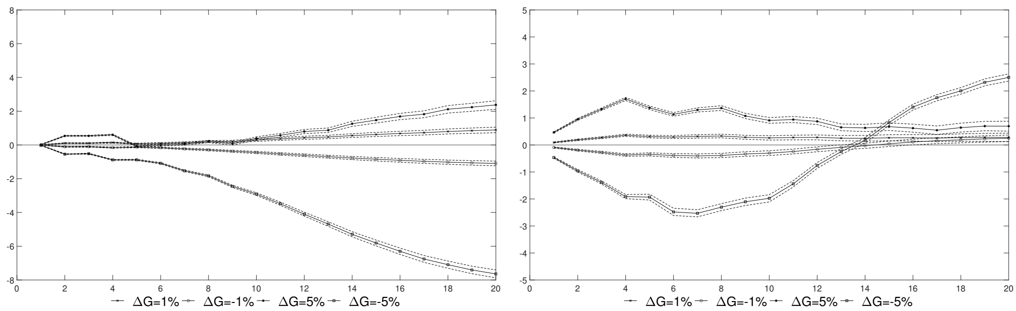
Note: Cumulative linear (a) and generalized (b) impulse responses. Percentage GDP response to a unit standard deviation (a) or to percentages of government expenditure (b) fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, public debt, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Linear responses are now more diverse and less clearly identified, likely due to the lower number of observations used to estimate coefficients for one more variable. If the response during an extreme expansion appears rather stable, the contraction phase yields more dynamic behaviour, with a medium- and long-run response definitely larger than the expansionary counterpart.

The non-linear GIRFs keep some of the features shown by the baseline specification, such as the inversion in the sign of the responses between short and long periods, the impact effect being considerably smaller than the equilibrium long-run value, and the presence of diminishing returns of the expansionary response, where the larger shock does not yield a proportionally larger reaction. However, the most striking difference is in the concordance of the sign of shocks and reactions, where now a positive (negative) fiscal shock brings forth a positive (negative) GDP response. Such an effect appears to be entirely due to augmenting the specification with the ratio of public debt-to-GDP rather than due to the reduced sample size, as clearly shown in Appendix B.1 where a baseline specification estimated on the shorter sample preserves the discordance between sign of the shock and sign of the corresponding IRF.

To complement our analysis, Figure 2.8 presents the evolution of the private credit-to-GDP and public debt-to-GDP following the fiscal shock.

Figure 2.8: Augmented specification, credit-to-GDP and debt-to-GDP response



(a) Generalised IRF (b) Generalised IRF

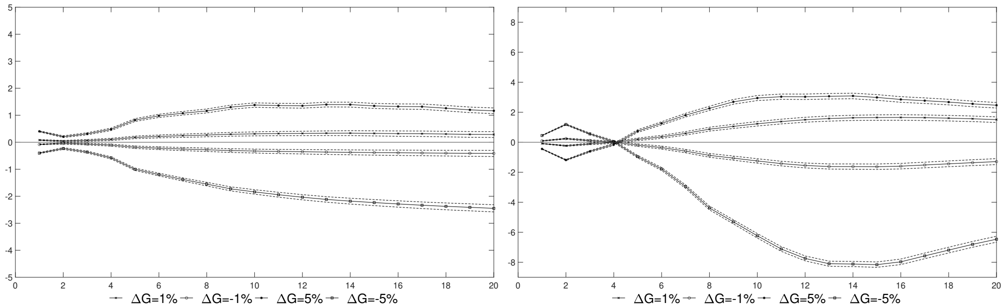
Note: Generalised impulse responses. Percentage private credit and debt response to a fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, public debt, GDP and private credit. Confidence bands are at 5th and 95th percentile.

The credit behaviour is consistent with what we already observed for the baseline specification: results suggest that private credit moves strongly pro-cyclically, as a positive (negative) stimulus is paired with a growth (fall) of the private credit-to-GDP ratio. On the other hand, the behaviour of public debt-to-GDP ratio appears to be more diverse. Results clearly suggest that public debt variation will have the same sign as the fiscal shock. Rather than interpreting the result as public debt moving pro-cyclically, we favour the intuition that the fiscal shock itself is connected to the debt via deficit expansion of reduction. In this context, the long-run change in behaviour of the ratio after a larger negative shock can be seen as a first pro-cyclical moment, where the budget cut puts a downward pressure on the GDP, and it is directly used to lower the amount of public debt, followed by a phase where the debt dynamic wanes out (or even slightly rebounds), thus pushing up the ratio.

Scenario analysis, augmented specification

Figure 2.9 presents the scenario analysis for our extended specification. Some key features of the general result of Figure 2.7 are carried over, such as the concordance between sign of the shock and sign of the response, the presence of a diminishing returns effect for the larger expansionary shock, and a discrepancy in the sign of the response between short- and long-run limited to the typical recession scenario. The most striking feature, however, is again that responses in a typical recession are larger than in a typical expansion.

Figure 2.9: Augmented specification, scenario analysis

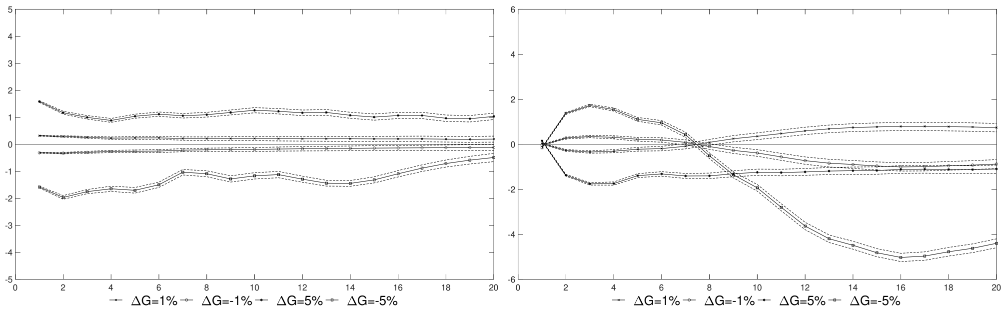


(a) Typical expansion (b) Typical recession

Note: Cumulative generalized impulse responses to a fiscal shock delivered in a median representative recession or expansion. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, public debt, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

A simple extension of the scenario analysis would be to explicitly assume how the fiscal shock influences the stock of public debt. We simulate an expenditure increase financed via public debt and a debt consolidation achieved via a one-time budget cut. Figure 2.10 shows that the results are qualitatively similar to the case of a typical expansion, with slightly higher magnitudes of responses in the short-run, and then lower in the long-term. On the other hand, the dynamics appear more diverse in a typical recession scenario. In the first place, we now have two inversions in the sign of the responses, one immediately after the impact and the other about two years in. However, such inversions do not affect the larger positive shock. Overall, the message yielded by the scenario is truly insightful: both large and small debt consolidations during a recession end up being recessionary, exactly as with the case of a large fiscal stimulus. The only strategy which appears successful in boosting the economy when the stimulus weighs entirely on debt is a small-sized fiscal package.

Figure 2.10: Augmented specification, scenario analysis with a shock to public debt



(a) Typical expansion (b) Typical recession

Note: Cumulative generalized impulse responses to a fiscal shock delivered in a median representative recession or expansion. The same shock is applied with opposite signs to government expenditure and public debt. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, public debt, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

2.4 Conclusion

A Smooth Transition VAR was adopted to allow the economy to fluctuate with the financial cycle. This choice is believed to have proven its worth. Our empirical evidence yields a plethora of conclusions, both for the baseline and for the extended specifications, where we control for public debt. A number of interesting asymmetries are brought to light, both between positive and negative shocks and in the response to larger government expenditure variations. Thus, the rich dynamics of public debt should not be excluded from the model.

The baseline specification shows that in a post-Great Recession world fiscal stimuli tend to favour an austerity-like approach, where budget cuts boost the economy, whereas fiscal expansions lead to recessions. However, the model also highlights a phenomenon of diminishing returns to increasing expansionary (in their effects) measures, where a more consistent cut does not bring a proportionally larger GDP expansion. Looking at the behaviour of the private credit-to-GDP ratio, the private credit component seems to react strongly pro-cyclically after the short-term horizon. Extending the specification with public debt completely changes the sign of the GDP reaction to a fiscal shock, meaning that a positive stimulus is expansionary and vice-versa, thus reversing the endorsement to austerity-like measures provided by the baseline. However, some important features are preserved, as the crucial effect of diminishing returns to larger expansionary stimuli, questioning how much the economy can be boosted by a fiscal shock. The analysis of the credit-to-GDP and debt-to-GDP ratio responses after a shock is broadly consistent with the baseline specification in the case of the former, while the behaviour of the latter is fully consistent with fiscal expenditure shocks weighing on public debt being at least partially financed by (or used to reduce the amount of) public debt.

For both specifications, the scenario analyses show the traditional finding that multipliers are larger in a typical recession rather then an expansion. A further extension of the exercise, in which the fiscal stimulus is entirely financed via public debt (or the budget cut is entirely spent in debt reduction) acts as warning about the risks of cutting public expenditure in recession as well as the danger of legislating an expansionary package that is excessively reliant on deficit.

From a policy perspective, both the diminishing returns to growing fiscal stimuli and the intricate dynamics of debt-financed packages advocate for caution when linear models, unable to capture such a degree of complexity, are used to simulate the effect of real-world policies. If the debt dynamics call for further and more specific investigation, the diminishing returns implicitly question the efficiency of any large expansionary package and suggest that a state-contingent golden return ratio may exist.

Chapter 3

Fiscal non-linearities induced by an informative real-financial economic cycle

3.1 Introduction

We consider a fluctuating economy along a combined economic cycle carrying information on both real activity and the financial sector, and focus on the state contingency of the effects of a fiscal stimulus. Specifically, we adopt a non-linear Smooth Transition VAR and we show the cumulative effect of a government expenditure policy shock. In line with what we find especially in Chapter 2, there are diminishing returns in terms of effect on GDP to a larger expansionary shock. Moreover, controlling for private credit and public debt does not qualitatively change the result shown by the baseline model. We attribute the stability of the key features of the specifications to the use of a cycle which already includes information about the financial sector and fiscal space. We also perform a scenario analysis exercise, delivering fiscal shocks either in an average contraction or in an average expansion of the cycle. We find unequivocal evidence that the fiscal expenditures multipliers are on average larger in a typical recession, rather that in an expansion, a result consistent with our findings in Chapter 2 and stable across all specifications used.

The cyclical behaviour of GDP – commonly known as the business cycle – has been widely accepted in the literature since Burns and Mitchell (1946) and, starting with Mankiw (1989), it has more recently been interpreted as the tell-tale sign of underlying economic fluctuations. Business cycle theories have by now become common and influential (Zarnowitz, 1992; Laidler, 1999; and Besomi, 2006). At the same time, even though the notion of financial booms and busts that could impact the economy is not new, the financial world came to assume an the ancillary role of either an accelerator or a delayer of the return to the natural steady state of the economy (Bernanke et al., 1999). Because of this, it came to be seen as something that could be ignored in first approximation (Woodford, 2003) and progressively disappeared from mainstream macroeconomics.

The financial crisis forcefully brought the spotlight back to the concept of "financially induced crisis" (Reinhart and Rogoff, 2014; Basel Committee on Banking Supervision, 2010; Jordà et al., 2017; and Ball, 2014) and triggered a growing advocacy to, in the words of Jordà et al. (2017), "take finance seriously". The intertwined nature of the real and financial economy has since been explored in depth. Arcand et al. (2015) consider whether there is a threshold over which the growth of the financial sector becomes detrimental to output. Credit and business cycle share a relationship investigated by Gertler and Kiyotaki (2015), while Ilzetzki et al. (2013) show how high levels of public debt make fiscal policy ineffective. The idea of a procyclicality of the financial system has become increasingly popular (Borio et al., 2001, Daníelsson et al., 2004, Kashyap and Stein, 2004, Brunnermeier et al., 2009, and Adrian and Song Shin, 2010), however there is still no broad consensus on what exactly a financial cycle is or how to measure it -with the notable exception of Drehmann et al. (2012).

The notion of time-varying behaviour within any given economy is crucial in the field of state contingency of fiscal multipliers, focusing on the ways in which the economy reacts differently to the same fiscal policy measure in different times. This amounts to believing that there exists a state variable on which fiscal multipliers are contingent, which in the literature is, commonly, considered to be the business cycle (Auerbach and Gorodnichenko, 2012; Callegari et al., 2012; Galvão and Owyang, 2018; Bolboaca and Fischer, 2019; Tenreyro and Thwaites, 2016; and Bruns and Piffer, 2019). We focus instead on a combined *economic cycle*, ideally merging the information coming from the business and the financial cycle, here loosely defined as the medium- and long-run fluctuations of various housing, interest rate, and stock market component variables. We make our economy proceed along such a cycle in an effort to better reproduce its evolution accounting for both real and financial drivers.

We specifically control for private credit to non-financial institutions and public debt, both normalized by GDP. The emphasis on measures of financial stress and fiscal burden comes from a deliberate effort to take the finance sector seriously. Gertler and Kiyotaki (2015) have already explored the pro-cyclical inter-linkages between credit and the business cycle, while the stifling effect of public debt on growth has already been substantiated in Reinhart and Rogoff (2011) and later further confirmed by Poghosyan (2018), whose findings – an asymmetrical relation between financial and debt cycles – particularly complement our own evidence of an asymmetrical and non-proportional output reaction to fiscal shocks. Moreover, we also find some empirical evidence that a growing amount of public debt is associated with a crippled GDP expansion, a crucial result already showcased in Ilzetzki et al. (2013) that highlights the complex relationship between public debt and economic growth.

The fluctuation along the economic cycle is reproduced using the approach of Auerbach and Gorodnichenko (2012, henceforth AG): a Smooth Transition VAR able to smoothly change the coefficients between two extreme regimes (a state of absolute contraction or expansion of the economy). The choice of a non-linear model is supported on one side by a growing awareness in the literature that complex phenomena require non-linear modelling techniques, and by a need to produce comparable results to those shown in Chapter 2.

Building further on the approach of AG, we focus on our economic cycle and we augment the model with, in turn, private credit and public debt. Furthermore, we add to the strictly linear impulse responses, as we use the generalized impulse response functions – GIRF – analysis pioneered by Koop et al. (1996). Detaching from the original approach, we are able to let go of the unintuitive assumption that after the shock is delivered, the model is stuck in one perpetual phase of the cycle, *de facto* suppressing the non-linear nature of the analysis. Generalised impulses are a powerful technique allowing enough flexibility to set the economy free to evolve according to its own mechanics. We further modify the original GIRF – the algorithm of Pesaran and Shin (1998) – to allow for structural government expenditure shocks.

The evidence drawn from GIRF analysis strongly supports the use of a cycle rich in information about the financial sector. Interestingly, we find that extending our baseline yields the same key features of the baseline specification, while a much more significant change in results is observed when we change the scenario in which the fiscal shock is delivered. From a policy perspective, the crucial result that expansionary stimuli are subject to diminishing returns questions the ability of fiscal policy to boost the economy at all. At the same time, it becomes evident that a better knowledge of the non-linear interactions taking place inside an economy is crucial to policy makers who want to make informed and efficient decisions.

The rest of this chapter is organized as follows. Section 3.2 details the model and the data, and Section 3.3 presents the empirical results. Section 3.4 concludes.

3.2 Methodology

This section reiterates the model and discusses the generalized impulse response analysis that will be used to investigate its dynamics, as a general reminder from Chapter 2.

3.2.1 The Smooth Transition VAR model

Our model of choice, the STVAR, is again the multivariate extension by van Dijk et al. (2002) of the univariate Smooth Transition AR introduced by Granger and Teräsvirta (1993). A further extension by AG adds the Smooth Transition dynamics to the variance-covariance matrix of the innovation process, allowing it to also become state-contingent. The econometric specification is as follows:

$$\mathbf{X}_t = \left[(1 - F(z_{t-1}))\mathbf{\Pi}_E + F(z_{t-1})\mathbf{\Pi}_C\right](L)\mathbf{X}_{t-1} + \mathbf{u}_t \tag{3.1}$$

$$\mathbf{u}_t \sim N(\mathbf{0}, \mathbf{\Omega}_t) \tag{3.2}$$

$$\mathbf{\Omega}_t = \mathbf{\Omega}_E(1 - F(z_{t-1})) + \mathbf{\Omega}_C F(z_{t-1}) \tag{3.3}$$

$$F(z_t) = \frac{e^{-\gamma z_t}}{1 + e^{-\gamma z_t}} \qquad \gamma > 0$$

$$\mathrm{Var}(z) = 1 \qquad \mathrm{E}[z] = 0,$$

We already know that $\mathbf{\Pi}_E$ and $\mathbf{\Pi}_C$ are the coefficient matrices corresponding to the extreme states of the cycle and $\mathbf{X}$ is the data matrix. The transition function $0 \leq F \leq 1$ governing the shift between the phases is in turn determined by the state-contingent variable z. γ is the parameter controlling the speed and the smoothness of the transition; the subscripts E and C again refer respectively to expansion and contraction phases of the cycle.

As we already pointed out, the model has two channels of transmission for shocks. The dynamic channel goes through the lag polynomials $\mathbf{\Pi}_E(L)$ and $\mathbf{\Pi}_C(L)$ in Equation (3.1), while the state-contingent variance-covariance matrix $\mathbf{\Omega}_t$ in equations (3.2)-(3.3) acts as a contemporaneous propagation mechanism. The model features a large number of parameters to be estimated and it shows true non-linearity in the parameters, since the data matrix will be augmented with the economic cycle. However, after taking the first order condition as in Equation 3.4, it becomes apparent that the model becomes linear for any given guess of the variance-covariance matrices s$\mathbf{\Omega}_E$ and $\mathbf{\Omega}_C$ and the computation of the coefficient matrix $\mathbf{\Pi} = [\mathbf{\Pi}_E, \mathbf{\Pi}_R]$ becomes trivial.

$$\mathrm{Vec}\left[\mathbf{\Pi}'\right] = \left(\sum_{t=1}^{T}\left[\mathbf{\Omega}_t^{-1} \otimes \mathbf{W}_t'\mathbf{W}_t\right]\right)^{-1} \mathrm{Vec}\left[\sum_{t=1}^{T}\mathbf{W}_t'\mathbf{X}_t\mathbf{\Omega}_t^{-1}\right] \tag{3.4}$$

Where

$$\mathbf{W}_t = [(1 - F(z_{t-1}))\mathbf{X}_{t-1},\ F(z_{t-1})\mathbf{X}_{t-1} \ldots\ (1 - F(z_{t-1}))\mathbf{X}_{t-p},\ F(z_{t-1})\mathbf{X}_{t-p}]$$

We apply the same estimation strategy as AG, as described in Appendix A.1, and we use the Markov Chain Monte Carlo method presented in Chernozhukov and Hong (2003), with Metropolis-Hastings algorithm and flat priors, to build building up a sequence of guesses leading to the highest likelihood. While the overall estimation procedure has Bayesian features, the model estimation step sees the use of GLS.

3.2.2 Impulse response functions

Since the model we are going to use possesses interesting non-linear features, we would like to preserve them in the analysis phase. This is not a trivial endeavour: the original AG work featured linear orthogonalized impulse response functions, assuming that the the model would perpetually stay in the same phase in which the shock was delivered. We regard such an assumption as generally difficult to defend and contrasting with the whole spirit of this thesis. Therefore, we again turn to the generalised impulse response analysis pioneered by Koop et al. (1996) and further described by Pesaran and Shin (1998).

The intuitive definition of the future effect of a shock on a system is the difference between the expectation of the shocked system and that of a baseline where the shock never happened. The formal definition of generalized impulse is as follows

$$GI_{\mathbf{X}}(h, s_t, \mathcal{H}_{t-1}) = \mathrm{E}\left[\mathbf{X}_{t+h} \mid \mathcal{H}_{t-1}, s_t\right] - \mathrm{E}\left[\mathbf{X}_{t+h} \mid \mathcal{H}_{t-1}\right], \qquad \text{for the horizon } h = 0, 1, \ldots. \tag{3.5}$$

The generalised impulse $GI_{\mathbf{X}}(h, s_t, \mathcal{H}_{t-1})$ is defined as the difference between the system expectation conditional on the history of realizations ($\mathcal{H}$) or on the history *and* the shock (s), thus averaging out future innovations that do not interest us. Both the conditional expectations can be seen as random variables, which makes GI a random variable itself. Since our model is known and specified, we can compute the expectations and then estimate the empirical distribution of GI. It is then sufficient to pick a measure of centrality of the distribution as the estimate of the shock and one of dispersion to serve as error.

We further develop the traditional analysis and we slightly modify the algorithm, as suggested by Kilian and Vigfusson (2011) and Pellegrino (2021). We use the model reduced-form residuals to estimate the structural innovations, therefore identifying fiscal shocks, via the usual short-run recursive restriction of the Cholesky decomposition. The algorithm modification sacrifices the traditional irrelevance of the ordering of variables, one of the distinctive features of the traditional GIRF approach.

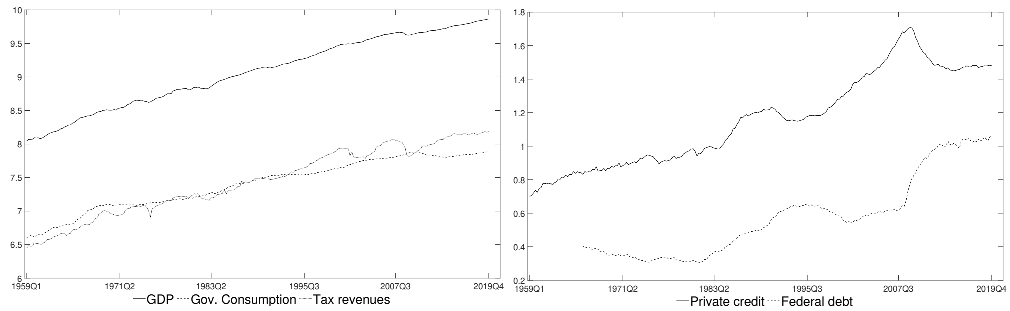
3.3 Empirical analysis

In what follows, we detail the variables and the data included in the analysis, and discuss the estimation strategy followed to create our economic cycle. A selection of empirical results is also presented.

3.3.1 Variables and data

We use U.S. quarterly data from 1966Q1 (1952Q2, for the specification not including debt) to 2019Q4. Figure 3.1 presents our variables: Government expenditure, tax receipts and GDP are all log real series; public debt and credit to private non financial institutions (for short, henceforth private credit) are normalized by GDP.

Figure 3.1: The data: macroeconomic and financial variables



(a) Macroeconomic variables (b) Financial variables

Source: Bureau of Economic Analysis.
Note: Log real data of (a) Government Expenditure, Tax Revenues, GDP, and (b) Public Debt, Private Credit (both normalized by GDP).

Government expenditure, tax revenues, and GDP has constituted the standard selection when estimating fiscal multipliers ever since Blanchard and Perotti (2002). Every specification includes the estimate of the economic cycle to allow for dynamic computation of truly non-linear impulse responses. The choice of private credit as a single indicator of financial stress is justified by the findings of Borio (2014) and Drehmann et al. (2012), who explicitly single out this variable as the carrier of all information on the financial sector. We already justified the choice of public debt in Chapter 2, pointing out that its relationship with fiscal multipliers has been identified by Perotti (1999) and Ilzetzki et al. (2013). Both studies find that a high level of fiscal burden, expressed as debt-to-GDP ratio, is able to cripple fiscal policy and quash the size of fiscal multipliers. Furthermore, we believe that model already features implicit deficit dynamics (as it includes public expenditures and revenues) and we see the inclusion of public debt as a natural complement. We estimate the model in first differences to ensure stationarity.

3.3.2 The economic cycle

The leading intuition behind our economic cycle is that the economy is contemporaneously under the influence of both a real and a financial cycle. To retrieve a measure able to include information about both worlds, we make use of FRED-MD, a macroeconomic database of 128 variables related to the U.S. economy at monthly frequency. The database, an ideal extension of the work of Stock and Watson (1996), is described and detailed at length in the accompanying paper (McCracken and Ng, 2016), and partially in Appendix C.1. The panel is formed by 742 monthly observations, from 1959:01 to 2020:10, but we limit the data we use to 2019:12, in line with the macro and financial variables. The first 2 observations are lost to perform data transformation to achieve stationarity and several series have missing observations at the beginning of the sample, making the panel unbalanced.

To build a synthetic measure of a comprehensive real and financial cycle, we follow a three-step approach. First, we need to efficiently extract the information from the monthly series. To this purpose, we follow McCracken and Ng (2016) in reducing the dimension of our database with a factor analysis strategy. Second, using the same reasoning as found in Chapter 2, we filter the factor scores to isolate the short- and medium-term components of the business cycle and the medium- and long-run frequencies of the financial cycle. Third, we project GDP onto the components to estimate the overall economic cycle and smooth it with a year long moving average.

It is well established that in large T and N settings,[1] static or dynamic principal

[1] Where T and N are, respectively, the number of observations and the number of variables.

components can be a consistent estimate of latent factors (see, Forni et al. (2005, 2000); Stock and Watson (2006); Boivin and Ng (2005); Bai and Ng (2008)). Since we have missing observations, we estimate the factors using the EM algorithm given in Stock and Watson (2002), which allows for a conveniently simple treatment of missing observations. After demeaning and standardizing the series, in the first iteration of the algorithm we rebalance the panel, initializing all empty observations to 0. Given a number r of factors, we estimate matrix $T \times r$ of factor scores $\mathbf{F} = (f_1, \ldots, f_T)$ paired with a $N \times r$ matrix of loadings $\mathbf{\Lambda} = (\lambda_1, \ldots, \lambda_N)'$ under the normalization $\frac{\mathbf{\Lambda}'\mathbf{\Lambda}}{N} = \mathbf{I}_r$. For each missing observation t of the ith series, the initial 0 guess is updated to $\widehat{\lambda_i}' \widehat{f_t}$, multiplied by the standard deviation of the series. Finally, the mean is added back and the resulting value is considered the tth observations of the ith series, which we demean and standardize again with the updated mean and standard deviation. The algorithm iterates until the estimated factors do not change any more.

Several criteria, imposing different assumptions upon the factor model, are available to find the optimal r number of significant factors. Bai and Ng (2002) proposed the PC_p criteria, which minimize the number of factors chosen, imposing a penalty of $\frac{\log(\min(N,T))}{\min(N,T)}$ to keep the model parsimonious. Since $\min(N,T)^{-1} \approx \frac{N+T}{NT}$ when $N, T \to \infty$, several functional forms of the criteria can be specified. We choose the specification with the better finite sample properties, $\frac{N+T}{T} \log(\min(N,T))$, corresponding to the PC_{p2} criterion in Bai and Ng (2002). The criterion selects seven significant factors, eight if the sample is not limited to 2019, as Appendix C.2 shows.

Once the $r = 7$ factors are estimated, we regress each series on an increasing subset of them to compute a measure of how much variability the orthogonal factors are able to explain for each series. That is, for the ith series and for each factor $k = 1, \ldots, r$ we compute $R_i^2(k)$ and an average across series yields how much a k given number of factors explain of our panel: $R^2(k) = \frac{1}{N} \sum_{i=1}^{N} R_i^2(k)$. Similarly, the marginal gain in explanatory power for the ith series obtained from adding an extra factor is, from the second factor onward, the difference in the ith series R-square values $mR_i^2(k) = R_i^2(k) - R_i^2(k-1),\ k = 2, \ldots, r$. In the case of the single-factor subset, the additional explanatory power trivially coincides with the overall variance explained, so that $mR_i^2(1) = R_i^2(1)$. We can compute how much adding a factor on average increases the average explanatory power over the whole panel, taking the mean of the marginal gains across the series $mR^2(k) = \frac{1}{N} \sum_{i=1}^{N} mR_i^2(k)$.

Table 3.1 lists the overall variance explained by the factors, $R^2(r)$, along with the ten series which load the most on each kth factor; that is, the series featuring the highest $mR_i^2(k)$. A description of all the variables used in the analysis is available in Appendix C.1.

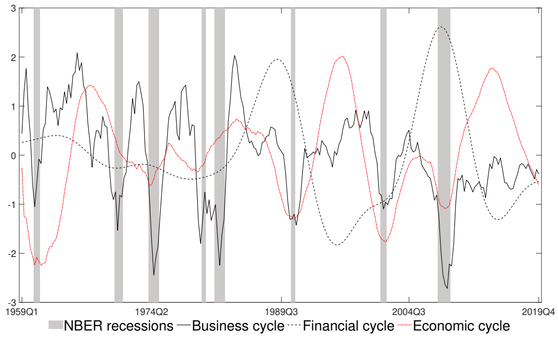
Table 3.1: Estimated factors and heavy loading series - $R^2(7) = 0.4480$

$mR^2(1)$	0.1441	$mR^2(2)$	0.0718	$mR^2(3)$	0.0680	$mR^2(4)$	0.0551
payems	0.7092	cusr0000sac	0.6921	aaaffm	0.5399	gs1	0.5123
usgood	0.7006	dndgrg3m086sbea	0.6805	t10yffm	0.5315	gs5	0.5004
ipmansics	0.6833	cusr0000sa0l2	0.6593	baaffm	0.5163	aaa	0.4894
indpro	0.6513	cpiaucsl	0.6407	t5yffm	0.4746	tb6ms	0.4714
manemp	0.6430	cusr0000sa0l5	0.6053	tb3smffm	0.4108	gs10	0.4602
dmanemp	0.6112	cpitrnsl	0.5816	tb6smffm	0.3926	baa	0.4488
ipfpnss	0.6034	pcepi	0.5783	t1yffm	0.3318	cp3mx	0.3757
cumfns	0.5897	cpiulfsl	0.5232	houst	0.2364	tb3ms	0.3732
ipfinal	0.5041	wpsfd49502	0.4593	houstmw	0.1954	twexafegsmthx	0.2230
ipdmat	0.4751	wpsfd49207	0.4417	houstne	0.1910	s&p div yield	0.1975
$mR^2(5)$	0.0431	$mR^2(6)$	0.0342	$mR^2(7)$	0.0317		
t1yffm	0.3174	awhman	0.2695	s&p 500	0.4945		
tb6smffm	0.2705	ces0600000007	0.2632	s&p: indust	0.4915		
t5yffm	0.2443	uemp15ov	0.2045	s&p div yield	0.3655		
tb3smffm	0.2288	s&p pe ratio	0.1807	s&p pe ratio	0.2560		
permit	0.2231	uemp27ov	0.1668	umcsentx	0.2341		
permitw	0.2147	acogno	0.1478	vxoclsx	0.1836		
houstw	0.1985	isratiox	0.1464	ipcongd	0.0864		
t10yffm	0.1869	ipcongd	0.1400	excausx	0.0640		
houst	0.1753	s&p div yield	0.1174	ipfinal	0.0621		
compapffx	0.1740	uempmean	0.1007	ipdcongd	0.0501		

Note: Seven factors selected by the PC_{p2} criterion and the ten series loading the most on each factor. The table also reports the total variation explained by the seven factors ($R^2(7)$), and the additional variation explained by adding the kth factor ($mR^2(k)$). As an example, the seven factors explain together 44.80% of the panel variation, while $mR^2(1) = 0.1441$ is the quota explained solely by the first factor. Moreover, 0.7092 is the fraction of variation in the variable payems explained by the first factor.

Factor 1 explains 0.1441 of the variation in the data and is easily interpreted as a real activity factor, since it is mostly loaded by series relating to industrial production and employment. The second factor, contributing 0.0718 to the whole variation in data, mainly affects price variables and can be read as an inflation factor. Both the third and the fifth factors feature forward-looking variables such as term interest rates spreads and inventories, with a more modest contribution from real estate variables. Factor 4 is dominated by interest rate variables, and factor 6 contributes mostly to employment variables, with some influence from stock market and financial variables. The last factor mostly explains stock market variables. Figure 3.2 shows the end product of our strategy, an economic cycle built from information on both the real economy and financial variables, also including employment and stock market information. The business cycle used in Chapter 1 and the financial cycle which was central to Chapter 2 are included for comparison. The economic cycle appears broadly well correlated with the NBER recessionary periods, while at the same time featuring a smoothness and an amplitude closer to the financial oscillations, rather than to the business cycle.

Figure 3.2: The economic cycle



Note: The business cycle is the $MA(7)$ of the ouput growth; the financial cycle is obtained via a band pass filter extracting the components fluctuating with frequency 32-120 quarters. The economic cycle is the smoothed GDP projection onto seven factor scores carrying information about the real economy, production, interest rates and financial markets.

3.3.3 Impulse responses

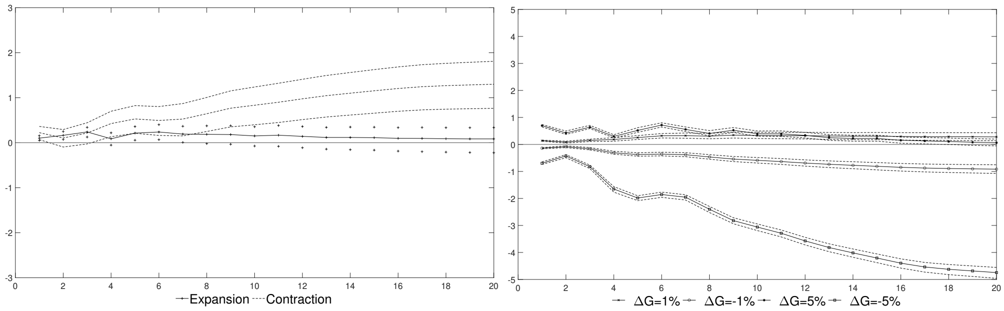
Our focus is on the response of GDP to a fiscal government expenditure shock. We consider three different specifications of the variables in $\mathbf{X}_t$: a standard BP-like $\mathbf{X}_t = [z_t,\ g_t,\ \tau_t,\ y_t]$, acting as the baseline, and two extended specifications, one with public debt and the other with private credit, similarly to the approach we took in Chapter 2 —while sample limitations prevent us from adopting a specification augmented with both. Let g denote government expenditure; τ is tax revenues; y is GDP; Pc denotes private credit (normalized by GDP); and d denotes public debt (normalized by GDP). All variables are first differences of the log real series and each STVAR model is augmented by the estimate of the economic cycle, denoted by the variable z. The shocks considered roughly correspond to $\pm 0.15\%$ and $\pm 0.8\%$ of GDP, namely $\pm 1\%$ and $\pm 5\%$ of U.S. government expenditure. The choice of a 5% shock is in line with the American Recovery and Reinvestment Act (ARRA) of 2009 (2009) stimulus package, which delivered an estimated combined impact of roughly 2.5% of GDP in the first year of enactment, as detailed in The Congress of the United States - Congressional Budget Office (2012). Furthermore, the most recent recession is already calling for an extremely large stimulus package, rumoured to be around 10% of GDP in total size.

As in Chapter 2, we perform a scenario analysis, delivering a shock when the model is artificially brought to an average, representative recession or expansion. This allows us to investigate the consequences of shocks of several sizes and signs impacting an economy in a well-defined state. We use our economic cycle to discriminate strong expansions from deep recessions and we select the quarters for each regime together with their lags, that is we build two synthetic histories of realizations. After taking the median, we augment our natural history with this synthetic data, effectively feeding the autoregressive mechanism of the model with representative values of the regime of interest, simulating a state of the economy to be in a median recession or expansion.

Baseline specification

We first present results for the baseline specification $\mathbf{X}_t = [z_t,\ g_t,\ \tau_t,\ y_t]$, which is consistent with the model specification used by Blanchard and Perotti (2002). Figure 3.3 shows both the linear and the non-linear impulse responses. As in Chapter 2, linear IRFs are used as a comparison in the unlikely scenario in which the transition function is stuck to either 0 or 1, thus collapsing the model to a standard linear VAR.

Figure 3.3: Baseline specification, GDP reaction



(a) Linear IRF (b) Generalised IRF

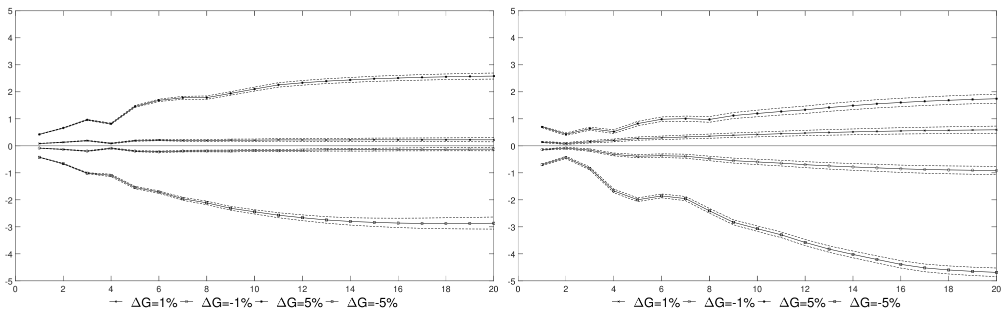
Note: Cumulative linear (a) and generalized (b) impulse responses. Percentage GDP response to a unit standard deviation (a) or to percentages of government expenditure (b) fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, and GDP. Confidence bands are at 5th and 95th percentile.

Overall, the results appear similar to the debt-augmented specification we presented in Section 2.3.3, with an even clearer message. Linear responses again appear rather stable after the very short horizon. Furthermore, they point unequivocally to fiscal shock in recession being more effective than in expansion, especially considering the longer horizon, a result we will investigate further with the scenario analysis exercise. The generalized responses, on the other hand, present again many of the points we already made in the previous chapter. There is concordance between the sign of the shock and the sign of the response, since a positive fiscal stimulus will have a positive effect on GDP and a budget cut will, on the other hand, yield a contractionary effect. We again find a clear phenomenon of diminishing returns to increasing expansionary stimuli, to the point where a larger budget expansion will only lead to a larger effect in the short-medium horizon. A larger cut in expenditure, on the other hand, appears to cause a smooth decline in GDP, taking a longer time to stabilize. Furthermore, there is no more difference between the impact and the medium-long horizon of the responses, with the effect being consistently positive or negative for all the quarters.

Scenario analysis, baseline specification

To shed some light on the question of whether expenditure multipliers are larger in (a typical) recession or expansion, Figure 3.4 presents evidence from the scenario analysis exercise using only the baseline specification.

Figure 3.4: Baseline specification, scenario analysis generalized IRFs



(a) Typical expansion (b) Typical recession

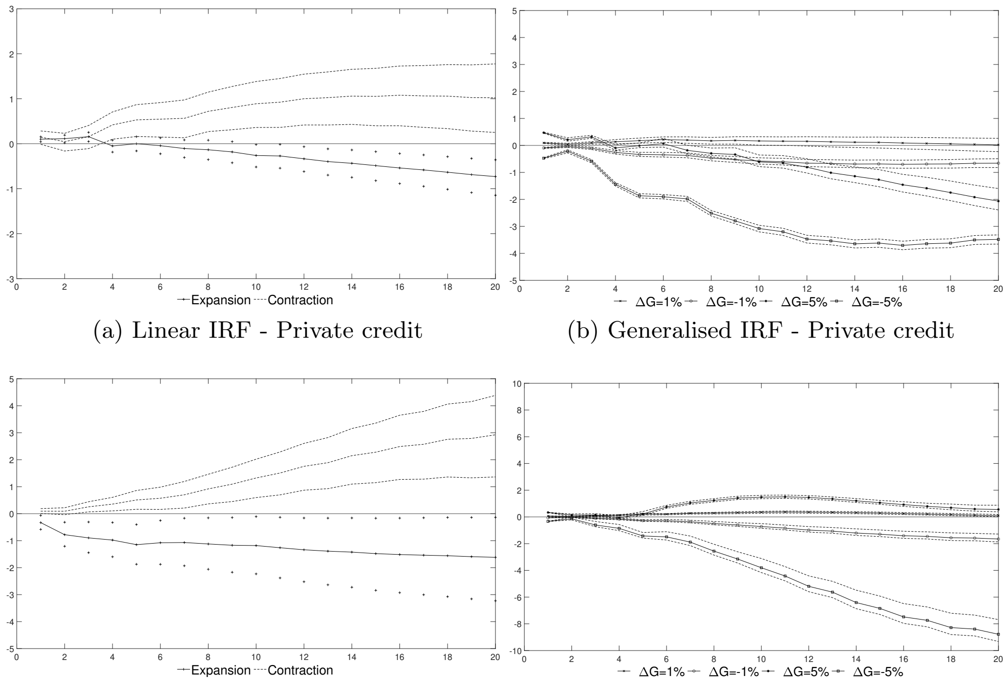
Note: Cumulative generalized impulse responses to a fiscal shock delivered in a median representative recession or expansion. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, and GDP. Confidence bands are at 5th and 95th percentile.

A number of differences appear evident as we compare the two scenarios. In a typical expansion, the GDP reaction to a fiscal shock appears to be more symmetric to the sign of the shock. Even the phenomenon of diminishing returns is weak to the point of being negligible. A representative recession yields a more diverse reaction to a fiscal expenditure shock. The responses are no longer symmetric and negative shocks produce a larger effect. Moreover, it is again evident that there are diminishing returns to larger expansionary measures. At the same time, some key characteristics noted in the baseline scenario still hold in this exercise, such as the concordance in sign between impact and long-run response. Crucially, positive shocks are still expansionary, and budget cuts lead to recession in both scenarios. Overall, whether fiscal multipliers are larger during a recession rather than during an expansion depends on the size and on the sign of the shock. The effect on GDP of a small shock, irrespective of the sign, appears to be larger in absolute value during a typical recession. However, non-linearities kick in when the size of the budget increase is scaled up, causing a large fiscal stimulus to yield less effect on GDP during a period of crisis than with a prospering economy. The results clearly suggest that the classical notion of larger multipliers in a recession needs to be revised to carefully account for the size and sign of the shock.

Augmented specifications

Next we show our findings when the model specification is changed to include either private credit or public debt, both normalized by GDP. Figure 3.5 presents linear and non-linear GDP impulses responses for these extended specifications.

Figure 3.5: Augmented specifications with private credit or public debt, GDP reaction



(a) Linear IRF - Private credit

(b) Generalised IRF - Private credit

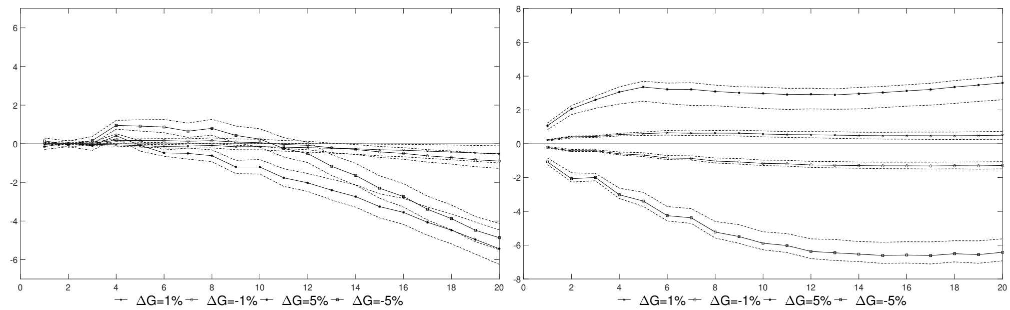
(c) Linear IRF - Public debt

(d) Generalised IRF - Public debt

Note: Cumulative linear (a, c) and generalised (b, d) impulse responses. Percentage GDP response to a unit standard deviation (a, c) or to percentages of government expenditure (b, d) fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, GDP, and either private credit or public debt. Confidence bands are at 5th and 95th percentile.

The interpretation of the extended specifications, read together with the behaviour of the extension variables presented in Figure 3.6, is broadly in line with the baseline key findings. In both the extensions, positive shocks still yield positive GDP effects and vice versa. Furthermore, the diminishing return of expansionary stimuli is still in place. A notable exception is the GDP reaction following a large expenditure increase in the case in which we check for private credit. This pairs with the behaviour of the credit-to-GDP ratio itself, which is similar in the case of large shocks, regardless of their sign. The evidence suggests that the credit mechanism is also responsive to the size of the shock, and that a large expansionary shock may trigger a negative feedback on the economy. The debt-to-GDP ratio also appears strongly procyclical, confirming what we already observed in Chapter 2. Furthermore, it can observed that the reaction of the debt-to-GDP ratio to a larger shock is proportionally larger than that of GDP and that the growth in the initial quarters of the response is faster. An interpretation in line with Perotti (1999) and Ilzetzki et al. (2013) is that the outstanding debt stock increase ends up impairing a further GDP expansion.

Figure 3.6: Augmented specifications, generalised IRFs for the augmentation variables



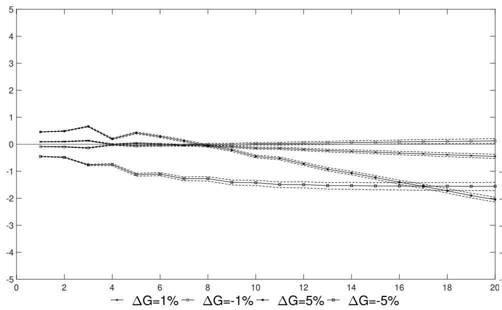
(a) Credit-to-GDP (b) Debt-to-GDP

Note: Cumulative generalised impulse responses. Percentage private credit or public debt response to a fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes an estimate of combined cycle, government expenditure, tax revenues, GDP, and either public debt or private credit. Confidence bands are at 5th and 95th percentile.

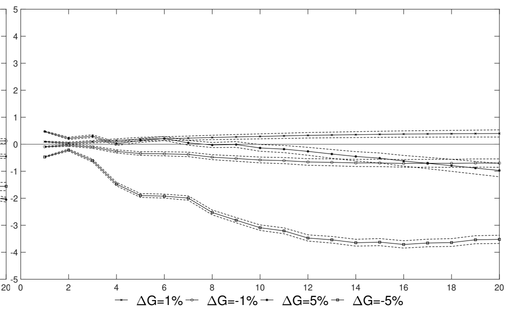
Scenario analysis, augmented specifications

Figure 3.7 presents the scenario analysis exercise for both the extended specifications. All the responses are well defined, with the exception of the larger shocks in the typical expansion scenario for the debt-extended specification, which are reported only in Appendix C.4.1 for better readability of results. The overall conclusion is consistent with the findings of Chapter 2 and the empirical evidence presented for the baseline specification in this chapter in Section 3.3.3.

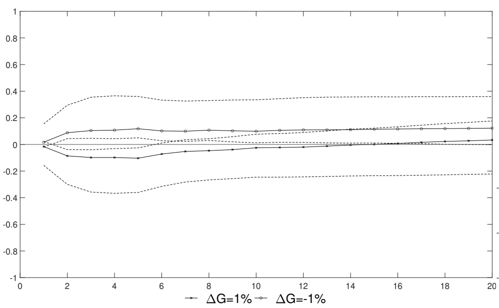
Figure 3.7: Augmented specifications, GIRFs for scenario analysis



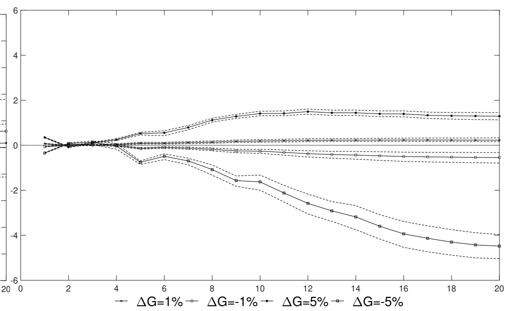
(a) Credit, typical expansion



(b) Credit, typical recession



(c) Debt, typical expansion

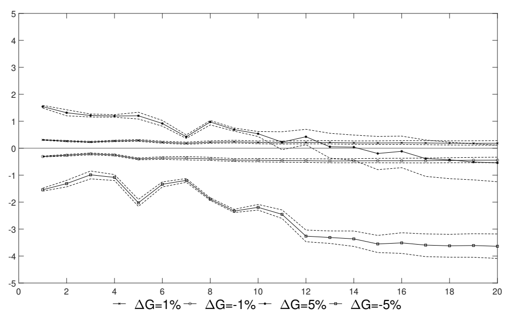


(d) Debt, typical recession

Note: Cumulative percentage GDP response to a fiscal shock. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. The STVAR includes an estimate of combined cycle, government expenditure, tax revenues, GDP and either private credit (a and b) or public debt (c and d). Confidence bands are at 5th and 95th percentile.

Figure 3.8 shows a simple extension to the scenario analysis exercise, limited to the specification augmented with public debt-to-GDP. We assume that the entirety of the fiscal shock translates onto debt via deficit, explicitly modelling a budget increase financed via debt and a debt reduction through a reduction in public expenditures. The model struggles to narrowly identify the dynamics yielded by fiscal shocks during typical expansions, which are reported only in Appendix C.4.1. In any case, a meaningful comparison can be reached, since the GDP dynamics in typical recessions fall outside the confidence bands for their typical expansion counterparts. Overall, the broad conclusion is again that GDP reaction to a fiscal expenditure shock is on average larger in absolute value during typical recessions.

Figure 3.8: Debt augmented specification, GIRFs for scenario analysis with a shock to public debt



Note: Cumulative generalised impulse responses to a fiscal shock delivered in a median representative recession. The same shock is applied with opposite signs to government expenditure and public debt. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. The STVAR includes an estimate of combined cycle, government expenditure, tax revenues, public debt, and GDP. Confidence bands are at 5th and 95th percentile.

3.4 Conclusions and remarks

We estimated a combined economic cycle, a synthetic measure carrying information on both the real economy and production, and the financial cycle. Such an index appears well correlated with the official recession chronology published by the NBER and appears to have inherited the smoothness and the amplitude of movement of the financial cycle. Its features enable us to investigate the state-contingent response to a fiscal shock in a complex economy, where the real as well as the financial sectors exert their own measure of influence. The use of the economic cycle makes even the baseline specification assume the features of what in Chapter 2 was an extended specification with measures of financial stress and fiscal burden.

We used a Smooth Transition VAR to allow the economy to fluctuate along the cycle and analysed the reaction of GDP to shocks of different sign and size. As we observed with more complete specifications in the previous chapter, asymmetries in terms of sign and size of the shock do emerge, mostly for larger expansionary shocks. Such asymmetries are brought to light by the non-linear features of the model and of the impulse responses, whereas in the same context a linear setting would suppress this richness of reaction, forcing symmetry in the results.

The baseline specification shows unequivocal concordance between the sign of the shock and the sign of the response. These dynamics carry over to our extended specifications and scenario analysis exercises, in concordance with what an extended specification would yield when made contingent to a purely financial cycle, as seen in Chapter 2. The most interesting empirical finding remains the phenomenon of limited returns to increasing expansionary stimuli or, in other words, the persistence of the evidence that it appears easier to tank an economy rather than to boost it. From a policy perspective, these results further depart from the notion of expansionary budget cuts á la Alesina and Ardagna (2013). An analysis of the behaviour of public debt and private credit after the shock provides further insight, mostly in line with the findings of the previous chapter. Both private credit and public debt appear to be strongly pro-cyclical, broadly in line with what has already been established by previous literature on the relationship between sovereign debt and GDP.

The scenario analysis complements the results yielded by our specifications and further endorses the hypothesis of a larger multiplier during a recession, tempered by the diminishing returns of larger expansionary packages. Overall, the results seems to hint at the existence of an optimally sized measure, able to achieve the optimal efficiency between cost and result of the intervention.

Overall, our results advocate caution in the context of the traditional countercyclical public intervention during recessions: the existence of a limiting mechanism to the effect of expansionary packages may result in a waste of public resources. On the other hand, the confirmation of the existence of complex dynamics between fiscal space, financial stress, and the economy as a whole calls for further investigation in this line of research, in order to unravel the structural interactions of such a complex relationship.

Chapter 4

Cyclical drivers of euro area consumption: what can we learn from durable goods?

4.1 Introduction

An extensive body of theoretical and empirical research is devoted to the behaviour of private consumption, which is the largest component of demand. Yet, relatively few studies distinguish between durable and nondurable consumption. In particular, model-based analyses exploring the factors that drive durable goods expenditure in the euro area, and how they relate to overall consumption, are virtually non-existent at the time of writing. This is not entirely surprising; aggregate data on euro area durable consumption expenditure is not yet published officially and only recently became available for all 19 individual euro area countries. In the present study we focus on this important component of consumption.

Expenditure on consumer durables – like cars, furniture and electronics – makes up a small share of total consumption, but accounts for a disproportionately large fraction of its overall fluctuation. Durable goods feature specific characteristics which substantially complicate the task of a modeller when they enter into a consumption function. First, a durable good provides utility over multiple periods and (as with capital) is subject to depreciation. This allows consumers to postpone purchases of durables in times of economic hardship, while still benefiting from the service flow coming from the accumulated stock, and to catch up with upgrades to the desired stock in times when the economy is doing better. Secondly, durables can often be financed with credit and at the same time they may serve as collateral to secure the claim of a lender. This characteristic makes them more exposed to credit conditions and lending rates. Indeed, using US data, Monacelli (2009), Sterk and Tenreyro (2018), Cantelmo and Melina (2018) and Di Pace and Hertweck (2019) find that the reaction of durable expenditure to monetary shocks is larger than that relating to nondurables, and that in all cases, they co-move. Finally, changes in the stock of durables may be subject to adjustment costs. This accounts for sluggish adjustments and protracted cycles in durable expenditure, since the presence of such costs determines "inaction zones" for which it is optimal for a consumer not to adjust small differences between the actual and the desired durable stock (see Caballero, 1993).

We start by setting up a theoretical model of durable and nondurable consumption. The model features non-linear dynamics and occasionally binding liquidity constraints.[1] When they bind, consumers are not fully able to smooth consumption and the path of

[1]The presence of non-linearities is consistent with findings from the literature on durable goods. For instance, Berger and Vavra (2015) find that durable expenditure reacts more strongly to monetary shocks during expansions than during recessions.

durables becomes informative about future expenditure on nondurables. This result, derived in Chah et al. (1995), represents a deviation from the standard random walk model of consumption initiated by Hall (1978), and provides a strong justification to model these two components of consumption separately. Simulations from the theoretical model show that shocks to durable preferences and to relative prices induce important lagged interactions with the path of nondurable consumption.

In a second step, we employ a structural VAR with time-varying parameters (TVP) and apply it to study durable and nondurable consumption in the US, the euro area (EA) and the four largest EA countries – Germany, France, Italy, and Spain. Our identification strategy is based on a combination of zero and sign restrictions, and distinguishes shocks to monetary conditions and aggregate from durable-specific supply and demand shocks, while accounting for non-linearities.

We find a number of results from our empirical analysis that align well with the predictions from the theoretical framework. Theory points to spillovers between durable and nondurable consumption when agents are constrained. Since we work with aggregate data, we exploit the heterogeneity across countries in terms of liquid asset availability along the income distribution, to check whether in countries where households are – on average – more likely to be constrained, the spillovers are stronger. Our empirical findings confirm the theoretical prediction, as we observe a larger magnitude of the effect on nondurables from both durable-specific demand and supply shocks in those countries with a larger fraction of constrained households. This complements the results of Flavin and Nakagawa (2008) on the housing stock (which they treat as a durable good), the analysis of Li and Martin (2019) regarding the sectoral spillovers during the Great Recession, and the evidence from Attanasio et al. (2008) on the existence of binding borrowing constraints in the US car loan market, particularly affecting the behaviour of low income households.

Following a shock to monetary conditions (defined such that they encompass the monetary policy and the idiosyncratic country-level credit environment), we find that the impact on durables is stronger than on nondurable consumption, and reaches its peak earlier. This evidence agrees with results found in the bulk of literature on US data (see, among others, Mankiw, 1985; Erceg and Levin, 2006; Forni and Gambetti, 2010; Mallick and Mohsin, 2016; Tenreyro and Thwaites, 2016; Miranda-Agrippino and Ricco, 2018).

Our methodology allows us to aggregate durable and nondurable consumption so that we can decompose the contribution of structural shocks to total consumption. This provides ample insights on how demand, supply, and monetary factors interacted during the recent crisis and subsequent recovery, thus shedding light on cross-country heterogeneity. Our analysis suggests that monetary condition factors played a key role during the Great Recession in France, Italy, and Spain, while Germany experienced a relatively smaller contraction in consumption growth that was driven by supply-side, durable-specific factors. The crisis in Spain, on the other hand, was further compounded by durable-specific negative demand shocks.

An even more variegated picture emerges from the second recession, the 2011-2014 sovereign debt crisis, which did not affect Germany, was more diluted over time for France, and strongly affected Italy and Spain, where durable-specific factors strongly influenced the deep contraction in consumption, alongside aggregate demand factors. The heterogeneous evolution of consumption continued up to the post-2014 recovery, which was mainly animated by durable-specific factors in Italy and Spain. In the last part of the sample, the slowdown was driven by a combination of factors, rather than having a specific cause.

The rest of the chapter is organised as follows. Section 4.2 sketches a theoretical model of consumption with durable and nondurable expenditures and shows their simulated path under occasionally binding liquidity constraints. Section 4.3 describes the data and shows some stylised facts. Section 4.4 discusses our empirical framework, identification strategy, and results. The heterogeneity of the results for the four biggest euro area countries is examined in Section 4.5. Section 4.6 concludes.

4.2 Theoretical framework

The theoretical framework draws upon Chah et al. (1995) and José Luengo-Prado (2006). Facing an income stream $\{Y_t\}_{t=0}^{\infty}$, a consumer maximises the present discounted value of expected lifetime utility by choosing assets A_t, nondurable consumption C_t and the flow of services provided by a durable good D_t. Formally, the consumer solves the problem

$$\max_{\{C,D,A\}} \qquad E_0 \sum_{t=0}^{\infty} \frac{1}{(1+\rho)^t} U\left(C_t, D_t\right)$$

subject to

$$\begin{aligned} A_t &= RA_{t-1} + Y_t - C_t - P^d d_t \\ D_t &= d_t + (1-\delta) D_{t-1} \\ A_t &+ \varphi P^d D_t \geq 0 \\ A_{-1}&, D_{-1} \text{ given;} \\ t &= 0, 1, \ldots, \infty. \end{aligned}$$

The durable good is subject to a rate of depreciation δ and is financiable up to φ i.e. in any given moment, the consumer borrowing limit is a fraction φ of the value of the durable stock and is thus equal to $\varphi P^d D_t$. Equivalently, one can interpret $\theta = (1-\varphi)$ as a required down payment. The consumer faces a non-negativity constraint on her assets, which comprise both financial assets A_t and the portion of the durable good that is usable as collateral. Durable purchases are denoted by d_t.

In this simplified version of the model, we assume that the relative price of durables P^d is constant, as is the real interest rate, which equals the rate of time preference $(\rho = r)$.[2]

The Lagrangian for this problem is

$$\mathcal{L} = E_0 \textstyle\sum_{t=0}^{\infty} \frac{1}{(1+\rho)^t} \left\{U\left(Y_t + RA_{t-1} - A_t - P^d\left(D_t - (1-\delta) D_{t-1}\right), D_t\right) + \mu_t\left(A_t + \varphi P^d D_t\right)\right\}$$

Denote $U_c(t)$ and $U_d(t)$ the marginal utilities of nondurable and durable consumption, respectively, in period t. The first order conditions are

$$E_t U_c\left(t+1\right) = U_c(t) - \mu_t \tag{4.1}$$

$$U_d(t) = P^d\left[U_c(t) - \frac{1-\delta}{1+r} E_t U_c\left(t+1\right)\right] - \varphi P^d \mu_t \tag{4.2}$$

with supplementary slackness conditions

$$\mu_t \geq 0 \tag{4.3}$$

$$\mu_t\left(A_t + \varphi P^d D_t\right) = 0 \tag{4.4}$$

Substituting for $E_t U_c(t+1)$ from Eq. 4.1, Eq. 4.2 becomes (after re-arranging terms)

[2] Equivalently, $\beta R = 1$ where $\beta = 1/(1+\rho)$ is the discount factor and $R = 1+r$ is the compound interest.

$$U_c(t) = \underbrace{\frac{R}{R-(1-\delta)}}_{\Omega^{-1}} \frac{1}{P^d} U_d(t) + \frac{\varphi R - (1-\delta)}{R-(1-\delta)} \mu_t \tag{4.5}$$

where $\Omega = \frac{r+\delta}{1+r}$ is the user cost of durables.

Assume that the utility function takes the form $U(C_t, D_t) = log(C_t) + \gamma log(D_t)$.[3] When the liquidity constraint is not binding ($\mu_t = 0$) from the Euler Equation (Eq. 4.1) it follows that, under perfect foresight, the path of nondurables is smoothed over time. Eq. 4.5 sets the optimal intratemporal ratio of durables to nondurables, which in that case is constant. The ratio depends positively on the preference parameter γ, and negatively on the relative price and the user cost:

$$\frac{D_t}{C_t} = \frac{\gamma}{\Omega P^d}$$

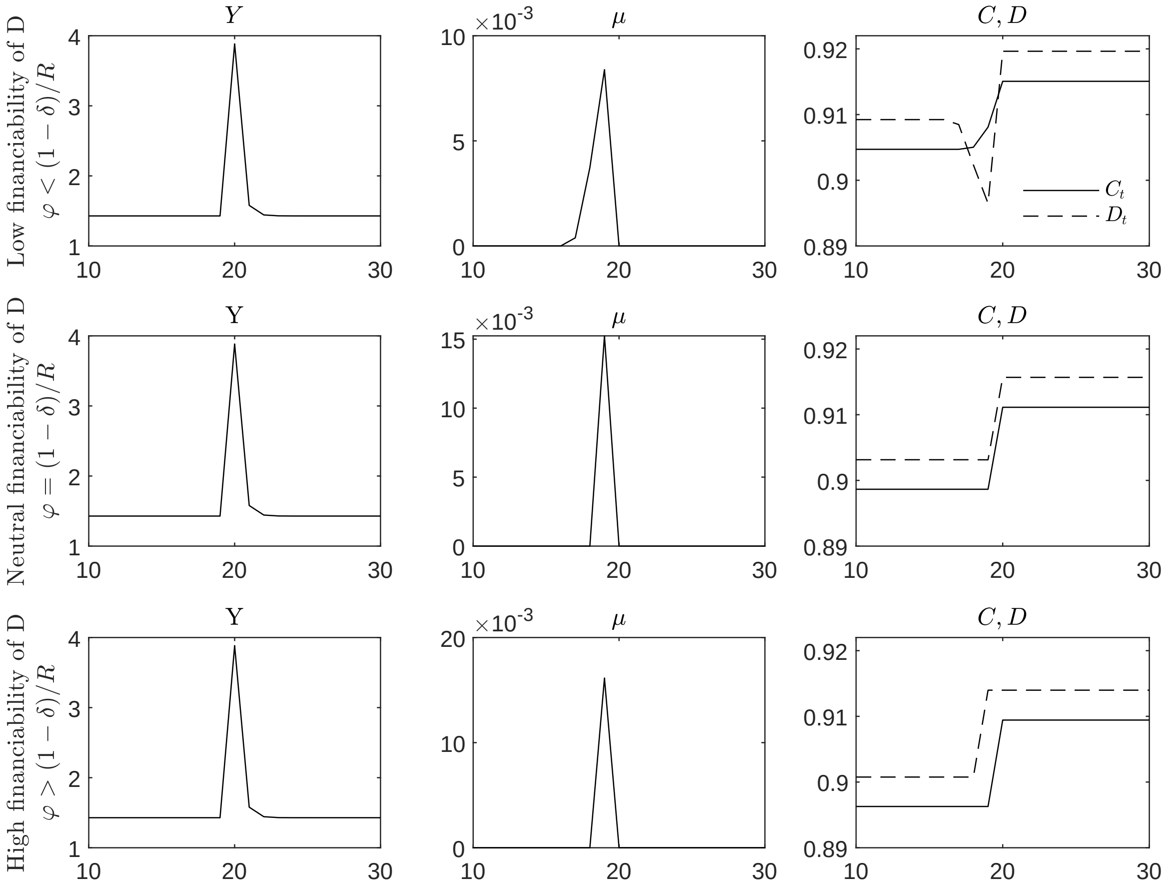
Under perfect foresight, it is possible that a predicted increase in income makes the liquidity constraint binding ($\mu_t > 0$) because, for instance, a low level of financial assets or insufficient collateral to borrow prevent the agent from smoothing consumption. As shown by Chah et al. (1995), in this context a temporary departure of durables from nondurables in anticipation of the change in income, proportional to the shadow price of the constraint, may carry information about future consumption. This stands in contrast to the random walk model of Hall (1978), derived under the standard life cycle-permanent income hypothesis with rational expectations, and thus recovers the argument of Mankiw (1982).

Figure 4.1 shows simulations under perfect foresight of a known increase in income occurring in period $t = 20$ under the assumption that $\gamma = 0.6$ in the utility function. As the predicted variation in income makes the liquidity constraint binding one or more periods ahead of the time when it occurs, the results illustrate the different reaction of C_t and D_t for high and low financiability of durables φ. As pointed by José Luengo-Prado (2006), the special case of $\varphi = (1-\delta)/R$ is a useful neutral benchmark. In that case, the intratemporal allocation between C_t and D_t is not distorted when the liquidity constraint becomes binding, as in the case when $\mu_t = 0$. For all other values of φ, a positive shadow price of borrowing triggers adjustments in the relative allocations of C_t and D_t which are informative for future consumption.

Our result echoes Chah et al. (1995) and stresses the need to model durable consumption in isolation to allow for asynchronous adjustment in the presence of borrowing constraints. The occasionally binding constraints induce non-linearities that may be further reinforced by changes in the degree of financiability of durables φ over time. Overall, the results hint that it would be wise to model the relationship between durable and nondurable consumption in a time-contingent manner.

[3] This form of the utility function assumes separability of durables and nondurables, which is consistent with empirical findings in the literature (see Bernanke, 1985). The model is in quarterly frequency and assumes that both the interest rate and the rate of time preference equal 2% in annual terms. The annual rate of depreciation for durables is calibrated at 15%, a value which stands between the 20% in Chah et al. (1995) and 8.5% in José Luengo-Prado (2006). The study of Stacchetti and Stolyarov (2015) on durability and obsolescence reports depreciation rates of 10%, 18%, and 45% for furniture, automobiles, and computers, respectively.

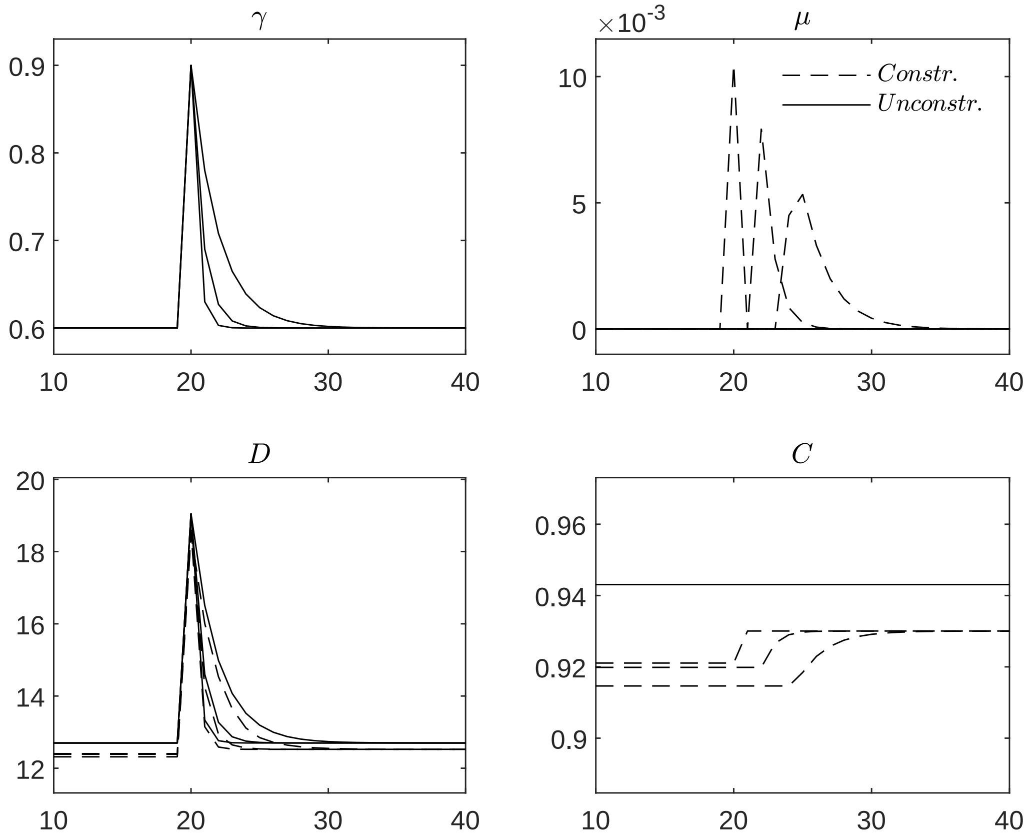
Figure 4.1: Adjustment of durables and nondurables in the presence of liquidity constraints



Note: For the cases of low, neutral, and high financiability of D (first, second, and third row above), φ takes the values, respectively, 0.85, 0.9554, and 1.0 at quarterly frequency. The D series are rebased for better visualisation.

In our next step (described in Appendix D.1) we extend our model to allow for time variation in relative prices, preferences and the interest rate.[4] Simulation results from shocks to these variables show important lagged interactions from durable to nondurable consumption. Figure 4.2 illustrates the case of a temporary positive shock to the preference parameter γ. As the level of persistence increases, the shock triggers increasingly delayed spillovers onto nondurables C_t for an agent sufficiently close to the boundary to become liquidity-constrained in response to the shock. For very persistent shocks, or permanent ones, the constraint does not kick-in and thus the durable-specific shock has no effect on C_t, just as in the case for the non-liquidity constrained agent. In all cases, the adjustment of D_t remains very similar.[5]

Figure 4.2: Effects from a temporary increase in the preference parameter γ for durables



Note: The figures display a temporary increase in the preference parameter γ for three cases of different persistence of the shock, governed by an AR(1) process with autoregressive parameter taking values of 0.1, 0.3, and 0.6.

Appendix D.2 shows a set of additional simulation results under perfect foresight for a set of shocks to relative prices, preferences, and the interest rate. It is worthwhile to note that whenever shocks trigger binding borrowing constraints and hence spillovers onto nondurable consumption, the reaction in C_t never occurs contemporaneously, but only with a lag. We will use this result in our VAR identification scheme to distinguish durable-specific from aggregate shocks.

In our framework, occasionally binding constraints – expected to affect only households with little liquid wealth – in conjunction with the assumption of separability of durables from nondurables in the utility function, are the key ingredients to generate lagged spillovers from durable-specific shocks to nondurable consumption. This mechanism differs from that presented in Bernanke (1985) where durables and nondurables are nonseparable in the utility function and furthermore there are adjustment costs. In

[4]The extended model nests the simple version described above.

[5]Naturally, this particular result is contingent to the parameterisation used.

that case, durables and nondurables are either complements or substitutes depending on the parameterisation, and moreover spillovers, if they occur, are contemporaneous.

Before proceeding, a few caveats are worth mentioning. Admittedly, our approach provides more limited insights in terms of propagation mechanisms compared to a fully-fledged general equilibrium framework. Adopting such an alternative framework, however, would also entail the inclusion of many more assumptions, making it more difficult to recover a clear inference about the role of occasionally binding constraints. Hence we believe the parsimonious specification presented here to be optimal for the purpose at hand. The model is able to represent forward-looking consumer behaviour, emphasising the distinction between durable and nondurable consumption, while offering a tractable solution in the presence of non-linearities and occasionally binding constraints.

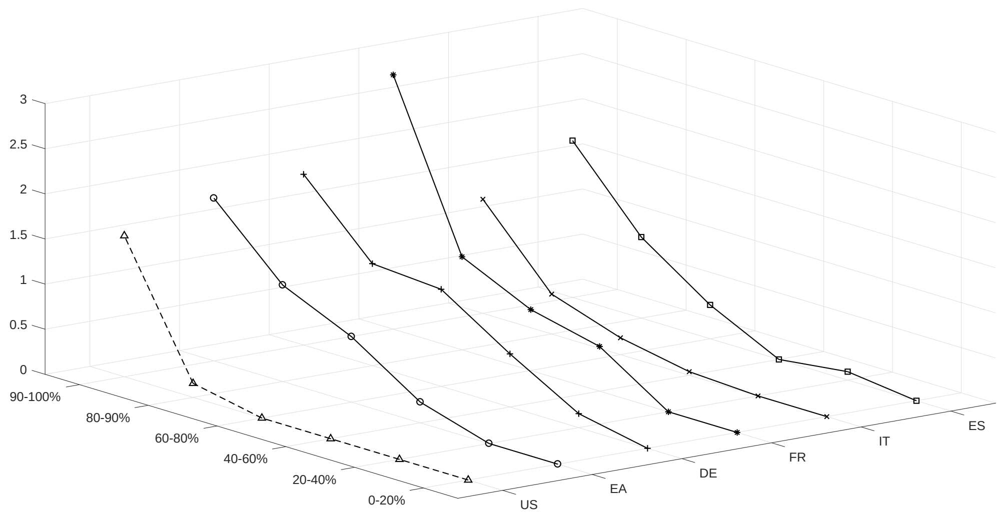
Secondly, our model does not feature adjustment costs. Their presence, explored for instance in José Luengo-Prado (2006) and Caballero (1993), adds realism at the cost of significant complications to modelling. This caveat is of little practical relevance here since we use the theoretical model to build intuition and expose the channels at play, before moving on to the empirical analysis. The lack of such costs does not change the conclusions presented earlier, but is a useful reminder that the magnitude of the adjustments in durables in response to various shocks – which we have purposefully abstained from commenting on – are likely to be overstated in the simulation results shown here.

The adjustments highlighted above occur at the micro level for an individual consumer. At the aggregate level, various agents will be constrained at different moments in time and subjected to both common and idiosyncratic shocks. This raises a third caveat, the issue of aggregation and the relevance of the results in a general equilibrium setting, discussed for instance in Heaton (1993), Chah et al. (1995), and José Luengo-Prado (2006).

Here, we limit ourselves to noting that the strength of the spillovers from durable-specific shocks to nondurable consumption in our setting will depend, among other things, on the distribution of liquidity-constrained households across the population. A larger fraction of constrained households will result in stronger spillovers in the aggregate. In this context, results from the Household Finance and Consumption Survey (HFCS) in Figure 4.3 show that a larger fraction of households in Italy and Spain appear likely to face liquidity-constrained reactions, rather than in Germany, due to the lower ratio of liquid assets relative to income in the former two countries.[6] While in Italy and Spain, households up until the third quintile in the income distribution barely hold financial assets in excess of one quarter worth of income, in Germany this holds true only for the first quintile in the income distribution. On the basis of this evidence, one might speculate that stronger interactions from durable-specific shocks onto nondurable consumption can be expected in Italy and Spain, rather than in Germany at the aggregate level. The results from our empirical model presented in Section 4.5 support this intuition.

[6] The result is based on one popular measure in the literature for approximating liquidity constraints, namely the ratio of financial assets (used as a proxy for liquid assets) to income (see Hall, 2011). Based on self-reported evidence from the HFCS, Le Blanc et al. (2015) similarly find more credit constrained euro area households in Mediterranean countries (e.g. Italy and Spain) than in Continental countries (e.g. Germany and France).

Figure 4.3: Distribution of financial assets across households by income quintiles



Source: Author's calculations based on the HFCS 2017 (for EA countries) and on the SCF 2016 (for the US). The figure shows the ratio of financial assets (FA) to quarterly income (I) among US and EA households ordered by different quintiles of income. The ratio of FA/I is shown only for the portion in excess of one quarter worth of income. Due to accounting differences, US and EA data are not directly comparable.

4.3 Data and stylised facts

In this section we present and discuss the data used to estimate our empirical model.

4.3.1 Data

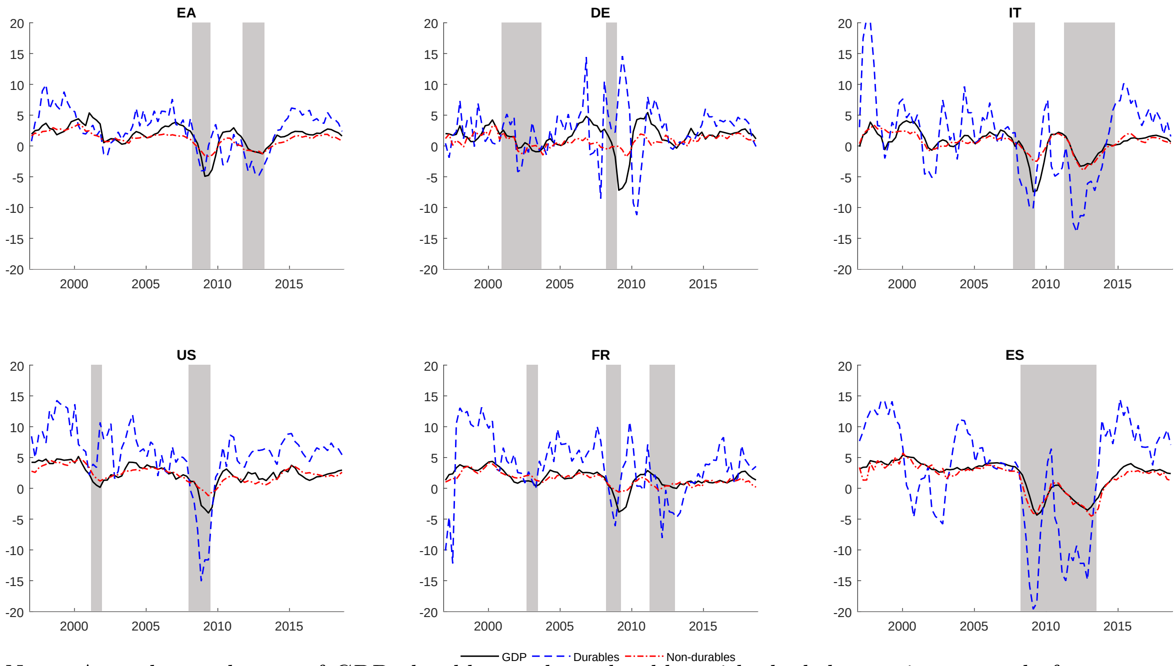
We use quarterly data from 1996Q1 to 2018Q3 for the biggest four euro area countries and for the euro area as a whole. Our empirical model uses five variables: real expenditure on durables and nondurables (including services), the corresponding deflators of durables and nondurables, and the nominal consumer lending rate. We compute the prices for consumption using the implicit deflator from real and nominal series. Since Eurostat does not publish data for the euro area as a whole, we sum up the series for consumption of all the 19 eurozone member states and then proceed to compute the prices for the countries. We also include US data over the same sample period for comparison. Further details about the data can be found in Appendix D.3.

4.3.2 Stylised facts

In our empirical application, we use real expenditure on nondurable consumption and the corresponding price deflator as proxies for the whole economy, in lieu of GDP and consumer price inflation. The main reason for this choice is to be able to show results for total consumption, aggregating durables and nondurables. We believe we are not losing generality with this choice: as Figure 4.4 shows, the annual growth rates of nondurable consumption and GDP are highly correlated.[7]

[7] As we shall see later, when we estimate our empirical model using GDP excluding durables instead of nondurable consumption as a robustness check, the results remain qualitatively comparable.

Figure 4.4: Cyclicalities of GDP, durables, and nondurables



Note: Annual growth rate of GDP, durables, and nondurables with shaded recessions, sample from 1997Q1 to 2018Q3. Recession dating based on NBER (for the US), CEPR (for EA), and ECRI (for DE, FR, IT, and ES).

One feature evident in Figure 4.4 is the volatility of durables compared to GDP. In particular, expenditure on durables tends to grow faster during periods of economic expansion, and to contract more sharply during recessions. Table 4.1 provides a breakdown of consumption components in terms of GDP shares and shares of GDP variance explained. Durable expenditure accounts for a more than proportional fraction of the variance of GDP, further justifying the principle of treating durables as a separate variable in the model.[8]

Table 4.1: Cyclical properties of consumption and its components

	US		**EA**		**DE**		**FR**		**IT**		**ES**	
	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$
Consumption	67.4	54.7	55.4	33.7	52.6	9.7	53.2	34.0	60.8	43.9	59.6	62.6
Dur	7.8	13.1	5.2	5.1	6.1	-2.6	4.8	5.8	5.2	8.8	4.3	9.0
Cars	*36.2*	*5.3*	*42.2*	*1.4*	*42.2*	*-5.2*	*42.4*	*3.1*	*37.8*	*2.6*	*48.1*	*4.9*
Semi-Dur	-	-	4.5	4.9	5.1	3.7	4.6	5.0	6.0	8.5	5.6	7.2
Non-Dur	14.9	13.1	14.5	6.5	14.6	0.9	16.2	5.4	19.7	13.0	18.2	16.5
Services	44.7	25.4	24.8	13.2	26.9	7.7	27.6	16.0	29.9	12.7	31.5	29.3

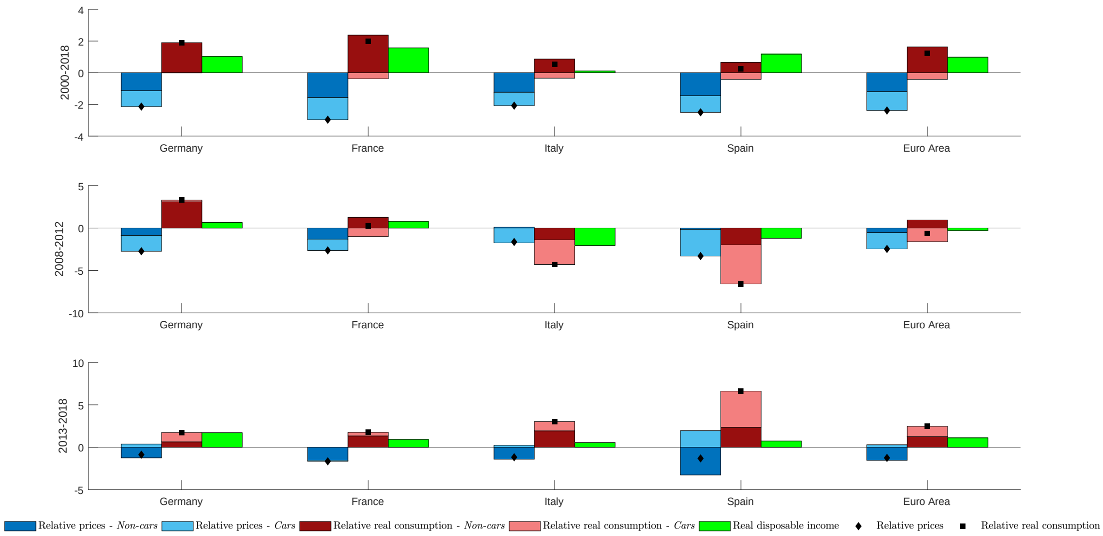
Note: Shares of GDP and percentage of GDP variance explained by consumption and its components in the period 1997Q1 to 2018Q3. *Cars* are reported as a percentage of durables.

Figure 4.5 presents relative consumption growth and relative price inflation of durables, together with the evolution of real disposable income. Over the long-run, we can observe a downward trend in relative prices, which causes upward pressure on relative consumption growth; this is equivalent to a rising share of durable expenditure in total consumption. However, this phenomenon appears absent during weak phases of the business cycle, when a decline in disposable income also drives down relative consumption, as observed in Italy and Spain during 2008-2012. At the same

[8]The only exception, Germany, provides a different kind of justification of our modelling choice as it exhibits a peculiar stabilizing effect.

time, expansions of the business cycle are also associated with catching-up effects of relative consumption. This intuition is confirmed by the analysis of Dossche and Saiz (2018), who found evidence of increasing age in the stock of durables in countries heavily affected by the financial crisis, giving rise to pent-up demand as soon as economic conditions improved.

Figure 4.5: Relative consumption, relative prices, and disposable income



Note: Average growth of relative consumption, prices, and disposable income for the periods 2000Q1-2018Q3, 2008Q1-2012Q4, 2013Q1-2018Q3.

4.4 Empirical analysis

In this section we describe our model, belonging to the family of structural VARs with time-contingent parameters, and our identification strategy, based on a mix of sign and zero restrictions.

The adoption of a time-varying parameter specification in the empirical framework is supported by our theoretical setup featuring occasionally binding constraints, as presented in Section 4.2. To complement the intuition from the theoretical model, we use two parameter stability tests: a Chow test and a Nyblom-Hansen test. Both test the null hypothesis of parameter stability against the alternative of, respectively, parameters changing at a specified break point, or parameters following a random walk evolution. To overcome possible small sample distortions, as Candelon and Lütkepohl (2001) point out, we also adopt the bootstrap approach of the Chow test, both in the *sample split* and in the *break point* versions, as documented in Lütkepohl and Krätzig (2004). Test results provided in Appendix D.5.2 generally reject the null hypothesis of parameter stability and support the use of a time-varying parameter model.

4.4.1 The model

We specify a structural vector autoregressive model with time varying parameters (TVP-SVAR) identified by a set of sign and zero restrictions. We name y the vector of endogenous variables, such that $y = \left[D, P^d, C, P, R\right]'$, where D denotes real expenditure on durables, P^d is the price of durables, C refers to nondurable consumption in real terms and P is the implicit deflator for nondurable consumption. R stands for the nominal interest rate on consumer credit. All variables are in year-on-year growth rates with the exception of the interest rate, which is in year-on-year changes. We choose to use one lag due to the series length. The choice is broadly consistent with formal model selection criteria as reported in Appendix D.5.1, in particular the Schwarz Bayesian criterion, while the Akaike criterion favours a somewhat longer lag structure. A common choice in the TVP-SVAR literature is to limit the amount of lags to two, due to the computation intensity of the model[9] (e.g. in Primiceri, 2005; Cogley and Sargent, 2005; Galí and Gambetti, 2009; D'Agostino et al., 2013; Koop and Korobilis, 2013; Canova and Pérez Forero, 2015; Lubik and Matthes, 2015; Legrand, 2018). We perform the estimation via the BEAR toolbox, as described in Dieppe et al. (2016), using Bayesian techniques, as described in Appendix D.6.

The baseline model can then be written as in Equation 4.6:

$$\mathbf{A}_0 X_t = \mathbf{A}_{i,t}(L) X_{t-1} + \varepsilon_t \tag{4.6}$$

$\mathbf{A}_0$ is the matrix of contemporaneous relations and $\mathbf{A}_{i,t}(L)$ represents the lag-polynomial matrix of coefficients in time t for lag i. The reduced form residuals are distributed following

$$\eta_t = \mathbf{A}_0^{-1}\varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \mathbf{\Sigma}_t) \tag{4.7}$$

We allow both the matrix of coefficients and the structural innovation variance-covariance matrix to be time contingent. In a more compact form the model becomes

$$X_t = \beta_t \overline{X}_{t-1} + \eta_t \tag{4.8}$$

where

$$\overline{X}_{t-1} = \mathbf{I}_n \otimes (L) X_{t-1} \tag{4.9}$$

and

$$\beta_t = \mathrm{vec}(\mathbf{B}_t), \qquad \mathbf{B}_t = \begin{pmatrix} \mathbf{A}_0^{-1}\mathbf{A}_{1,t} \\ \mathbf{A}_0^{-1}\mathbf{A}_{2,t} \\ \vdots \\ \mathbf{A}_0^{-1}\mathbf{A}_{p,t} \end{pmatrix} \tag{4.10}$$

We let the coefficient matrix β evolve according to a random walk process with an endogenously determined variance-covariance matrix $\mathbf{\Omega}$:

$$\beta_t = \beta_{t-1} + \nu_t, \qquad \nu_t \sim \mathcal{N}(0, \mathbf{\Omega}) \tag{4.11}$$

To address the stochastic volatility introduced by the time contingency of the structural variance matrix $\mathbf{\Sigma_t}$ we adopt the approach of Cogley and Sargent (2005), who generalise to the multivariate case the stochastic volatility model of Jacquier et al. (1994). Specifically, we assume that $\mathbf{\Sigma_t}$ can be written as

$$\mathbf{\Sigma}_t = \mathbf{Z}^{-1}\mathbf{H}_t\mathbf{Z}^{-1\prime} \tag{4.12}$$

where $\mathbf{Z}$ is lower triangular and orthogonalizes the structural innovations ε_t without being an identification scheme. The matrix $\mathbf{H}_t$ is diagonal:

$$\mathbf{H}_t = \begin{pmatrix} \lambda_1 h_{1t} & 0 & 0 \\ 0 & \lambda_2 h_{2t} & 0 \\ 0 & 0 & \lambda_3 h_{3t} \end{pmatrix}, \qquad \mathbf{Z} = \begin{pmatrix} 1 & 0 & 0 \\ \zeta_{21} & 1 & 0 \\ \zeta_{31} & \zeta_{32} & 1 \end{pmatrix} \tag{4.13}$$

We denote known scaling terms with λ_i. As in Cogley and Sargent (2005), the diagonal elements of $\mathbf{H}_t$ are assumed to be independent, univariate stochastic volatilities evolving as driftless geometric random walks:

$$\ln h_{it} = \ln h_{it-1} + \upsilon_{it}, \qquad \upsilon_{it} \sim \mathcal{N}(0, \mathbf{\Phi}_i) \tag{4.14}$$

[9] We also estimated the model with 2 lags, finding qualitatively comparable results, albeit affected by the increased dimensionality.

This formulation implies that the growth rate of the stochastic volatility is normally distributed around zero. Generalizing the notation and implicitly allowing for a drift in the growth rate, we can then rewrite

$$\mathbf{H}_t = \begin{pmatrix} \lambda_1 \exp(h_{1t}) & 0 & 0 \\ 0 & \lambda_2 \exp(h_{2t}) & 0 \\ 0 & 0 & \lambda_3 \exp(h_{3t}) \end{pmatrix} \tag{4.15}$$

where the scaled diagonal elements are approximately log-normally distributed and grow according to an AR(1) process with standard independent innovations:

$$h_{it} = \gamma h_{it-1} + \upsilon_{it}, \qquad \upsilon_{it} \sim \mathcal{N}(0, \mathbf{\Phi}_i) \tag{4.16}$$

4.4.2 Identification strategy

We use a combination of sign and zero restrictions à la Arias et al. (2018), as reported in Table 4.2.

Table 4.2: Sign restrictions

Var\Shock	Durable Demand	Durable Supply	Aggregate Demand	Aggregate Supply	Monetary
D	+	+			+
P^D	+	−			
C	0	0	+	+	+
P	0	0	+	−	+
R			+		−

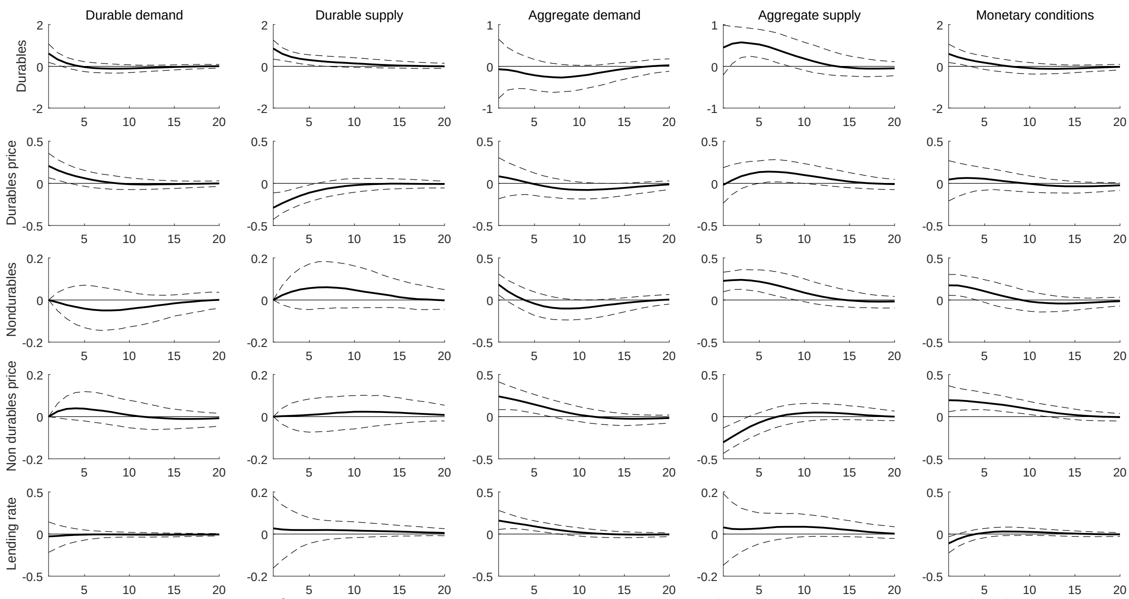
Our modelling strategy rests on two main choices: to model durables and nondurables separately, and to use nondurables as a proxy for GDP. We include in the model both durable and nondurable consumption expenditures so that we are able to aggregate them to total consumption.

Given our approach, we identify two fairly standard aggregate demand and supply shocks. In the former, a positive demand shock pushes up both quantity and prices, as well as the nominal interest rate. In the latter, a positive supply shock is associated with a fall in prices and a rise in quantities. With the same logic we add durable-specific shocks, identified with the help of a corresponding zero restriction on both the quantity and the price of nondurables. Our choice of zero restrictions is supported by the theoretical model presented in Section 4.2, showing that spillovers from D to C, when present, occur only with a lag. Furthermore, it is possible to find real-world examples of such shocks: Appendix D.4 provides an example from the home appliances market in the US. The monetary condition shock follows a standard textbook identification and, given that we use the lending rate, it captures both monetary policy shocks and country-idiosyncratic broader credit supply conditions.

4.4.3 Results

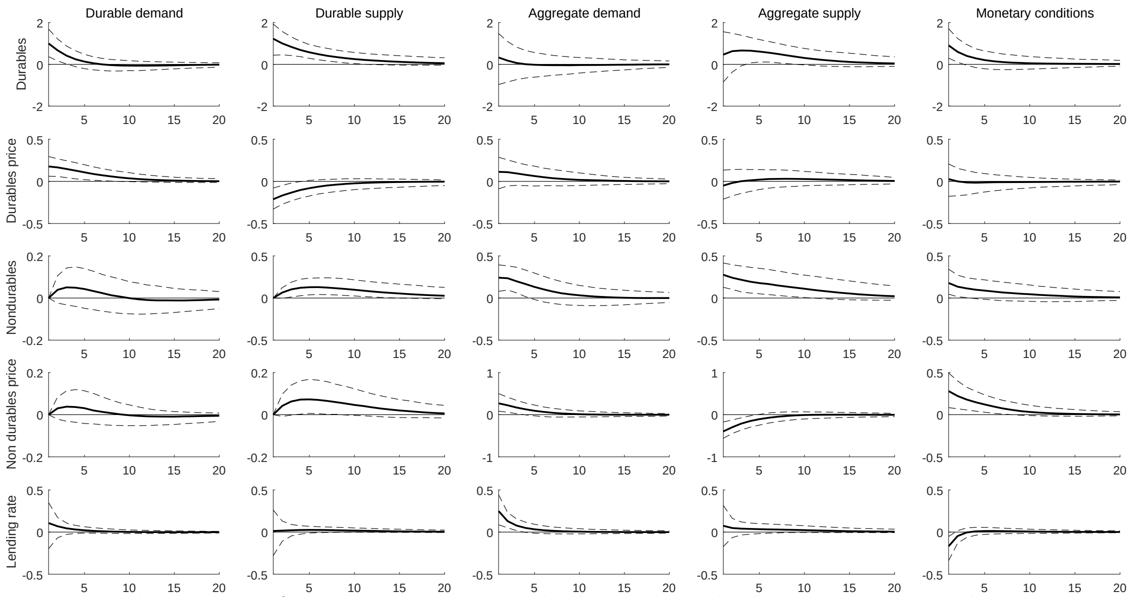
In what follows we present a selection of results. Impulse response functions displayed in Figures 4.6 and 4.7 represent the expected response of the model to the identified structural shocks and are therefore computed using the long-term, homoskedastic value for the variance-covariance matrix $\mathbf{\Sigma}_t$. The model is estimated in annual growth rates, over the period from 1997Q1 to 2018Q3. Euro area series are a bottom-up aggregation of country-level data for the 19 individual member states.

Figure 4.6: Euro area: impulse responses



Note: Impulse response functions to a one standard deviation shock computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure 4.7: United States: impulse responses



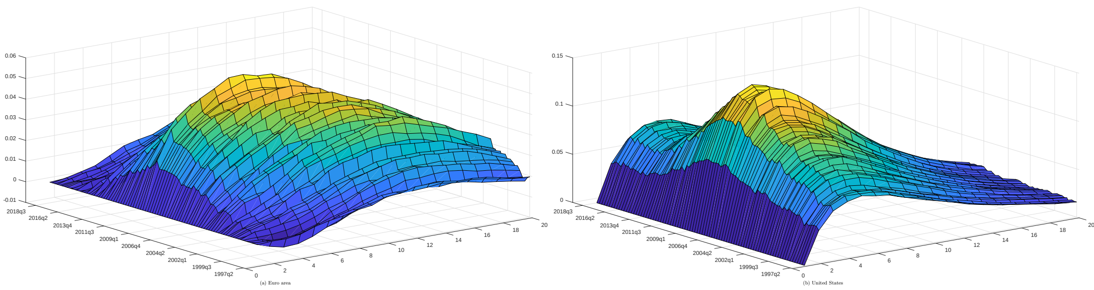
Note: Impulse response functions to a one standard deviation shock computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

In Appendix D.7.2 we also show a version of the IRFs computed using the time-varying variance-covariance matrix $\mathbf{\Sigma}_t$.

From a first comparison of Figures 4.6 and 4.7, some regularities are visible between the euro area and the US. The reaction of durables to a monetary condition shock is larger than that of nondurable consumption, confirming the common wisdom in the literature (as found in Monacelli, 2009; Cantelmo and Melina, 2018; Sterk and Tenreyro, 2018; Di Pace and Hertweck, 2019). However, this result looks heavily influenced by the assumption of homoskedasticity: once relaxed, the difference in the magnitude of reactions wanes. At the same time, some differences arise: it is easy to spot that in the US case durable and nondurable consumption expenditures co-move regardless of the nature of the shock. On the other hand, in the euro area we observe either co-movement or substitution depending on the nature of the shock: demand-side shocks trigger substitution, while supply-side shocks imply co-movement.

Comparing the magnitudes of impulse response functions for different countries calls for caution, as they also reflect differences in the size of the structural shocks. However, if we look at the evolution of the impulse response functions over time, the response of nondurable prices to a durable-specific supply shock appears to be weaker in the post crisis period for both the US and the euro area. As shown in Figure 4.8, the effect of the shock reaches its peak faster in the US around the fourth quarter after the impact, while lagging behind in the euro area. It is easy to see that the peak reaction is at its highest close to the crisis period, and then settles down at lower values in the post-crisis period.

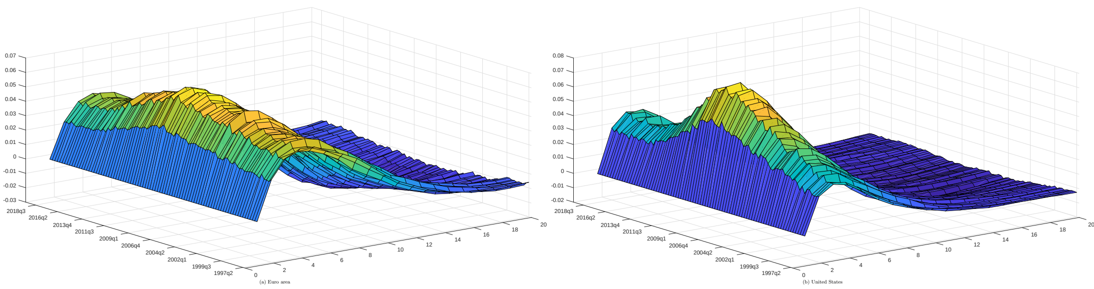
Figure 4.8: Reaction of the price of nondurables to a durable-specific supply shock



Note: Response of the price of nondurables to a positive durables-specific supply shock for (a) euro area and (b) United States.

We can uncover similar insights by looking at the effect on the price of nondurables following a durable-specific demand shock: the peak effect comes slightly faster in the US, around the second and third quarter after the impact, and the largest effect occurs during the crisis period, as shown in Figure 4.9.

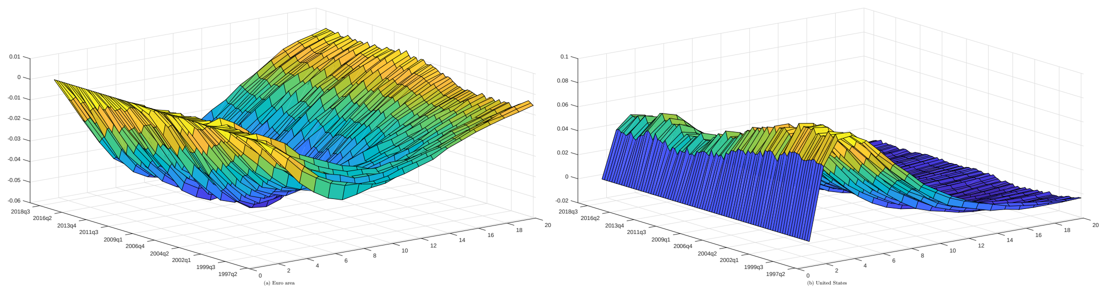
Figure 4.9: Reaction of the price of nondurables to a durable-specific demand shock



Note: Response of the price of nondurables to a positive durables-specific demand shock for (a) euro area and (b) United States.

Interestingly, the effect of a durable-specific demand shock on nondurable consumption for the euro area and the US is of opposite sign, clearly showing substitution in the former case and co-movement in the latter case. The reaction peaks faster in the US during the crisis with a declining magnitude of the effect stabilising over the post-crisis period. A similar dynamic can be retrieved for the euro area, as shown in Figure 4.10, even if with negative sign. Mirroring a weakened co-movement in the US, the empirical evidence shows a strengthened substitution effect in the euro area.

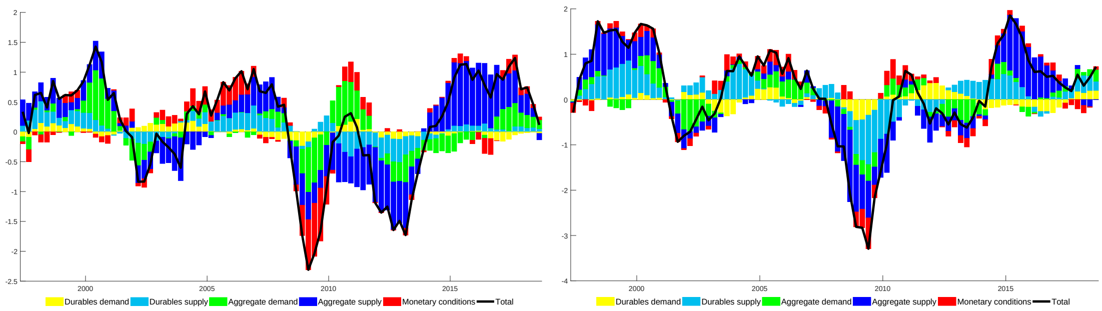
Figure 4.10: Reaction of nondurable consumption to a durable-specific demand shock



Note: Response of nondurables to a positive durables-specific demand shock for the (a) euro area and (b) United States.

The historical decomposition of the annual growth of total consumption sheds further light on the crisis dynamics in Europe as well as in the US. As Figure 4.11 shows, the 2008-09 crisis was strongly driven by both supply and demand in the US, while the main contributor to the first crisis in the euro area was the demand side, together with unfavourable monetary conditions, with a strong negative contribution from supply hindering the recovery after the crisis. In both cases, the recovery that began in 2014 appears to be boosted by supply factors, with the most recent differences due to the dissipation of such positive effects which, in the euro area, was compounded by a weakening of both durable-specific and, later on, aggregate demand.

Figure 4.11: Total consumption: historical decomposition



(a) Euro area (b) United States

Note: Historical decomposition of the year-on-year total consumption growth. Total consumption is an aggregate of durable and nondurable consumption. Data for (a) euro area and (b) United States.

In Appendix D.8, we present results for a SVAR with constant parameters estimated in levels and in y-o-y differences, a TVP-SVAR as in the baseline specification but using GDP excluding durable instead of nondurable consumption, and adding housing to the list of durables, as a sensitivity check. The results are broadly comparable in qualitative terms.[10]

4.5 Heterogeneity among countries

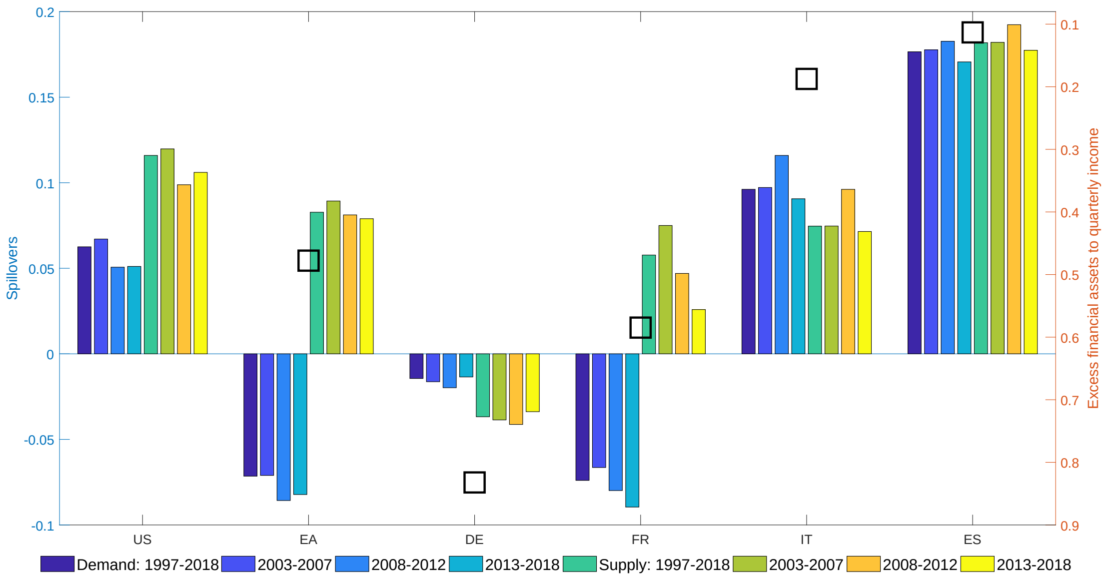
The theoretical model predicts spillovers between durables and nondurables when agents suffer from liquidity constraints. As discussed in Section 4.2, at the aggregate level agents will become constrained at different moments in time, blurring the general picture due to aggregation effects. However, in Figure 4.3 we showed important differences across countries in the likelihood of households becoming affected by

[10]Specifically, as the housing variables we use residential investment for the US and investment in dwellings for the euro area, Germany, France, Italy, and Spain.

liquidity constraints, and therefore in the likelihood of observing stronger effects at the aggregate level.

The predictions of the theoretical model are confirmed by the empirical evidence recovered from the TVP-VAR, as shown in Figure 4.12. More constrained countries, like Italy and Spain, exhibit larger (in absolute size) spillover effects, particularly during the crisis period. Moreover, data suggests that the sign of the spillover has a relationship with the income distribution, with less constrained countries showing a substitution effect. We show the distribution of maxima for each quarter in Appendix D.7.5.

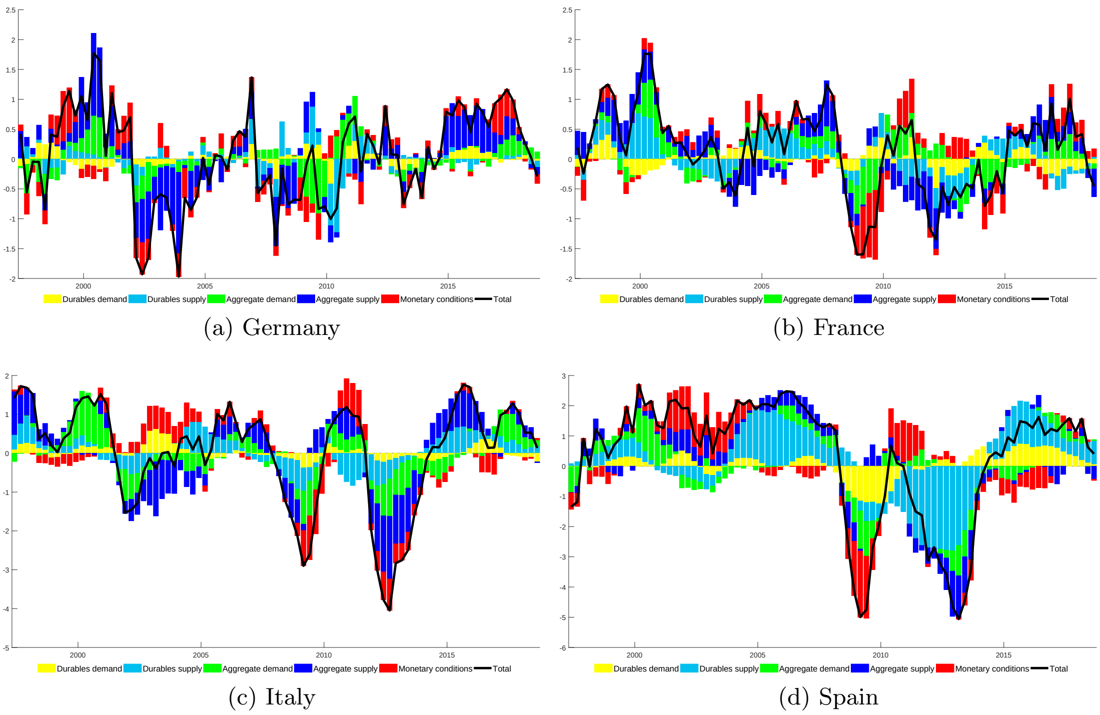
Figure 4.12: Spillovers from durable-specific shocks to nondurable consumption



Note: The bars represent peak effects of durable-specific demand and supply shocks on nondurable consumption, disaggregated by pre-crisis, crisis and post-crisis sub-samples. Magnitudes have been rescaled to be comparable across countries and are reported on the left scale. On the right scale, in reverse order, the black squares show a measure of financial constraints of households. The measure represents financial assets held in excess of quarterly income and is computed from HFCS data, as in Figure 4.3, averaged for the third and fourth quintiles of the income distribution for EA countries and the euro area aggregate.

As expected, the historical decomposition of the annual growth in total consumption exhibits heterogeneity at the level of euro area member states. Focusing on crisis and post-crisis periods, Figure 4.13 shows how the four largest economies of the euro area differ both in the size of consumption contractions and in the drivers behind them.

Figure 4.13: Total consumption: historical decomposition



(a) Germany

(b) France

(c) Italy

(d) Spain

Note: Historical decomposition of the year-on-year total consumption growth. Total consumption is an aggregate of durable and nondurable consumption.

The Great Recession of 2008-09 and the sovereign debt crisis that followed is specifically evident in France, Italy, and Spain and much less pronounced in Germany. Moreover, Figure (a) shows how the relatively small contraction in consumption growth is due to supply side factors, specifically of durables. This contribution can also be found in France and Italy, while in Spain the demand side, both durable-specific and aggregate, appears to be among the main drivers. Figures (b), (c) and (d) also suggest that monetary conditions (which captures both common monetary policy and the country-idiosyncratic consumer credit environment) play a key role depicting a picture of economic contraction also on the financial side during the Great Recession, but much less so in the sovereign debt crisis.

The sovereign debt crisis – a second recession between the years 2011 and 2014 – does not affect Germany, but it is even worse than the first recession in Italy and Spain, and more contained in France. In Italy and Spain durable-specific factors seem to play a strong role in the second recession, as well as in the subsequent recovery. The consumption slowdown in the last part of the sample (up to the third quarter of 2018) appears to be driven by a combination of demand- and supply-side factors, including the waning support from durable-specific demand contributions in Italy and Spain. The monetary conditions contribution appears limited.

4.6 Concluding remarks

We used a theoretical partial equilibrium model to inform a structural TVP-SVAR where the structural shocks were identified with a mixture of sign and zero restrictions.

One interesting prediction from the theoretical model is that liquidity constrained agents will experience spillovers from durable-specific shocks to nondurable consumption. Notwithstanding the consideration that the aggregation of agents to country-level data would reasonably weaken such effects due to different households being constrained at different moments in time, our empirical evidence still suggests that countries with a larger share of liquidity-constrained households show larger spillover magnitudes. Countries with less constrained households even exhibit substitution effects, albeit small and not significant, rather than positive (co-movement) effects.

Moreover, we are able to confirm for the euro area and the largest four euro area countries that durable expenditure reacts more strongly and faster in response to a shock to monetary conditions, a standard result commonly reported in the literature on US consumption. An analysis of the role played by different factors during the recent crisis highlights a significant degree of cross-country heterogeneity.

Conclusion

We focused on how a non-linear empirical framework can improve our understanding of economic phenomena, specifically looking at expenditure fiscal multipliers in the US and consumption dynamics in the euro area.

We established an overarching conclusion regarding the merits of non-linear modelling in any empirical investigation of sufficiently complex economic phenomena. At the same time, we produced some interesting findings in relation to our objects of inquiry, namely fiscal multipliers and consumption dynamics. After a careful analysis of the STVAR model, we set the economy free to fluctuate around a cycle carrying information about the financial environment to study how a government expenditure fiscal shock can impact the economy, using both a parsimonious baseline specification and an extended choice of variables to control for a measure of fiscal burden. We expanded our approach, designing and estimating a richer cycle, which could carry information about both the financial environment and the real side of the economy, so as to model a comprehensive economic cycle including the features of both the business and the financial cycle. We confirmed that an economy contingent on the economic cycle keeps some features induced by both the cycles, and even extending a baseline parsimonious specification does not change its key properties. Some overall crucial findings can be adduced among the abundant results yielded by our empirical investigations.

First, the Great Recession acts as a game changer in models considering the business cycle, as the inclusion of the 2009-2011 crisis in the sample is able to reverse the sign of the effect of a fiscal shock yielded by the model. Second, it appears that there exists a phenomenon of diminishing returns to larger expansionary fiscal shocks. Furthermore, this result appears consistent across specifications, and across recession, as well as expansion, scenarios. We regard both these findings as crucial from a policy perspective. They advocate for extreme caution in delivering large expansionary stimuli during peri-crisis periods, where the two mechanics may merge. On top of that, all our empirical evidence consistently suggests that it is easier to plunge an economy into recession than to boost it, making the cost of a mistaken policy dangerously steep. The third outcome, also fairly robust across specifications, arises from our scenario experiment, in which we observe that the size of the GDP response to a shock is, in absolute value, usually larger during a typical recession, rather than a typical expansion. The narrative of larger slack in the economy during crisis periods, and therefore of a larger response to expansionary fiscal stimuli, is in line with most of the classic literature on fiscal multipliers, regardless of the econometric specification they use. A possible future expansion of our research would be to build on our empirical investigation and match the response of our atheoretical model with those of a more complete – still non-linear – structural model which, at the price of some limiting assumptions, could expand our general understanding of how fiscal policy is received.

While exploring the dynamics of consumption in the euro area, one interesting prediction from the theoretical model is that liquidity-constrained agents will experience spillovers from durable-specific shocks to nondurable consumption. Notwithstanding that the aggregation of agents to country-level data would reasonably weaken such effects due to different households being constrained at different moments in time, our empirical evidence still suggests that countries with a larger share of liquidity-constrained households show larger spillover magnitudes. Countries with less constrained households even exhibit substitution effects, albeit small and not significant, rather than positive (co-movement) effects. Moreover, we are able to confirm for the euro area and the largest four euro area countries that durable expenditure reacts more strongly and faster in response to a shock to monetary conditions, a standard result commonly reported in the literature on US consumption. An analysis on the role played by different factors during the recent crisis highlights a significant degree of cross-country heterogeneity. A natural extension of this line of investigation would be the adoption of a full-scale general equilibrium model, able to deepen our understanding of the consumption dynamics in a broader economic framework.

Overall, we believe that a non-linear approach yields richer, more complete, and ultimately more informative results. A linearised approach to economic phenomena, albeit usefully simple, too often occludes important dynamics and interactions. Such a statement, too large to present itself as a research agenda, rather aims to be an underlying key tenet, in accordance with Greenspan's inspiring principle that "An assumption of linearity may be adequate for estimating average relationships, but few expect that an economy will respond linearly to every aberration".

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Appendix A

Appendix to Chapter 1

A.1 Estimation procedure

The STVAR model is defined as

$$\mathbf{X}_t = \left[(1 - F(z_{t-1}))\mathbf{\Pi}_E + F(z_{t-1})\mathbf{\Pi}_R\right](L)\mathbf{X}_{t-1} + \mathbf{u}_t \tag{A.1}$$

$$\mathbf{u}_t \sim N(\mathbf{0}, \mathbf{\Omega}_t) \tag{A.2}$$

$$\mathbf{\Omega}_t = \mathbf{\Omega}_E(1 - F(z_{t-1})) + \mathbf{\Omega}_R F(z_{t-1}) \tag{A.3}$$

$$F(z_t) = \frac{e^{-\gamma z_t}}{1 + e^{-\gamma z_t}} \qquad \gamma > 0 \tag{A.4}$$

$$\mathrm{Var}(z) = 1 \qquad \mathrm{E}[z] = 0, \tag{A.5}$$

where $\mathbf{X}$ is the data matrix, $\mathbf{\Pi}_E$ and $\mathbf{\Pi}_C$ are the coefficient matrices; z is the switching variable, ruling the transition on the cycle, and computed as the 7-quarters moving average of the GDP growth; and $0 \leq F \leq 1$ is the smoothing function. The subscripts E and R refer respectively to expansion and recession phases of the business cycle.

The model log-likelihood is given by

$$\mathcal{L} = a - \frac{1}{2}\sum_{t=1}^{T} \log\left(|\mathbf{\Omega}_t|\right) - \frac{1}{2}\sum_{t=1}^{T} \mathbf{u}_t' \mathbf{\Omega}_t^{-1} \mathbf{u}_t \tag{A.6}$$

where

$$u_t = \mathbf{X}_t - (1 - F(z_{t-1}))\mathbf{\Pi}_E(L)\mathbf{X}_{t-1} - F(z_{t-1})\mathbf{\Pi}_R(L)\mathbf{X}_{t-1} \tag{A.7}$$

and a is a constant.

The model has many parameters $\mathbf{\Psi} = \{\gamma,\ \mathbf{\Omega}_E,\ \mathbf{\Omega}_R,\ \mathbf{\Pi}_E,\ \mathbf{\Pi}_R\}$ and, as it appears from Equation A.6, becomes linear in the lag polynomials $\{\mathbf{\Pi}_E,\ \mathbf{\Pi}_R\}$ for any guess of $\{\gamma,\ \mathbf{\Omega}_E,\ \mathbf{\Omega}_R\}$. The lag polynomials can be estimated with weighted least squares, where the weights are given by $\mathbf{\Omega}_t^{-1}$ and the estimates must minimize the target function

$$\frac{1}{2}\sum_{t=1}^{T} \mathbf{u}_t' \mathbf{\Omega}_t^{-1} \mathbf{u}_t \tag{A.8}$$

We set $\mathbf{\Pi} = [\mathbf{\Pi}_E, \mathbf{\Pi}_R]$ and then build an extended vector of regressors

$$\mathbf{W}_t = \left[(1 - F(z_{t-1}))\mathbf{X}_{t-1},\ F(z_{t-1})\mathbf{X}_{t-1} \ldots\ (1 - F(z_{t-1}))\mathbf{X}_{t-p},\ F(z_{t-1})\mathbf{X}_{t-p}\right] \tag{A.9}$$

so that we can rewrite Equation A.7 in a more compact form, $\mathbf{u}_t = \mathbf{X}_t - \mathbf{\Pi}\mathbf{W}_t'$. The target function A.8 can then be rewritten as

$$\frac{1}{2}\sum_{t=1}^{T} \left(\mathbf{X}_t - \mathbf{\Pi}\mathbf{W}_t'\right)' \mathbf{\Omega}_t^{-1} \left(\mathbf{X}_t - \mathbf{\Pi}\mathbf{W}_t'\right) \tag{A.10}$$

Taking the first order condition with respect to $\mathbf{\Pi}$:

$$\sum_{t=1}^{T}(\mathbf{W}_t'\mathbf{X}_t\mathbf{\Omega}_t^{-1} - \mathbf{W}_t'\mathbf{W}_t\mathbf{\Pi}'\mathbf{\Omega}_t^{-1}) = 0 \tag{A.11}$$

we rewrite it as

$$\sum_{t=1}^{T}\mathbf{W}_t'\mathbf{X}_t\mathbf{\Omega}_t^{-1} = \sum_{t=1}^{T}\mathbf{W}_t'\mathbf{W}_t\mathbf{\Pi}_t'\mathbf{\Omega}_t^{-1} \tag{A.12}$$

and apply the vectorization operator

$$\text{Vec}\left[\sum_{t=1}^{T}\mathbf{W}_t'\mathbf{X}_t\mathbf{\Omega}_t^{-1}\right] = \sum_{t=1}^{T}\text{Vec}\left[\mathbf{W}_t'\mathbf{W}_t\mathbf{\Pi}_t'\mathbf{\Omega}_t^{-1}\right] \tag{A.13}$$

Applying the properties of the Kronecker operator, the equation becomes

$$= \sum_{t=1}^{T}\text{Vec}\left[\mathbf{\Pi}'\right][\mathbf{\Omega}_t^{-1} \otimes \mathbf{W}_t'\mathbf{W}_t] = \text{Vec}\left[\mathbf{\Pi}'\right]\sum_{t=1}^{T}[\mathbf{\Omega}_t^{-1} \otimes \mathbf{W}_t'\mathbf{W}_t\Bigg] \tag{A.14}$$

and eventually we obtain the final form:

$$\text{Vec}[\mathbf{\Pi}'] = \left(\sum_{t=1}^{T}[\mathbf{\Omega}_t^{-1} \otimes \mathbf{W}_t'\mathbf{W}_t]\right)^{-1}\text{Vec}\left[\sum_{t=1}^{T}\mathbf{W}_t'\mathbf{X}_t\mathbf{\Omega}_t^{-1}\right] \tag{A.15}$$

Equation A.15 enables us to obtain, given any guess of $\{\gamma,\ \mathbf{\Omega}_E,\ \mathbf{\Omega}_R\}$, the associated $\mathbf{\Pi}$, and thus the likelihood: it will be sufficient to iterate over the guesses to find the global maximum. Since the problem presents itself as highly non-linear, use the Markov Chain Monte Carlo (MCMC) method developed by Chernozhukov and Hong (2003), implemented with the Metropolis-Hastings (MH) algorithm. The procedure consists in building a chain $\mathbf{\Psi} = \{\text{Chol}\left(\mathbf{\Omega}_C\right),\ \text{Chol}\left(\mathbf{\Omega}_E\right)\}$ of drawings converging to the true distribution of parameters. We leave out γ, which is calibrated, and draw the Cholesky decomposition of the covariance matrices to ensure that $\mathbf{\Omega}_E$ and $\mathbf{\Omega}_R$ are always positive definite.

The MH algorithm is initialised with a $\mathbf{\Psi}^0$ entry, which is estimated from a linearised version of the model. A new *candidate* member $\mathbf{\Theta}$ will be generated as $\mathbf{\Theta} = \mathbf{\Psi}^0 + \psi$, with ψ i.i.d. $\sim \mathcal{N}\left(\mathbf{0}, \mathbf{\Sigma}_\psi\right)$. $\mathbf{\Theta}$ is accepted and becomes $\mathbf{\Psi}^1$ if it improves the convergence of the chain, that is with probability $\min\left\{1,\ \exp\left[\mathcal{L}\left(\mathbf{\Theta}\right) - \mathcal{L}\left(\mathbf{\Psi}^0\right)\right]\right\}$.

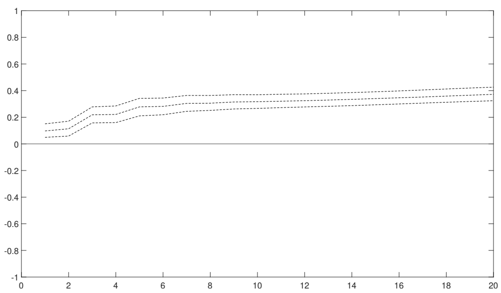
$\mathbf{\Sigma}_\psi$ is adjusted on the fly to target an acceptance rate of around 30%. We perform 200.000 iterations and discard the first half as burn-in period.

A.2 Additional figures for original sample

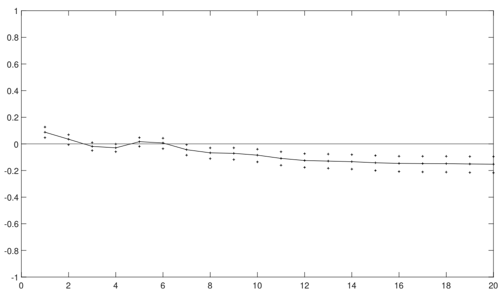
The original AG sample goes from 1947Q1 to 2008Q4. We estimate it in both levels and first differences showing the consequence of the inclusion of foreign variables (lags of the indicator variable) in the model design matrix.

A.2.1 Estimation in levels

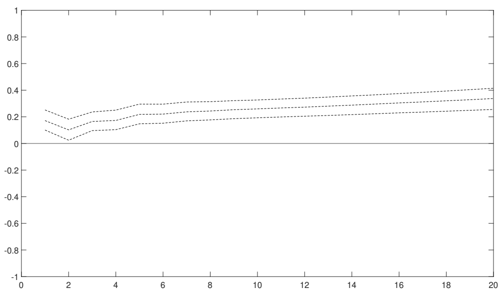
Figure A.1: Effect of foreign variables (FX), linear IRFs



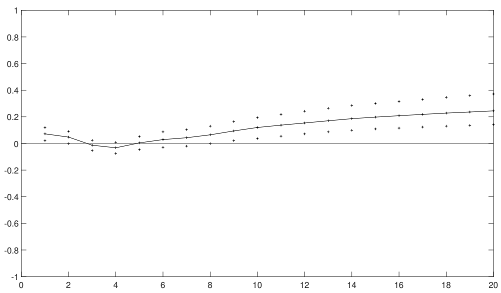
(a) With FX - Contraction



(b) With FX - Expansion



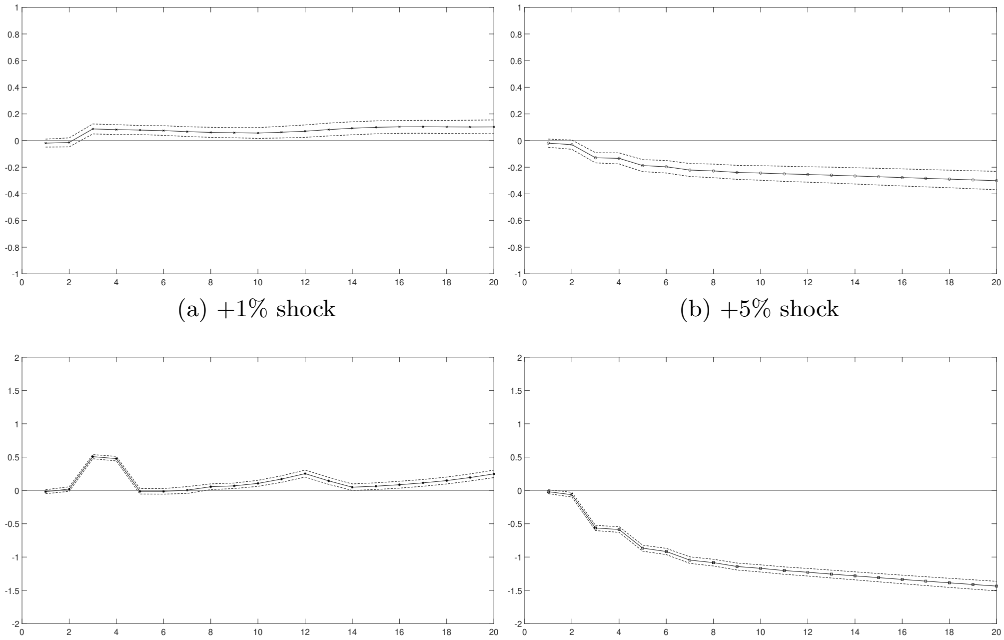
(c) Without FX - Contraction



(d) Without FX - Expansion

Note: Cumulative GDP response to a unit standard deviation of government expenditure for a model with (a, b) and without (c, d) augmentation of the design matrix **W**. STVAR(x) includes (log real) government expenditure, tax revenues, and GDP. Confidence bands are at 5th and 95th percentile. The estimation is performed in levels.

Figure A.2: Generalised IRFs with FX, shocks are percentages of government expenditure

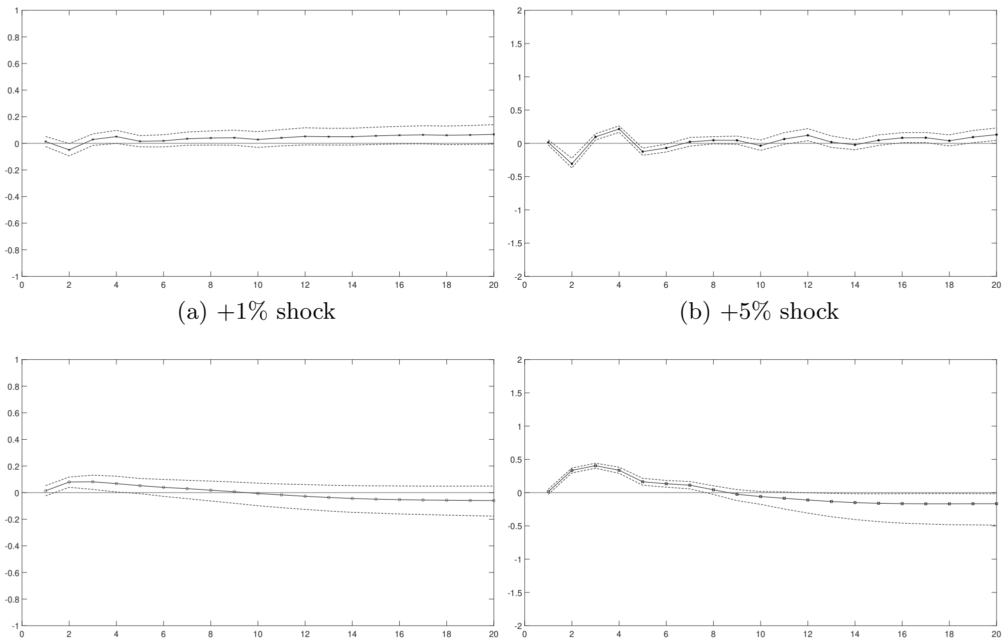


(a) +1% shock (b) +5% shock

(c) −1% shock (d) −5% shock

Note: Cumulative percentage GDP response to a percentage of fiscal shock with confidence bands at 5th and 95th percentile. STVARx includes government expenditure, tax revenues, and GDP. The estimation design matrix is augmented with lags of GDP growth. The estimation is performed in levels.

Figure A.3: Generalised IRFs with no FX, shocks are percentages of government expenditure



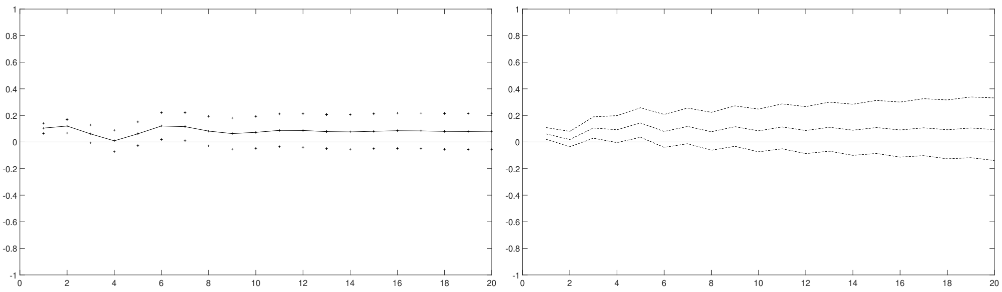
(a) +1% shock (b) +5% shock

(c) −1% shock (d) −5% shock

Note: Cumulative percentage GDP response to a percentage of fiscal shock with confidence bands at 5th and 95th percentile. STVAR includes government expenditure, tax revenues, and GDP.

A.2.2 Estimation in first differences

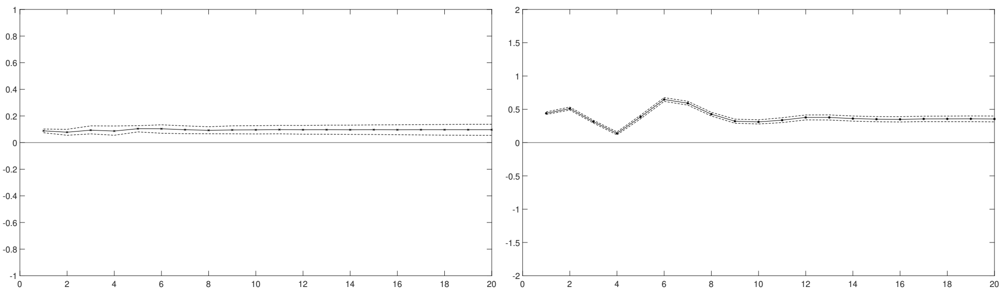
Figure A.4: Linear IRFs



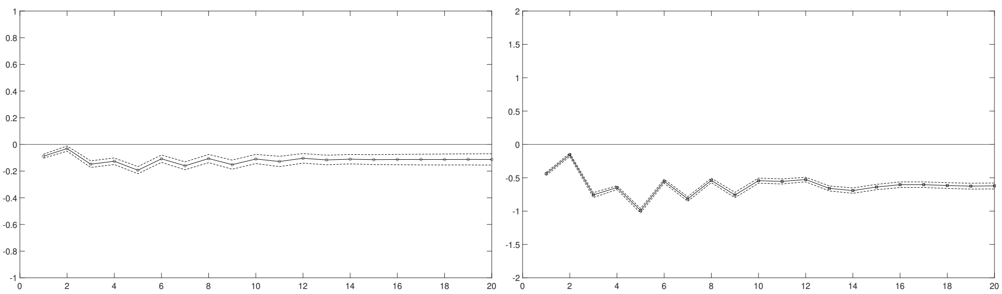
(a) Expansion (b) Contraction

Note: Cumulative linear impulse responses to a unit standard deviation with confidence bands at 5th and 95th percentile. STVAR includes public expenditure, tax revenues, and GDP.

Figure A.5: Generalised IRFs, shocks are percentages of government expenditure



(a) +1% shock (b) +5% shock



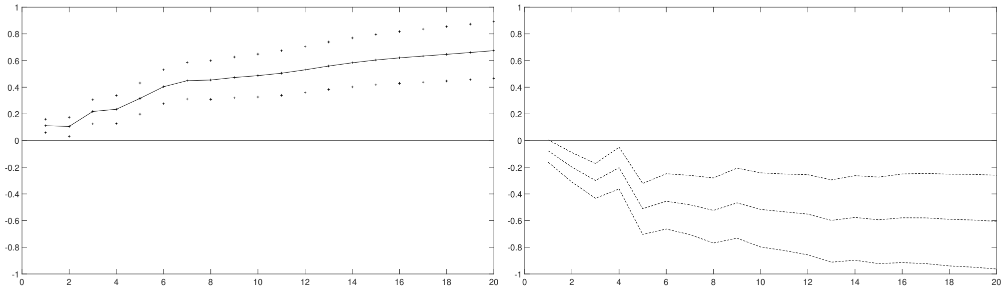
(c) −1% shock (d) −5% shock

Note: Cumulative percentage GDP response to a percentage of fiscal shock with confidence bands at 5th and 95th percentile. STVAR includes government expenditure, tax revenues, and GDP.

A.3 Additional figures for the longer sample

We extend our sample (starting from 1947Q1) to 2019Q4. We deliberately exclude the most recent 2020-21 recession as it was caused by exogenous policy measures following a global pandemic, rather than by an endogenous development within economy.

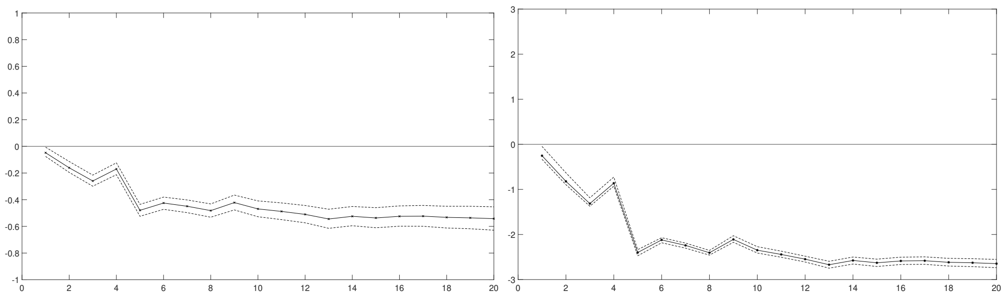
Figure A.6: Linear IRFs, estimation in differences



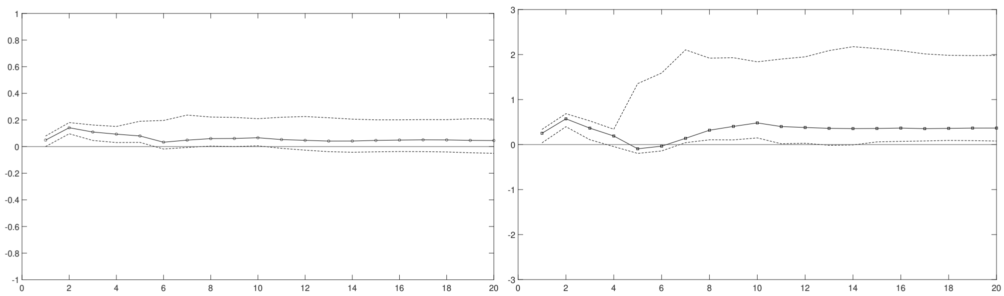
(a) Expansion (b) Contraction

Note: Cumulative linear impulse responses to a unit standard deviation with confidence bands at 5th and 95th percentile. STVAR includes public expenditure, tax revenues, and GDP.

Figure A.7: Generalised IRFs, shocks are percentages of government expenditure



(a) +1% shock (b) +5% shock



(c) −1% shock (d) −5% shock

Note: Cumulative percentage GDP response to a percentage of fiscal shock with confidence bands at 5th and 95th percentile. STVAR includes government expenditure, tax revenues, and GDP.

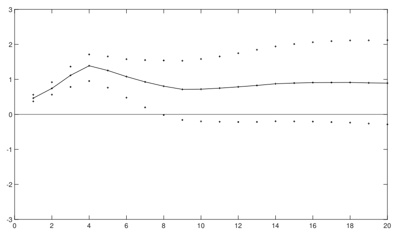
Appendix B

Appendix to Chapter 2

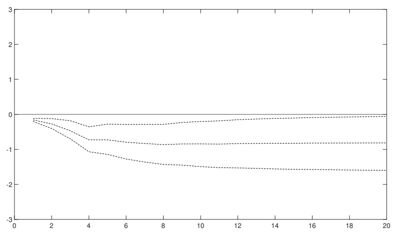
B.1 Additional figures for baseline specification

Our baseline specification includes (log real) government expenditure, tax revenues, GDP, and private credit. The main sample goes from 1947Q1 to 2019Q4, while the shorter sample used for comparison stops at 2008Q4.

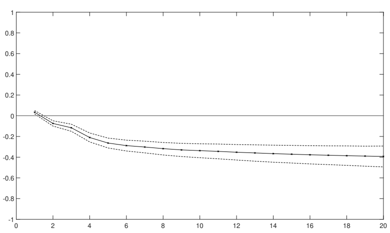
Figure B.1: Longer sample, linear and generalised IRFs, GDP response



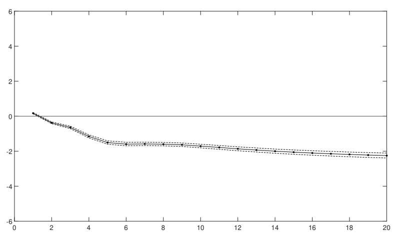
(a) Linear expansion



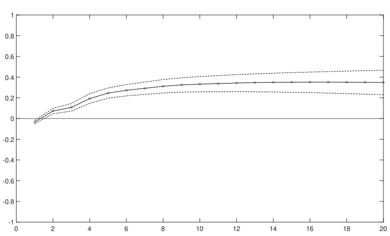
(b) Linear contraction



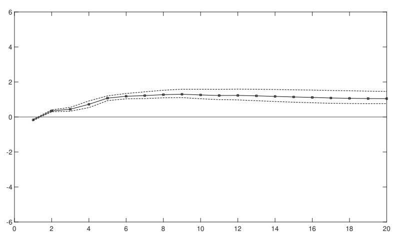
(c) +1% shock



(d) +5% shock



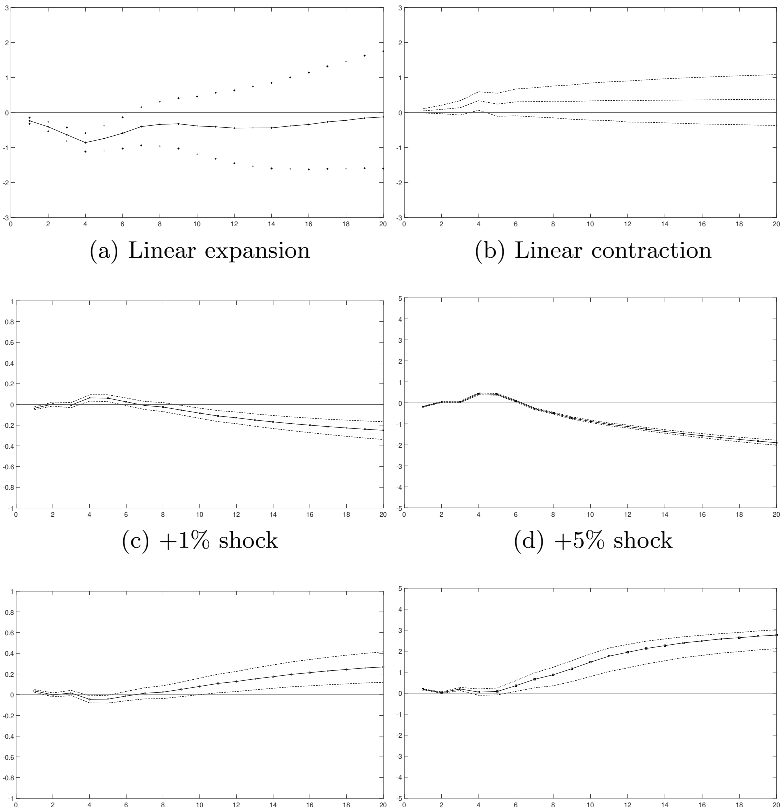
(e) −1% shock



(f) −5% shock

Note: Cumulative linear (a, b) and generalised impulse responses. Percentage GDP response to a unit standard deviation (a, b) or to a percentage of fiscal shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Figure B.2: Longer sample, linear and generalised IRFs, credit-to-GDP response



(a) Linear expansion

(b) Linear contraction

(c) +1% shock

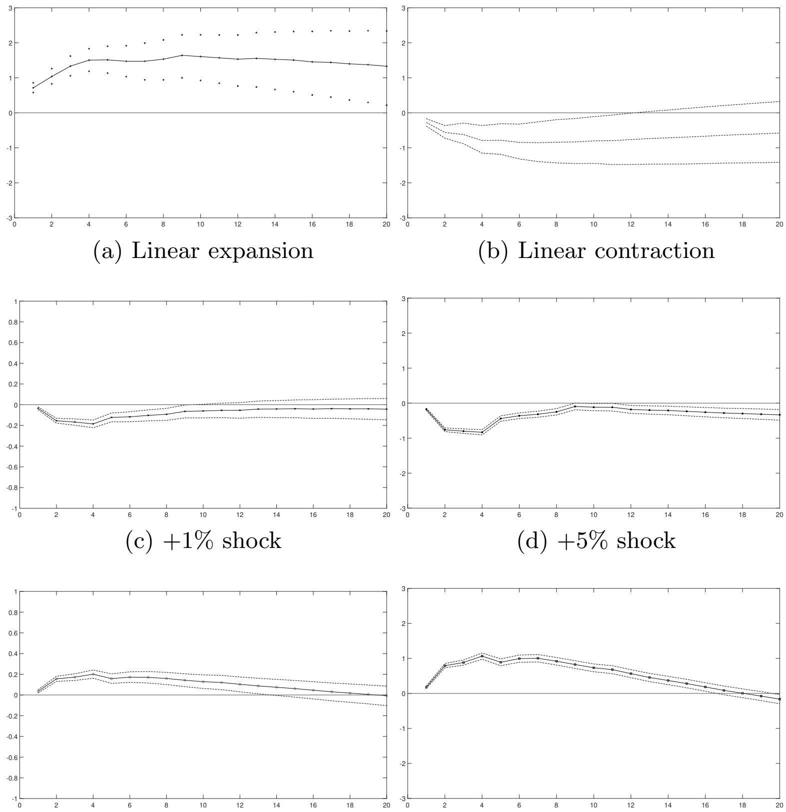
(d) +5% shock

(e) −1% shock

(f) −5% shock

Note: Cumulative linear (a, b) and generalised impulse responses. Percentage private credit response to a unit standard deviation (a, b) or to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Figure B.3: Shorter sample, linear and generalised IRFs, GDP response



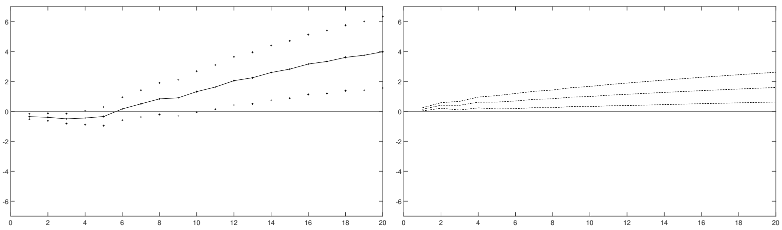
(a) Linear expansion (b) Linear contraction

(c) +1% shock (d) +5% shock

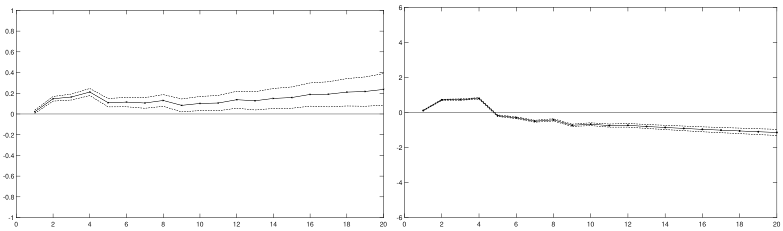
(e) −1% shock (f) −5% shock

Note: Cumulative linear (a, b) and generalised impulse responses. Percentage GDP response to a unit standard deviation (a, b) or to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

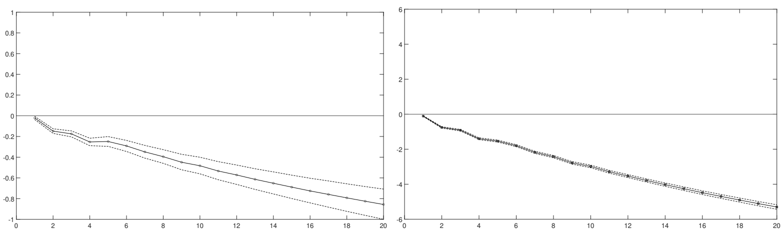
Figure B.4: Shorter sample, linear and generalised IRFs, credit-to-GDP response



(a) Linear expansion (b) Linear contraction



(c) +1% shock (d) +5% shock

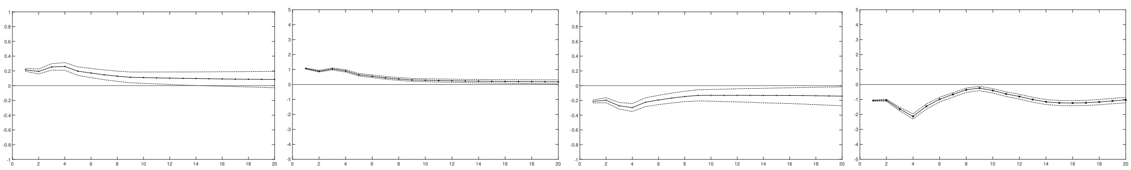


(e) −1% shock (f) −5% shock

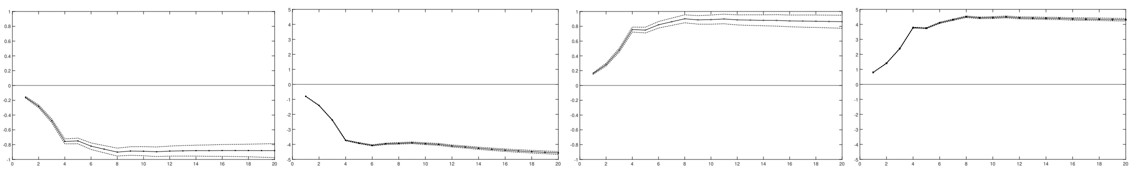
Note: Cumulative linear (a, b) and generalised impulse responses. Percentage private credit response to a unit standard deviation (a, b) or to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

B.1.1 Scenario analysis

Figure B.5: Scenario analysis, GIRFs for typical scenarios



(a) Expansion, +1% (b) Expansion, +5% (c) Expansion, −1% (d) Expansion, −5%



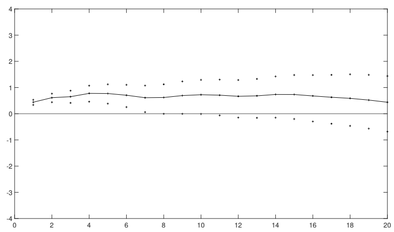
(e) Recession, +1% (f) Recession, +5% (g) Recession, −1% (h) Recession, −5%

Note: Cumulative generalised impulse responses to a shock delivered in a median representative recession or expansion. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

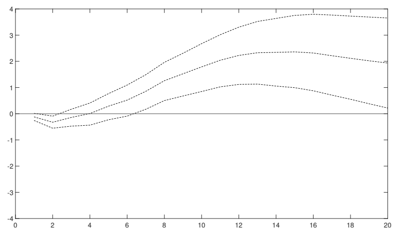
B.2 Additional figures for augmented specification

Our augmented specification includes (log real) government expenditure, tax revenues, public debt, GDP, and private credit.

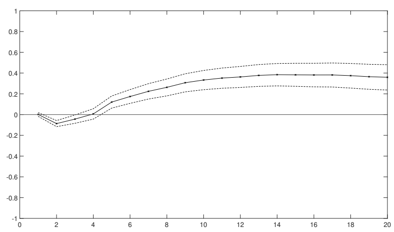
Figure B.6: Linear and generalised IRFs, GDP response



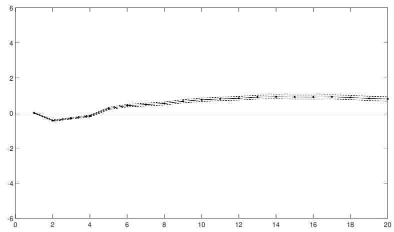
(a) Linear expansion



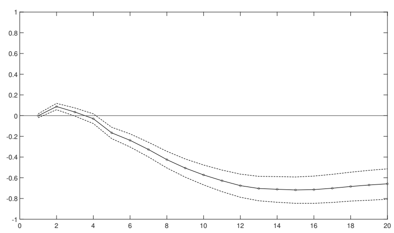
(b) Linear contraction



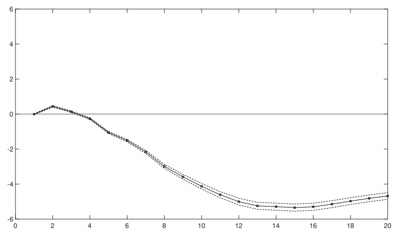
(c) +1% shock



(d) +5% shock



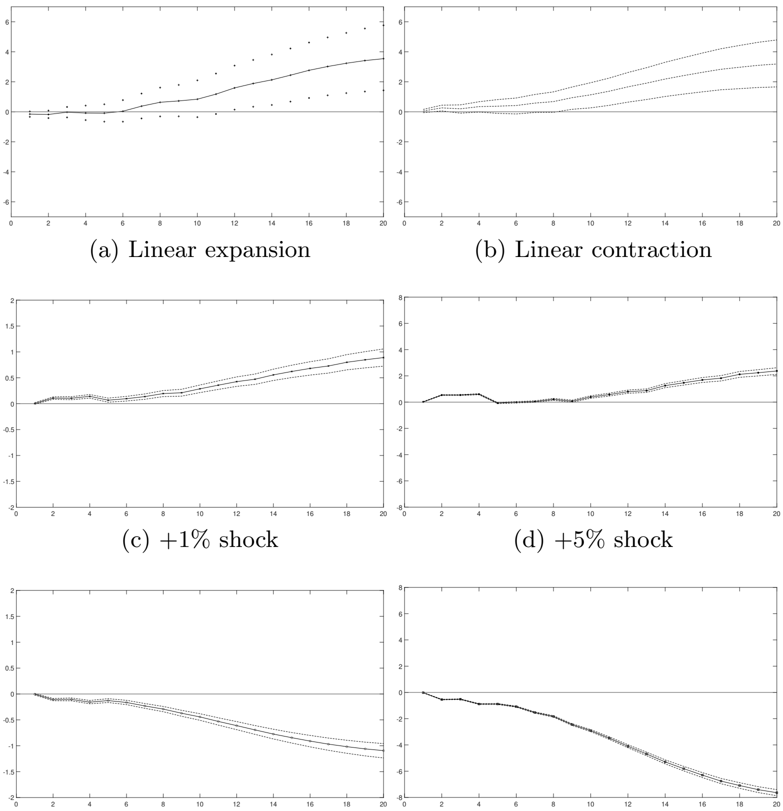
(e) −1% shock



(f) −5% shock

Note: Cumulative linear (a, b) and generalised impulse responses. Percentage GDP response to a unit standard deviation (a, b) or to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, public debt, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Figure B.7: Linear and generalised IRFs, credit-to-GDP response



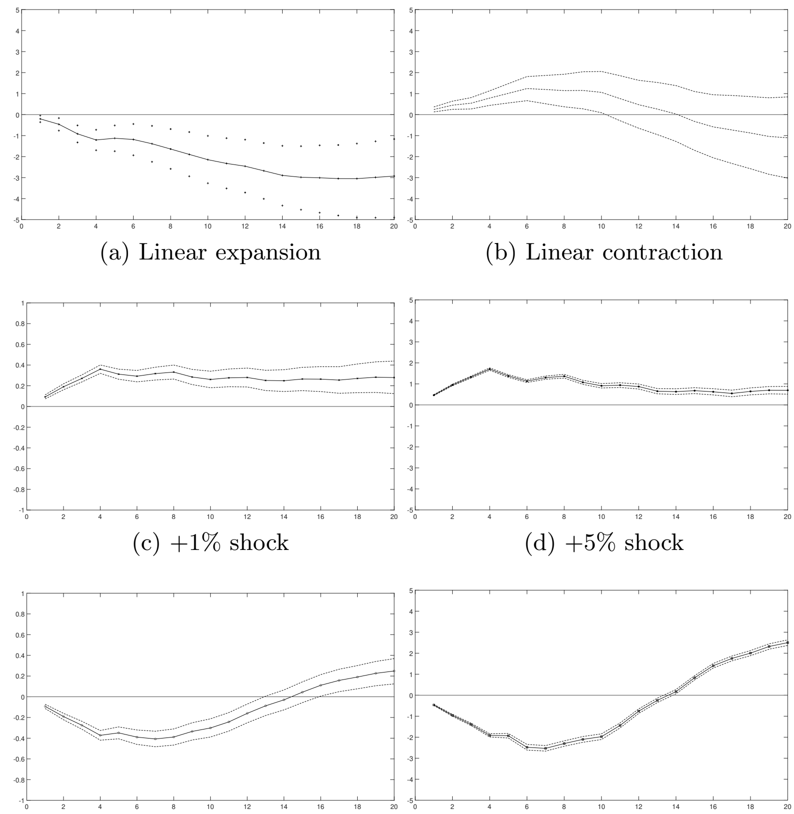
(a) Linear expansion (b) Linear contraction

(c) +1% shock (d) +5% shock

(e) −1% shock (f) −5% shock

Note: Cumulative linear (a, b) and generalised impulse responses. Percentage private credit response to a unit standard deviation (a, b) or to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, public debt, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Figure B.8: Linear and generalised IRFs, debt-to-GDP response



(a) Linear expansion (b) Linear contraction

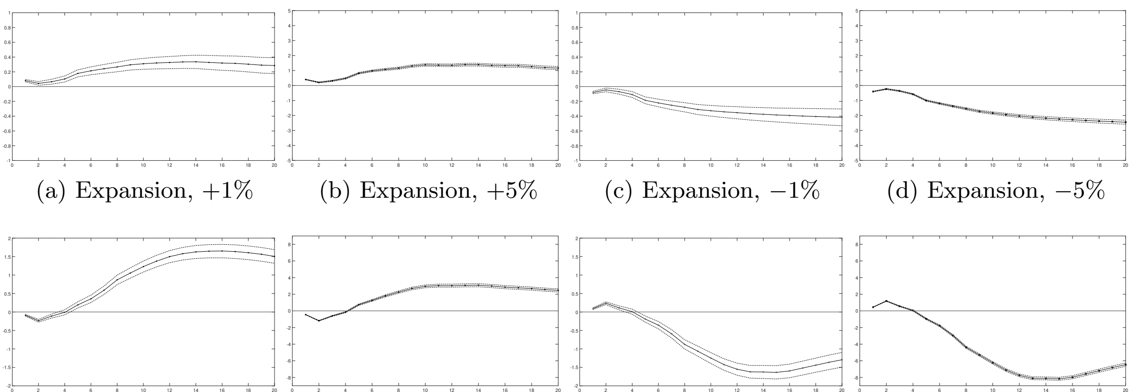
(c) +1% shock (d) +5% shock

(e) −1% shock (f) −5% shock

Note: Cumulative linear (a, b) and generalised impulse responses. Percentage public debt response to a unit standard deviation (a, b) or to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, public debt, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

B.2.1 Scenario analysis

Figure B.9: Scenario analysis, GIRFs for typical scenarios

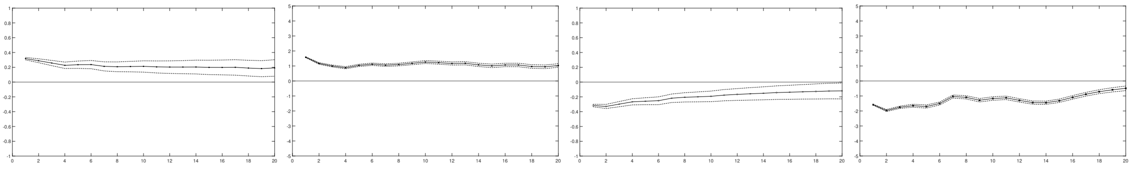


(a) Expansion, +1% (b) Expansion, +5% (c) Expansion, −1% (d) Expansion, −5%

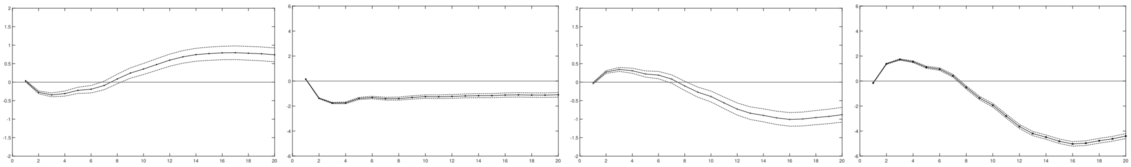
(e) Recession, +1% (f) Recession, +5% (g) Recession, −1% (h) Recession, −5%

Note: Cumulative generalised impulse responses to a shock triggered in a median recession/expansion history. STVAR includes public expenditure, tax revenues, public debt, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Figure B.10: Scenario analysis, GIRFs for typical scenarios with a shock to public debt



(a) Expansion, +1% (b) Expansion, +5% (c) Expansion, −1% (d) Expansion, −5%



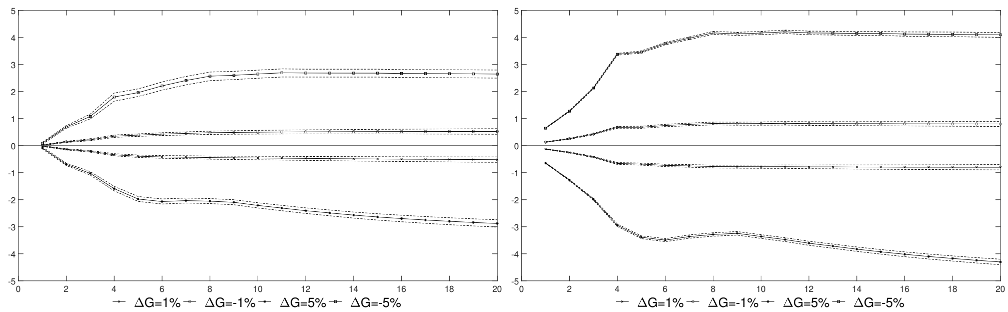
(e) Recession, +1% (f) Recession, +5% (g) Recession, −1% (h) Recession, −5%

Note: Cumulative generalised impulse responses to a shock triggered in a median representative recession or expansion. The same shock is applied with opposite signs to government expenditure and public debt. STVAR includes public expenditure, tax revenues, public debt, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

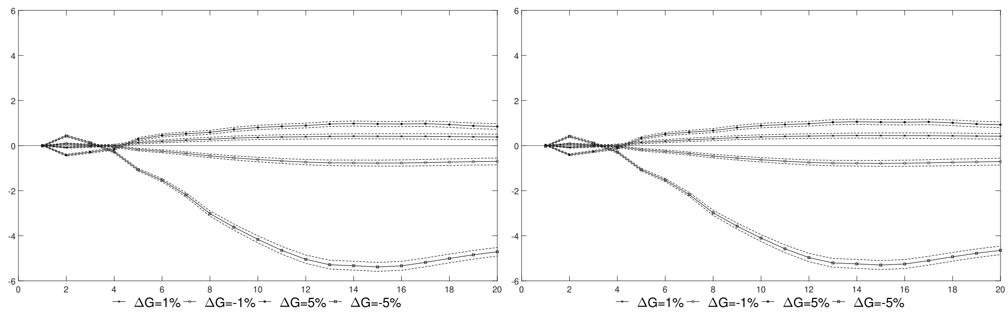
B.3 Alternative scenario analysis

This section presents the results of the scenario analysis where the typical recession and expansion histories are built using as a criterion the value of the transition F function. When $F < 0.2$ we consider the cycle to be in an extreme expansion and, vice versa, when $F > 0.8$ we regard the cycle as to be in an extreme contraction.

Figure B.11: Baseline and debt-augmented specifications, alternative scenario analysis



(a) Expansion - Baseline (b) Recession - Baseline



(c) Expansion - Augmented (d) Recession - Augmented

Note: Cumulative generalised impulse responses to a fiscal shock delivered in a median representative recession or expansion. ΔG denotes the variation in government expenditure, the percentage is the size of the shock. STVAR includes public expenditure, tax revenues, (public debt, in the extended specification) GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Appendix C

Appendix to Chapter 3

C.1 List of variables

We remained faithful to the original naming system used by McCracken and Ng (2016) and detailed in the appendix of their paper. The column tcode denotes the following data transformations for a series x: (1) no transformation; (2) Δx_t; (3) $\Delta^2 x_t$; (4) $\log(x_t)$; (5) $\Delta \log(x_t)$; (6) $\Delta^2 \log(x_t)$; (7) $\Delta \left(\frac{x_t}{x_{t-1}}\right)$. The FRED column gives mnemonics in FRED followed by a short description. The comparable series in Global Insight, from which the data are taken, is given in the column GSI.

Table C.1: Group 1: output and income

	id	tcode	FRED	Description	GSI	GSI: description
1	1	5	RPI	Real Personal Income	M_14386177	PI
2	2	5	W875RX1	Real personal income ex transfer receipts	M_145256755	PI less transfers
3	6	5	INDPRO	IP Index	M_116460980	IP: total
4	7	5	IPFPNSS	IP: Final Products and Nonindustrial Supplies	M_116460981	IP: products
5	8	5	IPFINAL	IP: Final Products (Market Group)	M_116461268	IP: final prod
6	9	5	IPCONGD	IP: Consumer Goods	M_116460982	IP: cons gds
7	10	5	IPDCONGD	IP: Durable Consumer Goods	M_116460983	IP: cons dble
8	11	5	IPNCONGD	IP: Nondurable Consumer Goods	M_116460988	IP: cons nondble
9	12	5	IPBUSEQ	IP: Business Equipment	M_116460995	IP: bus eqpt
10	13	5	IPMAT	IP: Materials	M_116461002	IP: matls
11	14	5	IPDMAT	IP: Durable Materials	M_116461004	IP: dble matls
12	15	5	IPNMAT	IP: Nondurable Materials	M_116461008	IP: nondble matls
13	16	5	IPMANSICS	IP: Manufacturing (SIC)	M_116461013	IP: mfg
14	17	5	IPB51222s	IP: Residential Utilities	M_116461276	IP: res util
15	18	5	IPFUELS	IP: Fuels	M_116461275	IP: fuels
16	19	1	NAPMPI	ISM Manufacturing: Production Index	M_110157212	NAPM prodn
17	20	2	CUMFNS	Capacity Utilization: Manufacturing	M_116461602	Cap util

Table C.2: Group 2: labour market

	id	tcode	FRED	Description	GSI	GSI: description
1	21*	2	HWI	Help-Wanted Index for United States		Help wanted indx
2	22*	2	HWIURATIO	Ratio of Help Wanted/No. Unemployed	M_110156531	Help wanted/unemp
3	23	5	CLF16OV	Civilian Labor Force	M_110156467	Emp CPS total
4	24	5	CE16OV	Civilian Employment	M_110156498	Emp CPS nonag
5	25	2	UNRATE	Civilian Unemployment Rate	M_110156541	U: all
6	26	2	UEMPMEAN	Average Duration of Unemployment (Weeks)	M_110156528	U: mean duration
7	27	5	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	M_110156527	U <5 wks
8	28	5	UEMP5TO14	Civilians Unemployed for 5–14 Weeks	M_110156523	U 5-14 wks
9	29	5	UEMP15OV	Civilians Unemployed - 15 Weeks & Over	M_110156524	U 15+ wks
10	30	5	UEMP15T26	Civilians Unemployed for 15–26 Weeks	M_110156525	U 15-26 wks
11	31	5	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	M_110156526	U 27+ wks
12	32*	5	CLAIMSx	Initial Claims	M_15186204	UI claims
13	33	5	PAYEMS	All Employees: Total nonfarm	M_123109146	Emp: total
14	34	5	USGOOD	All Employees: Goods-Producing Industries	M_123109172	Emp: gds prod
15	35	5	CES1021000001	All Employees: Mining and Logging: Mining	M_123109244	Emp: mining
16	36	5	USCONS	All Employees: Construction	M_123109331	Emp: const
17	37	5	MANEMP	All Employees: Manufacturing	M_123109542	Emp: mfg
18	38	5	DMANEMP	All Employees: Durable goods	M_123109573	Emp: dble gds
19	39	5	NDMANEMP	All Employees: Nondurable goods	M_123110741	Emp: nondbles
20	40	5	SRVPRD	All Employees: Service-Providing Industries	M_123109193	Emp: services
21	41	5	USTPU	All Employees: Trade, Transportation & Utilities	M_123111543	Emp: TTU
22	42	5	USWTRADE	All Employees: Wholesale Trade	M_123111563	Emp: wholesale
23	43	5	USTRADE	All Employees: Retail Trade	M_123111867	Emp: retail
24	44	5	USFIRE	All Employees: Financial Activities	M_123112777	Emp: FIRE
25	45	5	USGOVT	All Employees: Government	M_123114411	Emp: Govt
26	46	1	CES0600000007	Avg Weekly Hours: Goods-Producing	M_140687274	Avg hrs
27	47	2	AWOTMAN	Avg Weekly Overtime Hours: Manufacturing	M_123109554	Overtime: mfg
28	48	1	AWHMAN	Avg Weekly Hours: Manufacturing	M_14386098	Avg hrs: mfg
29	49	1	NAPMEI	ISM Manufacturing: Employment Index	M_110157206	NAPM empl
30	127	6	CES0600000008	Avg Hourly Earnings: Goods-Producing	M_123109182	AHE: goods
31	128	6	CES2000000008	Avg Hourly Earnings: Construction	M_123109341	AHE: const
32	129	6	CES3000000008	Avg Hourly Earnings: Manufacturing	M_123109552	AHE: mfg

Table C.3: Group 3: housing

	id	tcode	FRED	Description	GSI	GSI: description
1	50	4	HOUST	Housing Starts: Total New Privately Owned	M_110155536	Starts: nonfarm
2	51	4	HOUSTNE	Housing Starts, Northeast	M_110155538	Starts: NE
3	52	4	HOUSTMW	Housing Starts, Midwest	M_110155537	Starts: MW
4	53	4	HOUSTS	Housing Starts, South	M_110155543	Starts: South
5	54	4	HOUSTW	Housing Starts, West	M_110155544	Starts: West
6	55	4	PERMIT	New Private Housing Permits (SAAR)	M_110155532	BP: total
7	56	4	PERMITNE	New Private Housing Permits, Northeast (SAAR)	M_110155531	BP: NE
8	57	4	PERMITMW	New Private Housing Permits, Midwest (SAAR)	M_110155530	BP: MW
9	58	4	PERMITS	New Private Housing Permits, South (SAAR)	M_110155533	BP: South
10	59	4	PERMITW	New Private Housing Permits, West (SAAR)	M_110155534	BP: West

Table C.4: Group 4: consumption, orders, and inventories

	id	tcode	FRED	Description	GSI	GSI: description
1	3	5	DPCERA3M086SBEA	Real personal consumption expenditures	M_123008274	Real Consumption
2	4*	5	CMRMTSPLx	Real Manu. and Trade Industries Sales	M_110156998	M&T sales
3	5*	5	RETAILx	Retail and Food Services Sales	M_130439509	Retail sales
4	60	1	NAPM	ISM: PMI Composite Index	M_110157208	PMI
5	61	1	NAPMNOI	ISM: New Orders Index	M_110157210	NAPM new ordrs
6	62	1	NAPMSDI	ISM: Supplier Deliveries Index	M_110157205	NAPM vendor del
7	63	1	NAPMII	ISM: Inventories Index	M_110157211	NAPM Invent
8	64	5	ACOGNO	New Orders for Consumer Goods	M_14385863	Orders: cons gds
9	65*	5	AMDMNOx	New Orders for Durable Goods	M_14386110	Orders: dble gds
10	66*	5	ANDENOx	New Orders for Nondefense Capital Goods	M_178554409	Orders: cap gds
11	67*	5	AMDMUOx	Unfilled Orders for Durable Goods	M_14385946	Unf orders: dble
12	68*	5	BUSINVx	Total Business Inventories	M_15192014	M&T invent
13	69*	2	ISRATIOx	Total Business: Inventories to Sales Ratio	M_15191529	M&T invent/sales
14	130*	2	UMCSENTx	Consumer Sentiment Index	hhsntn	Consumer expect

Table C.5: Group 5: money and credit

	id	tcode	FRED	Description	GSI	GSI: description
1	3	5	DPCERA3M086SBEA	Real personal consumption expenditures	M_123008274	Real Consumption
2	4*	5	CMRMTSPLx	Real Manu. and Trade Industries Sales	M_110156998	M&T sales
3	5*	5	RETAILx	Retail and Food Services Sales	M_130439509	Retail sales
4	60	1	NAPM	ISM: PMI Composite Index	M_110157208	PMI
5	61	1	NAPMNOI	ISM: New Orders Index	M_110157210	NAPM new ordrs
6	62	1	NAPMSDI	ISM: Supplier Deliveries Index	M_110157205	NAPM vendor del
7	63	1	NAPMII	ISM: Inventories Index	M_110157211	NAPM Invent
8	64	5	ACOGNO	New Orders for Consumer Goods	M_14385863	Orders: cons gds
9	65*	5	AMDMNOx	New Orders for Durable Goods	M_14386110	Orders: dble gds
10	66*	5	ANDENOx	New Orders for Nondefense Capital Goods	M_178554409	Orders: cap gds
11	67*	5	AMDMUOx	Unfilled Orders for Durable Goods	M_14385946	Unf orders: dble
12	68*	5	BUSINVx	Total Business Inventories	M_15192014	M&T invent
13	69*	2	ISRATIOx	Total Business: Inventories to Sales Ratio	M_15191529	M&T invent/sales
14	130*	2	UMCSENTx	Consumer Sentiment Index	hhsntn	Consumer expect

Table C.6: Group 6: interest and exchange rates

	id	tcode	FRED	Description	GSI	GSI: description
1	84	2	FEDFUNDS	Effective Federal Funds Rate	M_110155157	Fed Funds
2	85*	2	CP3Mx	3-Month AA Financial Commercial Paper Rate	CPF3M	Comm paper
3	86	2	TB3MS	3-Month Treasury Bill	M_110155165	3 mo T-bill
4	87	2	TB6MS	6-Month Treasury Bill	M_110155166	6 mo T-bill
5	88	2	GS1	1-Year Treasury Rate	M_110155168	1 yr T-bond
6	89	2	GS5	5-Year Treasury Rate	M_110155174	5 yr T-bond
7	90	2	GS10	10-Year Treasury Rate	M_110155169	10 yr T-bond
8	91	2	AAA	Moody's Seasoned Aaa Corporate Bond Yield		Aaa bond
9	92	2	BAA	Moody's Seasoned Baa Corporate Bond Yield		Baa bond
10	93*	1	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS		CP-FF spread
11	94	1	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS		3 mo-FF spread
12	95	1	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS		6 mo-FF spread
13	96	1	T1YFFM	1-Year Treasury C Minus FEDFUNDS		1 yr-FF spread
14	97	1	T5YFFM	5-Year Treasury C Minus FEDFUNDS		5 yr-FF spread
15	98	1	T10YFFM	10-Year Treasury C Minus FEDFUNDS		10 yr-FF spread
16	99	1	AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS		Aaa-FF spread
17	100	1	BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS		Baa-FF spread
18	101	5	TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies		Ex rate: avg
19	102*	5	EXSZUSx	Switzerland/U.S. Foreign Exchange Rate	M_110154768	Ex rate: Switz
20	103*	5	EXJPUSx	Japan/U.S. Foreign Exchange Rate	M_110154755	Ex rate: Japan
21	104*	5	EXUSUKx	U.S./U.K. Foreign Exchange Rate	M_110154772	Ex rate: UK
22	105*	5	EXCAUSx	Canada/U.S. Foreign Exchange Rate	M_110154744	EX rate: Canada

Table C.7: Group 7: prices

	id	tcode	FRED	Description	GSI	GSI: description
1	106	6	PPIFGS	PPI: Finished Goods	M110157517	PPI: fin gds
2	107	6	PPIFCG	PPI: Finished Consumer Goods	M110157508	PPI: cons gds
3	108	6	PPIITM	PPI: Intermediate Materials	M_110157527	PPI: int matls
4	109	6	PPICRM	PPI: Crude Materials	M_110157500	PPI: crude matls
5	110*	6	OILPRICEx	Crude Oil, spliced WTI and Cushing	M_110157273	Spot market price
6	111	6	PPICMM	PPI: Metals and metal products:	M_110157335	PPI: nonferrous
7	112	1	NAPMPRI	ISM Manufacturing: Prices Index	M_110157204	NAPM com price
8	113	6	CPIAUCSL	CPI: All Items	M_110157323	CPI-U: all
9	114	6	CPIAPPSL	CPI: Apparel	M_110157299	CPI-U: apparel
10	115	6	CPITRNSL	CPI: Transportation	M_110157302	CPI-U: transp
11	116	6	CPIMEDSL	CPI: Medical Care	M_110157304	CPI-U: medical
12	117	6	CUSR0000SAC	CPI: Commodities	M_110157314	CPI-U: comm.
13	118	6	CUUR0000SAD	CPI: Durables	M_110157315	CPI-U: dbles
14	119	6	CUSR0000SAS	CPI: Services	M_110157325	CPI-U: services
15	120	6	CPIULFSL	CPI: All Items Less Food	M_110157328	CPI-U: ex food
16	121	6	CUUR0000SA0L2	CPI: All items less shelter	M_110157329	CPI-U: ex shelter
17	122	6	CUSR0000SA0L5	CPI: All items less medical care	M_110157330	CPI-U: ex med
18	123	6	PCEPI	Personal Cons. Expend.: Chain Index	gmdc	PCE defl
19	124	6	DDURRG3M086SBEA	Personal Cons. Exp: Durable goods	gmdcd	PCE defl: dlbes
20	125	6	DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods	gmdcn	PCE defl: nondble
21	126	6	DSERRG3M086SBEA	Personal Cons. Exp: Services	gmdcs	PCE defl: service

Table C.8: Group 8: stock market

	id	tcode	FRED	Description	GSI	GSI: description
1	80*	5	S&P 500	S&P's Common Stock Price Index: Composite	M_110155044	S&P 500
2	81*	5	S&P: indust	S&P's Common Stock Price Index: Industrials	M_110155047	S&P: indust
3	82*	2	S&P div yield	S&P's Composite Common Stock: Dividend Yield		S&P div yield
4	83*	5	S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio		S&P PE ratio

C.2 Alternative factor analysis

We presents the results of the factor analysis performed on the whole sample available, from 1959M01 to 2020M10 in Table C.9. The information criterion PC_{p2} selects eight relevant factors, which collectively explain a fraction of 0.5055 of the panel variance.

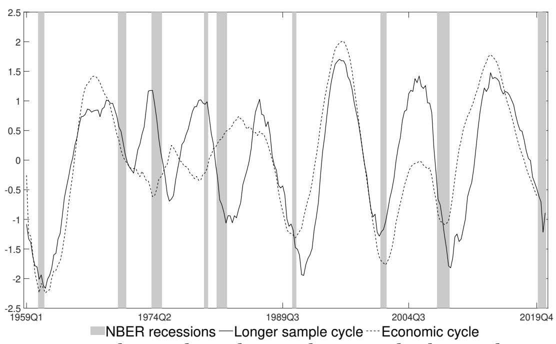
Table C.9: Estimated factors and heavy loading series - $R^2(8) = 0.5055$

$mR^2(1)$	0.1725	$mR^2(2)$	0.0745	$mR^2(3)$	0.0680	$mR^2(4)$	0.0537
ipmansics	0.8055	cusr0000sac	0.4023	aaaffm	0.3690	gs1	0.5058
payems	0.7989	cusr0000sa0l2	0.3871	t10yffm	0.3568	gs5	0.4989
ipfpnss	0.7579	dndgrg3m086sbea	0.3780	baaffm	0.3518	aaa	0.4772
indpro	0.7524	cpitrnsl	0.3733	dndgrg3m086sbea	0.3439	tb6ms	0.4594
cumfns	0.7409	cpiaucsl	0.3596	cusr0000sac	0.3437	gs10	0.4592
usgood	0.7375	pcepi	0.3499	cusr0000sa0l2	0.3252	baa	0.4238
ipfinal	0.6921	cusr0000sa0l5	0.3444	cpiaucsl	0.3220	cp3mx	0.3690
manemp	0.6886	cpiulfsl	0.3128	t5yffm	0.3156	tb3ms	0.3665
dmanemp	0.6437	wpsid61	0.2886	cusr0000sa0l5	0.3024	twexafegsmthx	0.1824
ipbuseq	0.6290	wpsfd49502	0.2816	pcepi	0.2868	houst	0.1819
$mR^2(5)$	0.0480	$mR^2(6)$	0.0339	$mR^2(7)$	0.0298	$mR^2(8)$	0.0252
t1yffm	0.5144	s&p pe ratio	0.3447	s&p 500	0.3206	twexafegsmthx	0.3828
tb6smffm	0.4914	s&p 500	0.2844	s&p: indust	0.3162	exszusx	0.1868
tb3smffm	0.4445	s&p: indust	0.2832	vxoclsx	0.2513	conspi	0.1825
t5yffm	0.4174	s&p div yield	0.2645	uemp15ov	0.2384	exusukx	0.1652
t10yffm	0.3497	awhman	0.2002	ces0600000007	0.2108	ces3000000008	0.1538
aaaffm	0.2689	ces0600000007	0.1950	awhman	0.2101	exjpusx	0.1293
compapffx	0.2589	uemp15ov	0.1460	s&p div yield	0.2091	ces0600000008	0.1070
baaffm	0.2015	umcsentx	0.1454	uemp27ov	0.1458	ustrade	0.0932
permit	0.1789	mzmsl	0.1397	s&p pe ratio	0.0942	acogno	0.0805
permitw	0.1567	m2sl	0.1084	uemp15t26	0.0883	ustpu	0.0795

Note: Note: Eight factors selected by the PC_{p2} criterion and the ten series loading the most on each factor. The table also reports the total variation explained by the eight factors ($R^2(8)$), the additional variation explained by adding the kth factor ($mR^2(k)$). As an example, the eight factors explain together 50.55% of the panel variation, while $mR^2(1) = 0.1725$ is the quota explained solely by the first factor. Moreover, 0.8055 is the fraction of variation of the series ipmansics explained by the first factor.

Factor interpretation is compatible with the results from the shorter sample. Factors 1 to 5 still carry information, respectively, on real production, prices, forward looking variables, interest rate, and a mixture of forward looking and housing variables. Factors 6 and 7 have explanatory power for the stock market and the labour market sectors, while the last factor concentrates on exchange rates. Figure C.1 shows the cycle estimated on the longer sample contrasted with the index we used in our analysis.

Figure C.1: Alternative economic cycle estimated on 8 factors

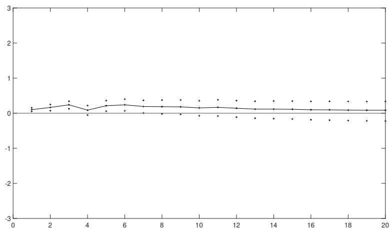


Note: Contrasting the economic cycle used in the analysis with the cycle estimated using a sample up to 2020M10. The selection criteria picks 8 significant factors.

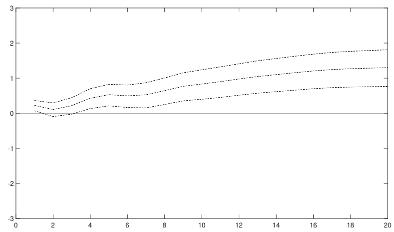
C.3 Additional figures for baseline specification

Our baseline specification includes (log real) government expenditure, tax revenues, GDP, and it is augmented with an estimate of the cycle.

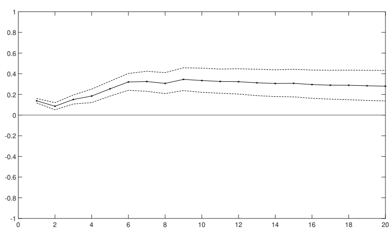
Figure C.2: Linear and generalised IRFs, GDP response



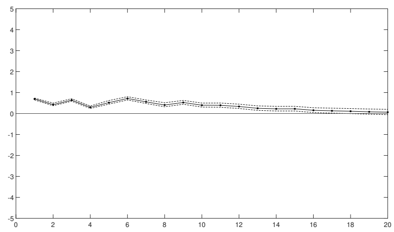
(a) Linear expansion



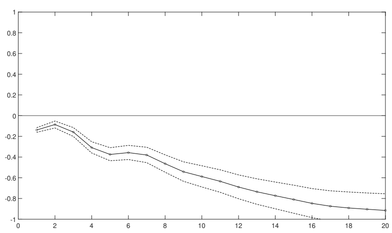
(b) Linear contraction



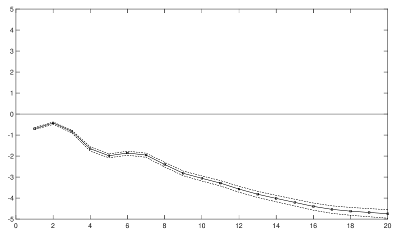
(c) +1% shock



(d) +5% shock



(e) −1% shock

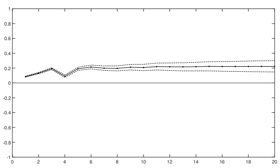


(f) −5% shock

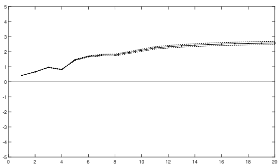
Note: Cumulative linear (a, b) and generalised impulse responses. Percentage GDP response to a unit standard deviation (a, b) or to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

C.3.1 Scenario analysis

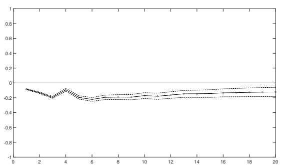
Figure C.3: Scenario analysis, GIRFs for typical scenarios



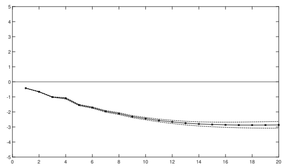
(a) Expansion, +1%



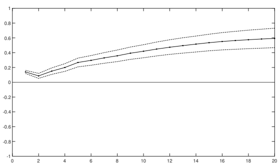
(b) Expansion, +5%



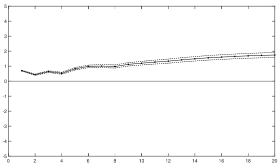
(c) Expansion, −1%



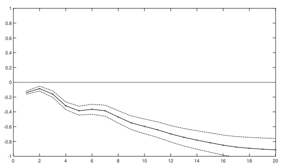
(d) Expansion, −5%



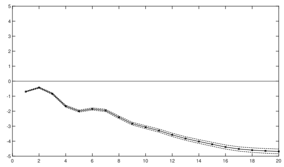
(e) Recession, +1%



(f) Recession, +5%



(g) Recession, −1%



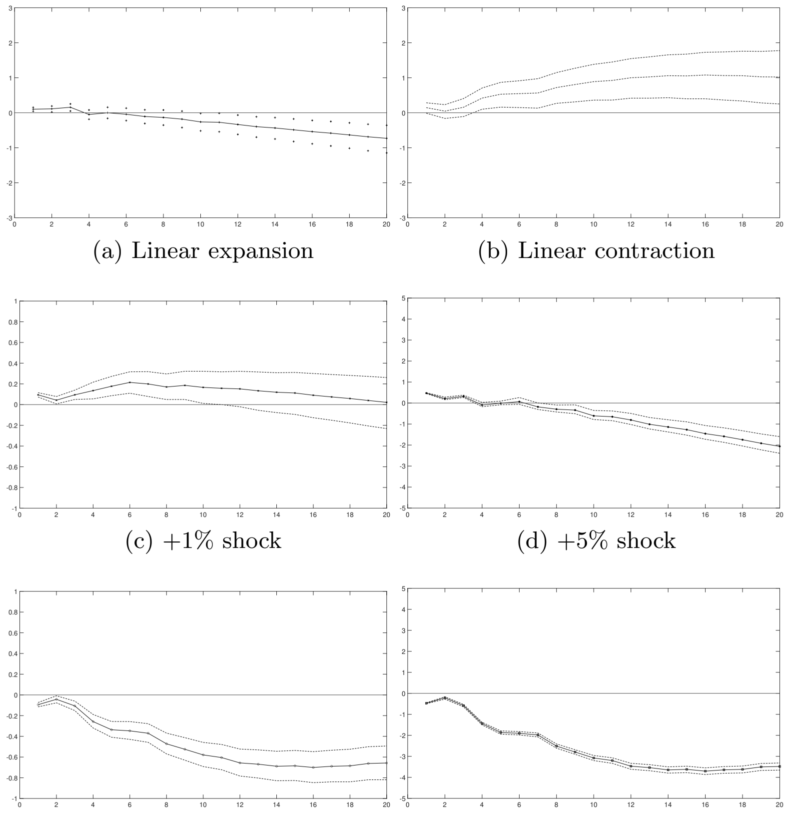
(h) Recession, −5%

Note: Cumulative generalised impulse responses to a shock triggered in a median representative recession or expansion. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

C.4 Additional figures for augmented specifications

We present additional figures for our two augmented specifications, one extending the baseline with a measure of private credit, and the other with public debt. Both the additional variables are normalized by GDP to carry information on financial stress and fiscal space, rather than on the variables themselves.

Figure C.4: Linear and generalised IRFs, GDP response



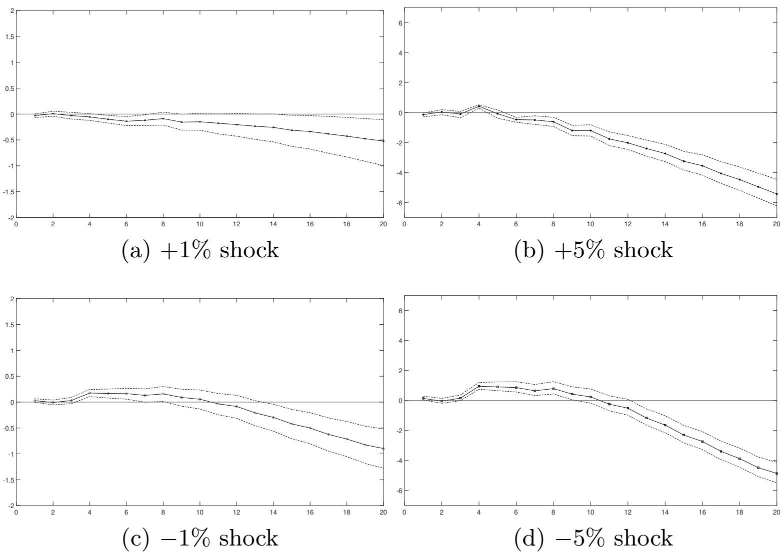
(a) Linear expansion (b) Linear contraction

(c) +1% shock (d) +5% shock

(e) −1% shock (f) −5% shock

Note: Cumulative linear (a, b) and generalised impulse responses. Percentage GDP response to a unit standard deviation (a, b) or to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Figure C.5: Generalised IRFs, credit-to-GDP response

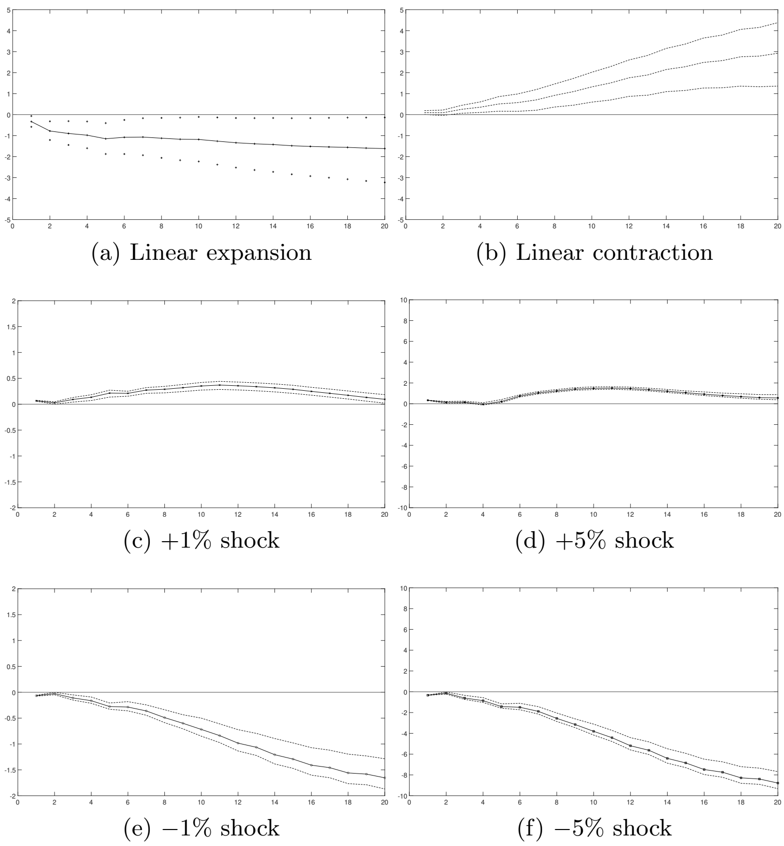


(a) +1% shock (b) +5% shock

(c) −1% shock (d) −5% shock

Note: Generalised impulse responses. Percentage private credit response to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Figure C.6: Linear and generalised IRFs, GDP response



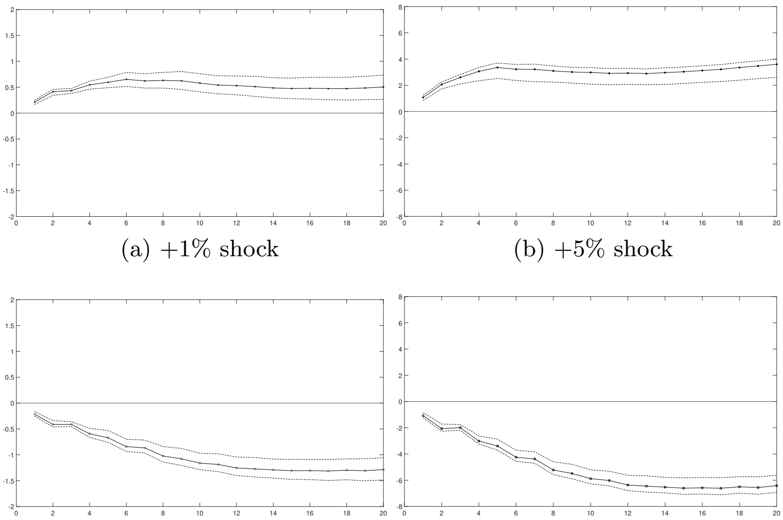
(a) Linear expansion (b) Linear contraction

(c) +1% shock (d) +5% shock

(e) −1% shock (f) −5% shock

Note: Cumulative linear (a, b) and generalised impulse responses. Percentage GDP response to a unit standard deviation (a, b) or to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, public debt, and GDP. Confidence bands are at 5th and 95th percentile.

Figure C.7: Generalised IRFs, debt-to-GDP response



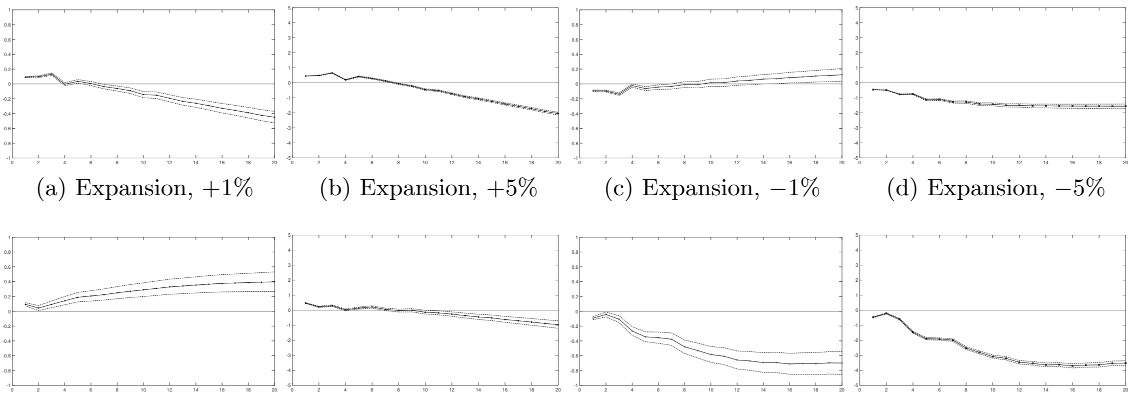
(a) +1% shock (b) +5% shock

(c) −1% shock (d) −5% shock

Note: Cumulative generalised impulse responses. Percentage public debt response to percentages of fiscal shock. STVAR includes public expenditure, tax revenues, public debt, and GDP. Confidence bands are at 5th and 95th percentile.

C.4.1 Scenario analysis

Figure C.8: Credit-augmented specification, scenario analysis, GIRFs for typical scenarios

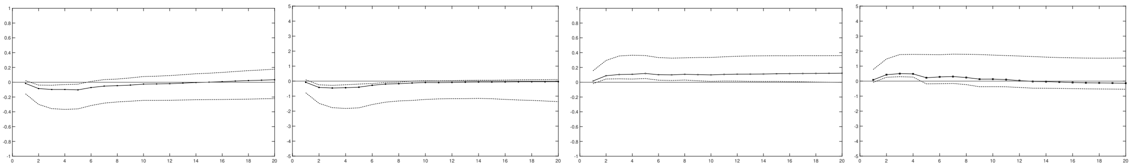


(a) Expansion, +1% (b) Expansion, +5% (c) Expansion, −1% (d) Expansion, −5%

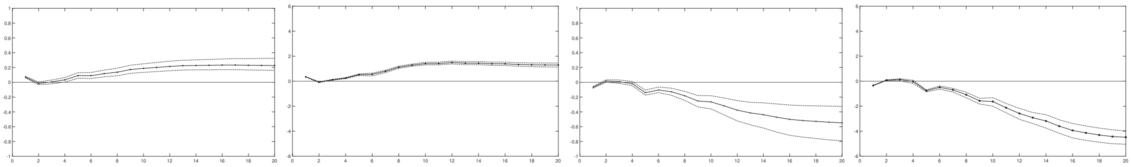
(e) Recession, +1% (f) Recession, +5% (g) Recession, −1% (h) Recession, −5%

Note: Cumulative generalised impulse responses to a shock triggered in a median representative recession or expansion. STVAR includes public expenditure, tax revenues, GDP, and private credit. Confidence bands are at 5th and 95th percentile.

Figure C.9: Debt-augmented specification, scenario analysis, GIRFs for typical scenarios



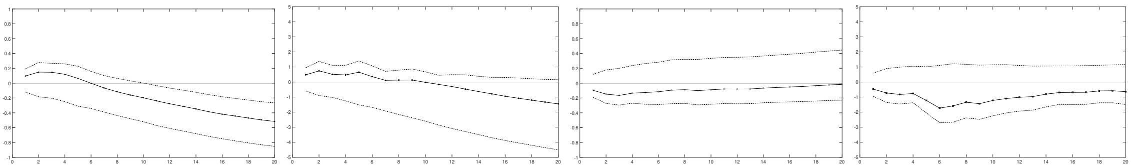
(a) Expansion, +1% (b) Expansion, +5% (c) Expansion, −1% (d) Expansion, −5%



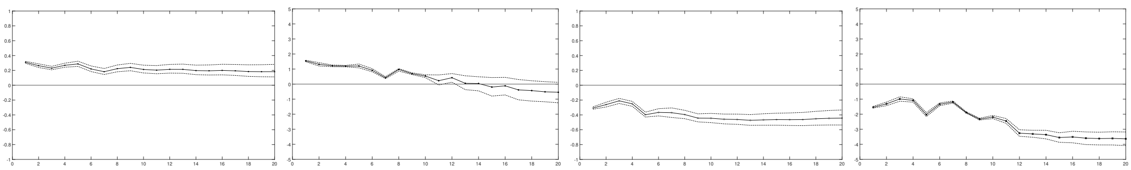
(e) Recession, +1% (f) Recession, +5% (g) Recession, −1% (h) Recession, −5%

Note: Cumulative generalised impulse responses to a shock triggered in a median representative recession or expansion. STVAR includes public expenditure, tax revenues, public debt, and GDP. Confidence bands are at 5th and 95th percentile.

Figure C.10: Debt-augmented specification, scenario analysis, GIRFs for typical scenarios with a shock to public debt



(a) Expansion, +1% (b) Expansion, +5% (c) Expansion, −1% (d) Expansion, −5%



(e) Recession, +1% (f) Recession, +5% (g) Recession, −1% (h) Recession, −5%

Note: Cumulative generalised impulse responses to a shock triggered in a median representative recession or expansion. The same shock is applied with opposite signs to government expenditure and public debt. STVAR includes public expenditure, tax revenues, public debt, and GDP. Confidence bands are at 5th and 95th percentile.

Appendix D

Appendix to Chapter 4

D.1 Theoretical model

The theoretical framework draws upon Chah et al. (1995) and José Luengo-Prado (2006).

Facing an income stream $\{Y_t\}_{t=0}^{\infty}$, a consumer solves the following problem

$$\max_{\{C,D,A\}} \qquad E_0 \sum_{t=0}^{\infty} \frac{1}{(1+\rho)^t} U(C_t, D_t)$$

subject to

$$\begin{aligned} A_t &= R_t A_{t-1} + Y_t - C_t - P_t^d d_t \\ D_t &= d_t + (1-\delta) D_{t-1} \\ A_t &+ \varphi P_t^d D_t \geq 0 \\ A_{-1}&, D_{-1} \text{ given;} \\ t &= 0, 1, \ldots, \infty. \end{aligned}$$

where
Y_t - labour income
A_t - assets at the end of period t
C_t - nondurable consumption
D_t - stock of durables at the end of period t
d_t - purchases of durables
ρ - rate of time preference ($\beta = (1+\rho)^{-1}$ is the discount factor)
δ - rate of depreciation on durables ($\psi = 1 - \delta$ is a depreciation factor)
φ - fraction of the durable stock that can be financed ($\theta = 1 - \varphi$ is the required down payment)
P_t^d - relative price of durables to nondurables ($\pi_t^d = \frac{P_{t+1}^d}{P_t^d} - 1$ is the relative price inflation)
r_t - real interest rate ($R_t = 1 + r_t$ is the compound real interest rate)

Assume that the income process is

$$\begin{aligned} Y_t &= Y^* \exp(u_t^y) \\ u_t^y &= \rho^y u_{t-1}^y + \varepsilon_t^y \end{aligned}$$

The Lagrangian for this problem is

$$\mathcal{L} = E_0 \sum_{t=0}^{\infty} \frac{1}{(1+\rho)^t} \left\{ U\left(Y_t + R_{t-1} A_{t-1} - A_t - P_t^d \left(D_t - (1-\delta) D_{t-1}\right), D_t\right) + \mu_t \left(A_t + \varphi P_t^d D_t\right) \right\}$$

Denote $U_c(t)$ and $U_d(t)$ the marginal utilities of nondurable and durable consumption, respectively, in period t.

The first order conditions are

$$\beta R_t E_t U_c(t+1) = U_c(t) - \mu_t \tag{D.1}$$

$$U_d(t) = P_t \left[U_c(t) - \frac{1-\delta}{1+\rho} E_t U_c(t+1) \frac{P^d_{t+1}}{P^d_t} \right] - \varphi P^d_t \mu_t \tag{D.2}$$

with supplementary slackness conditions

$$\mu_t \geq 0 \tag{D.3}$$

$$\mu_t \left(A_t + \varphi P^d_t D_t \right) = 0 \tag{D.4}$$

Substituting for $E_t U_c(t+1)$ from Eq. D.1, Eq. D.2 becomes (after re-arranging terms)

$$U_c(t) = \underbrace{\frac{R_t}{R_t - (1-\delta)\left(1+\pi^d_t\right)}}_{\Omega_t^{-1}} \frac{1}{P^d_t} U_d(t) + \frac{\varphi R_t - (1-\delta)\left(1+\pi^d_t\right)}{R_t - (1-\delta)\left(1+\pi^d_t\right)} \mu_t \tag{D.5}$$

where $\Omega_t = \frac{R_t - (1-\delta)\left(1+\pi^d_t\right)}{R_t}$ is the user cost of durables. It depends positively on the rate of depreciation δ and the interest rate r, and negatively on the inflation rate in the relative price of durables π^d.

Assume CRRA type of utility function, with separable utility of durables and nondurables.

$$U(C_t, D_t) = \frac{C_t^{1-\sigma}}{1-\sigma} + \gamma_t \frac{D_t^{1-\sigma}}{1-\sigma}$$

We allow for time variation in γ_t to capture the possibility of shocks to preferences for durables. In the special case of $\sigma = 1$, the utility function collapses to $U(C_t, D_t) = log(C_t) + \gamma_t log(D_t)$. Using this functional form and replacing for the marginal utilities $U_c(t)$ and $U_d(t)$, Eq. D.5 becomes

$$\frac{D_t}{C_t} = \gamma_t \underbrace{\frac{R_t}{R_t - (1-\delta)\left(1+\pi^d_t\right)}}_{\Omega_t^{-1}} \frac{1}{P^d_t} + D_t \frac{\varphi R_t - (1-\delta)\left(1+\pi^d_t\right)}{R_t - (1-\delta)\left(1+\pi^d_t\right)} \mu_t$$

which gives the optimal ratio of durables to nondurables. If liquidity constraints are non-binding ($\mu_t = 0$), this becomes

$$\frac{D_t}{C_t} = \gamma_t \frac{1}{\Omega_t} \frac{1}{P^d_t}$$

In this case, the optimal ratio of durables to nondurables depends positively on the durable preferences γ and (via Ω) on the inflation rate in the relative price of durables π^d and is a negative function of relative prices P^d and (via Ω) of the rate of depreciation δ and the interest rate r.

Assume the following exogeneous processes for the relative price of durables P^d

$$P^d_t = P^{d*} \exp(u^p_t)$$
$$u^p_t = \rho^p u^p_{t-1} + \varepsilon^p_t$$

for preferences for durables in the utility function γ

$$\begin{aligned} \gamma_t &= \gamma^* + u_t^\gamma \\ u_t^\gamma &= \rho^\gamma u_{t-1}^\gamma + \varepsilon_t^\gamma \end{aligned}$$

and for the compound interest rate R

$$\begin{aligned} R_t &= R^* \exp(u_t^R) \\ u_t^R &= \rho^R u_{t-1}^R + \varepsilon_t^R \end{aligned}$$

where the asterisk ($*$) denotes steady-state values.

Appendix D.2 shows results from a simulation under perfect foresight for the dynamic adjustment of C_t and D_t for a set of shocks to relative prices, preferences, and the interest rate. The results cover both temporary and permanent shocks and show adjustment paths for a consumer who becomes, or alternatively does not become, liquidity-constrained as a result of the shock.

In particular, Figures D.1 and D.2 show the response to a decline and an increase, respectively, in the relative price of durables P^d with autoregressive coefficients, respectively, $\rho^p = 0.1$ and $\rho^p = 1.0$ for the temporary and the permanent shock, respectively. Similarly, Figures D.3, D.4, D.5 and D.6 show responses to increases and declines in the preference for durables γ and the interest rate r with autoregressive coefficients for the temporary shocks equal, in both cases, to $\rho^\gamma = 0.1$ and $\rho^R = 0.1$.

D.2 Dynamic responses to shocks in the theoretical model

Figure D.1: Temporary and permanent decline of 1% in relative durable prices P^d

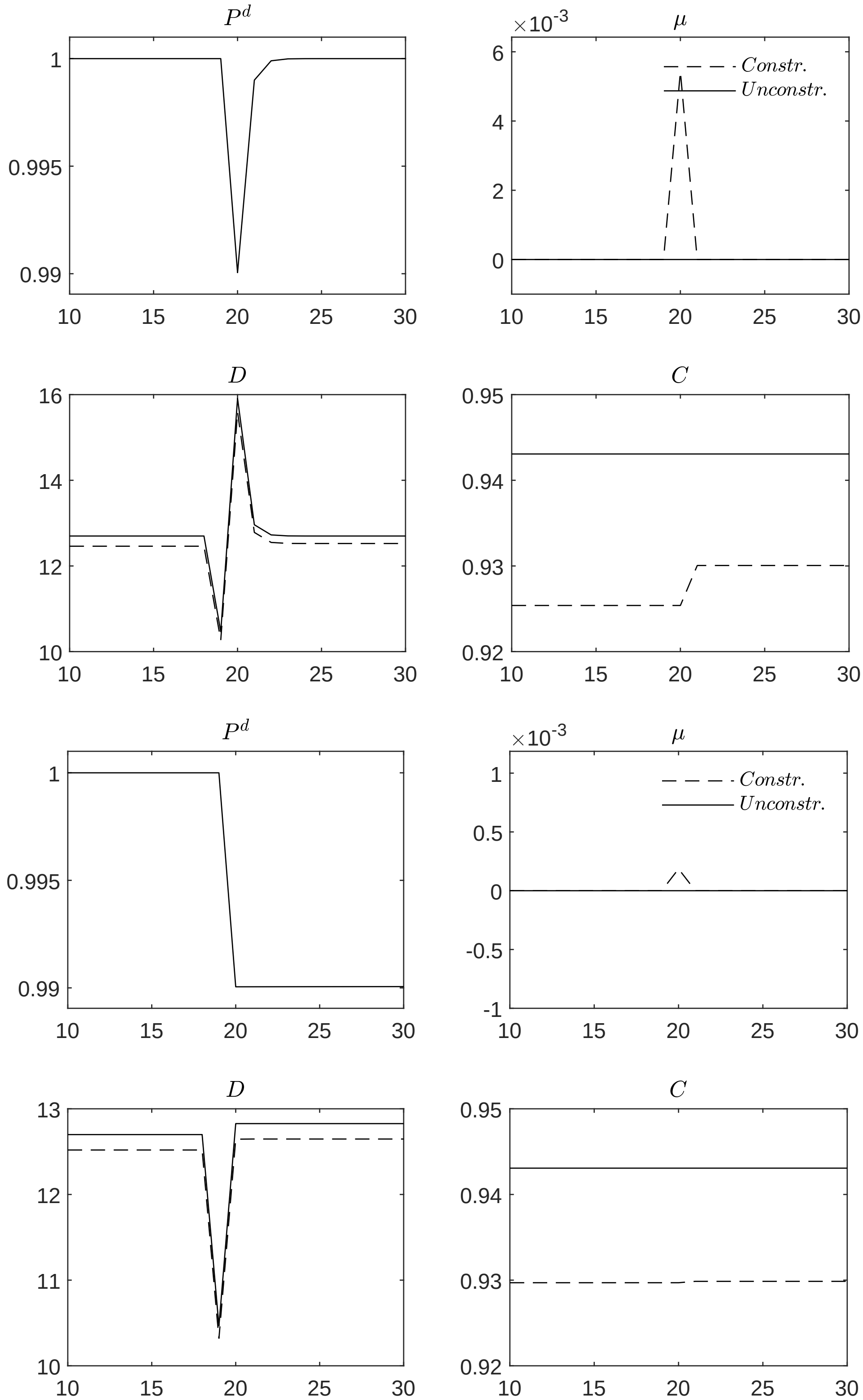


Figure D.2: Temporary and permanent increase of 1% in relative durable prices P^d

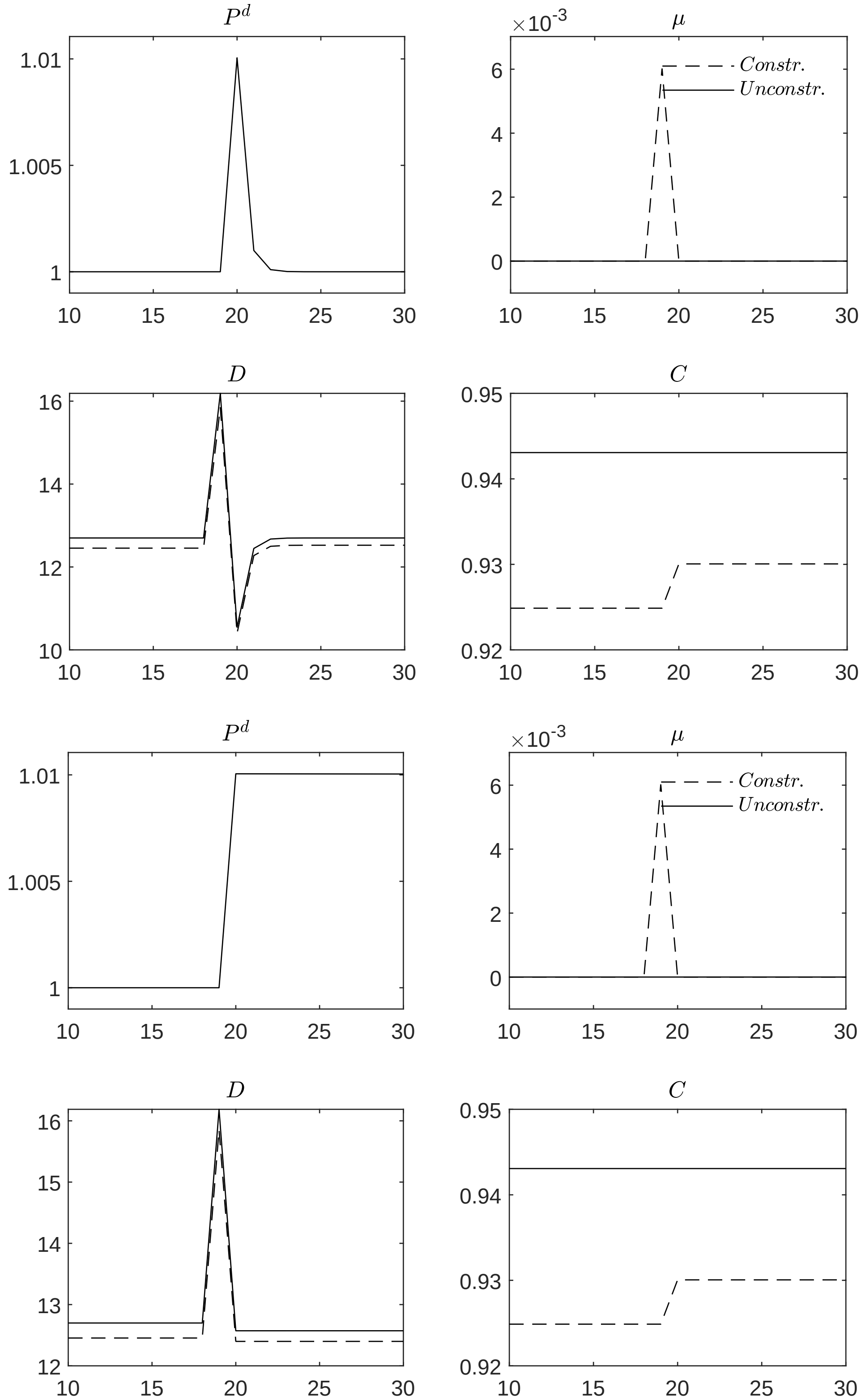


Figure D.3: Temporary and permanent increase in the preference parameter γ for durables

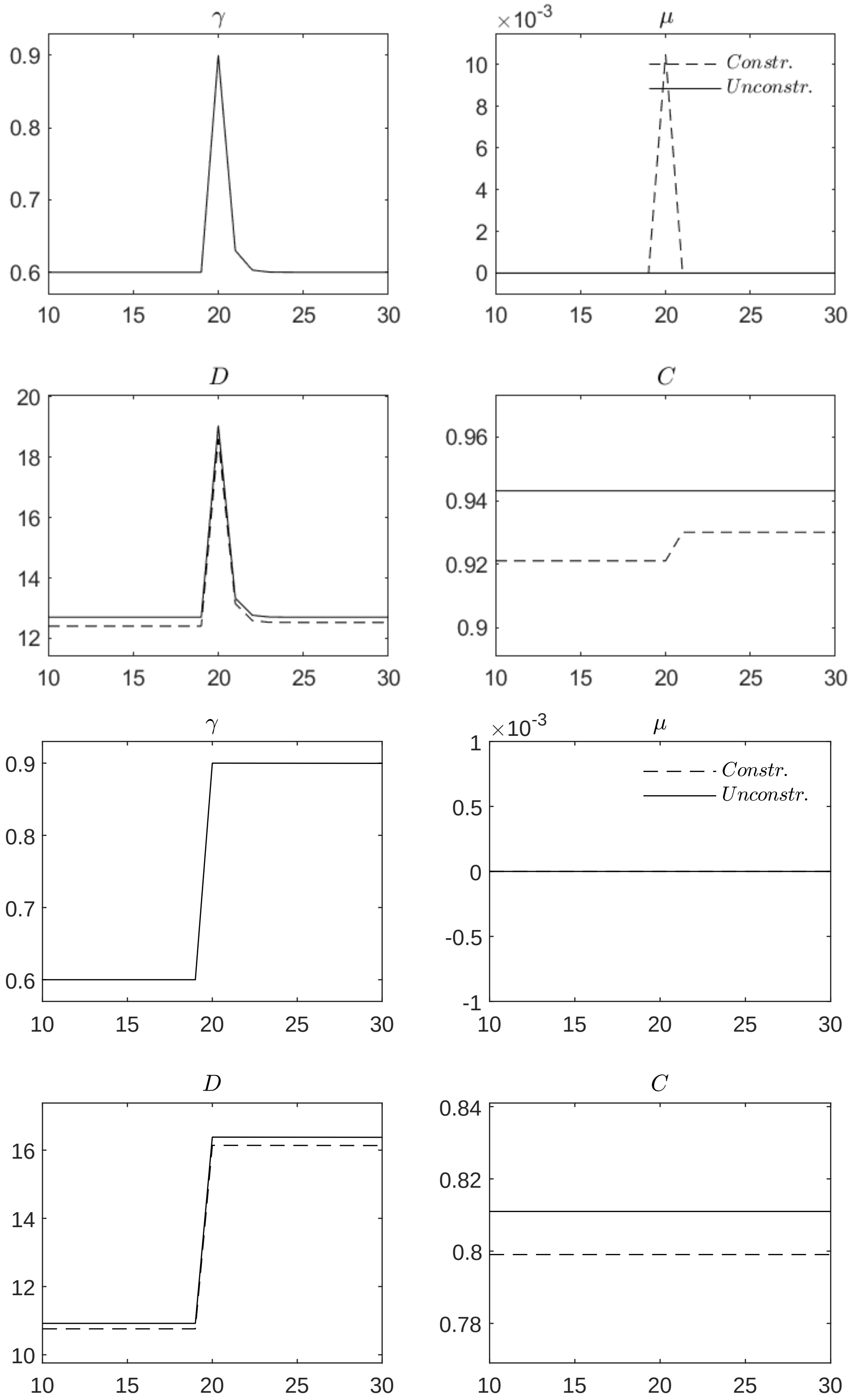


Figure D.4: Temporary and permanent decline in the preference parameter γ for durables

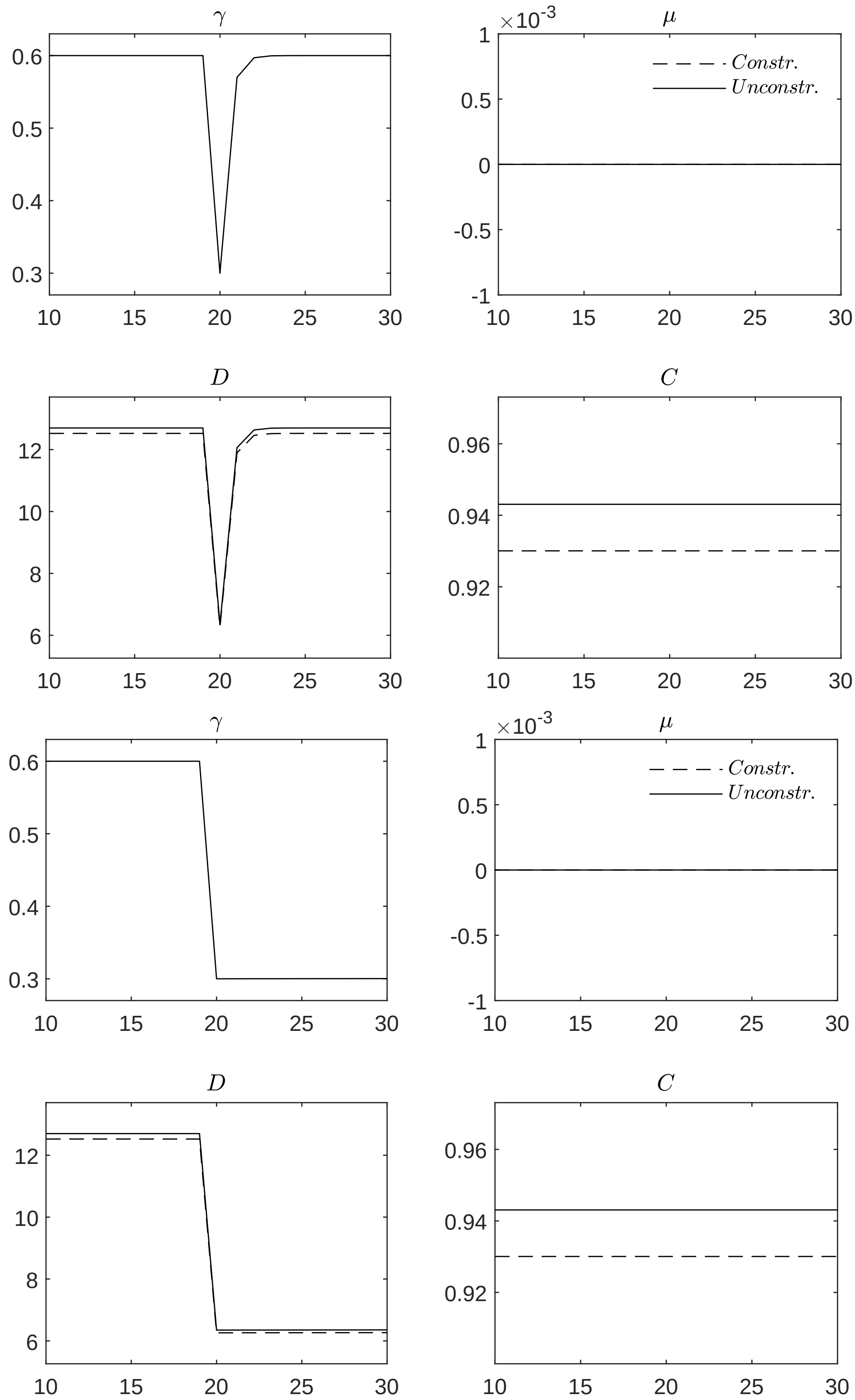


Figure D.5: Temporary and permanent decline in the interest rate r

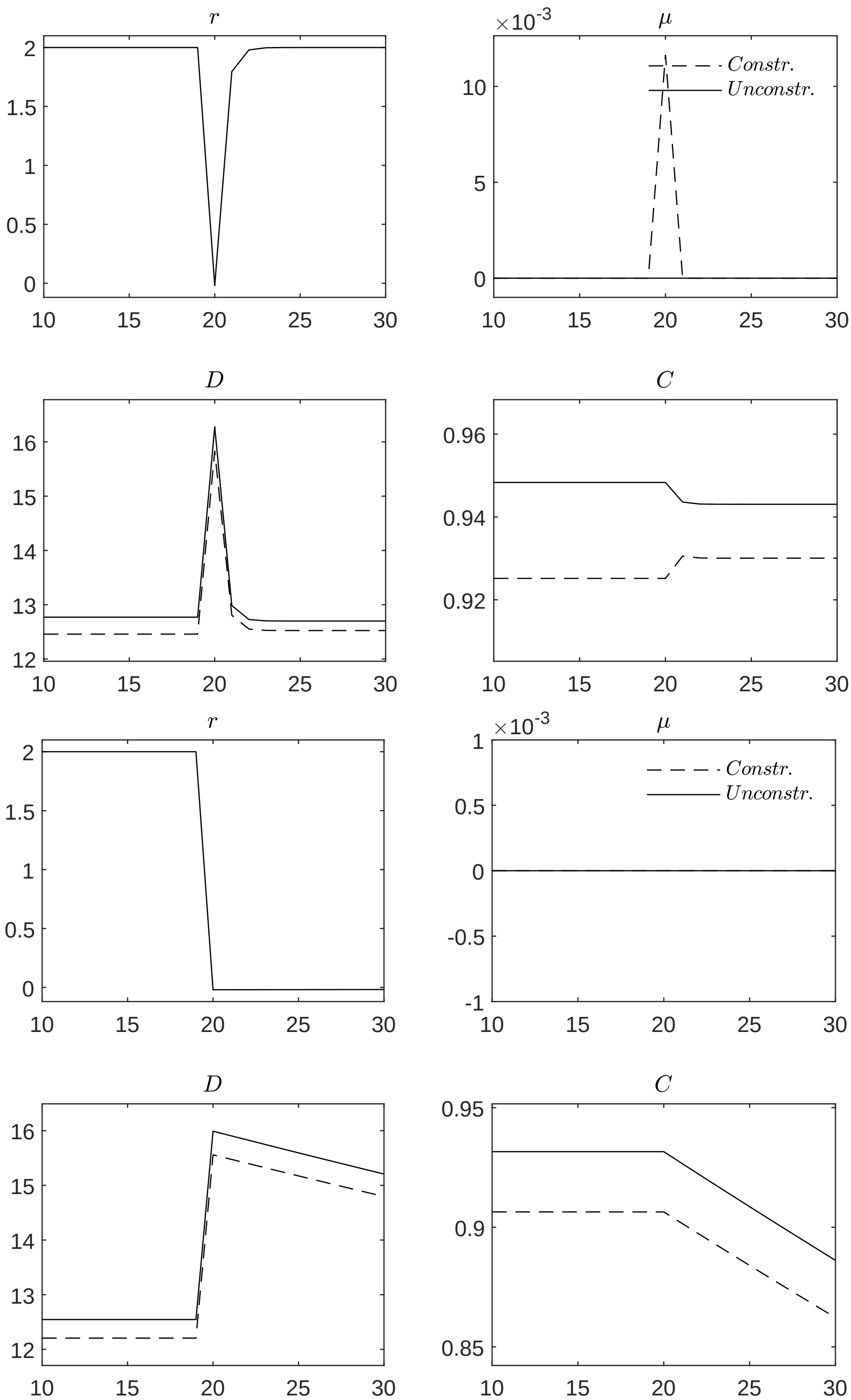
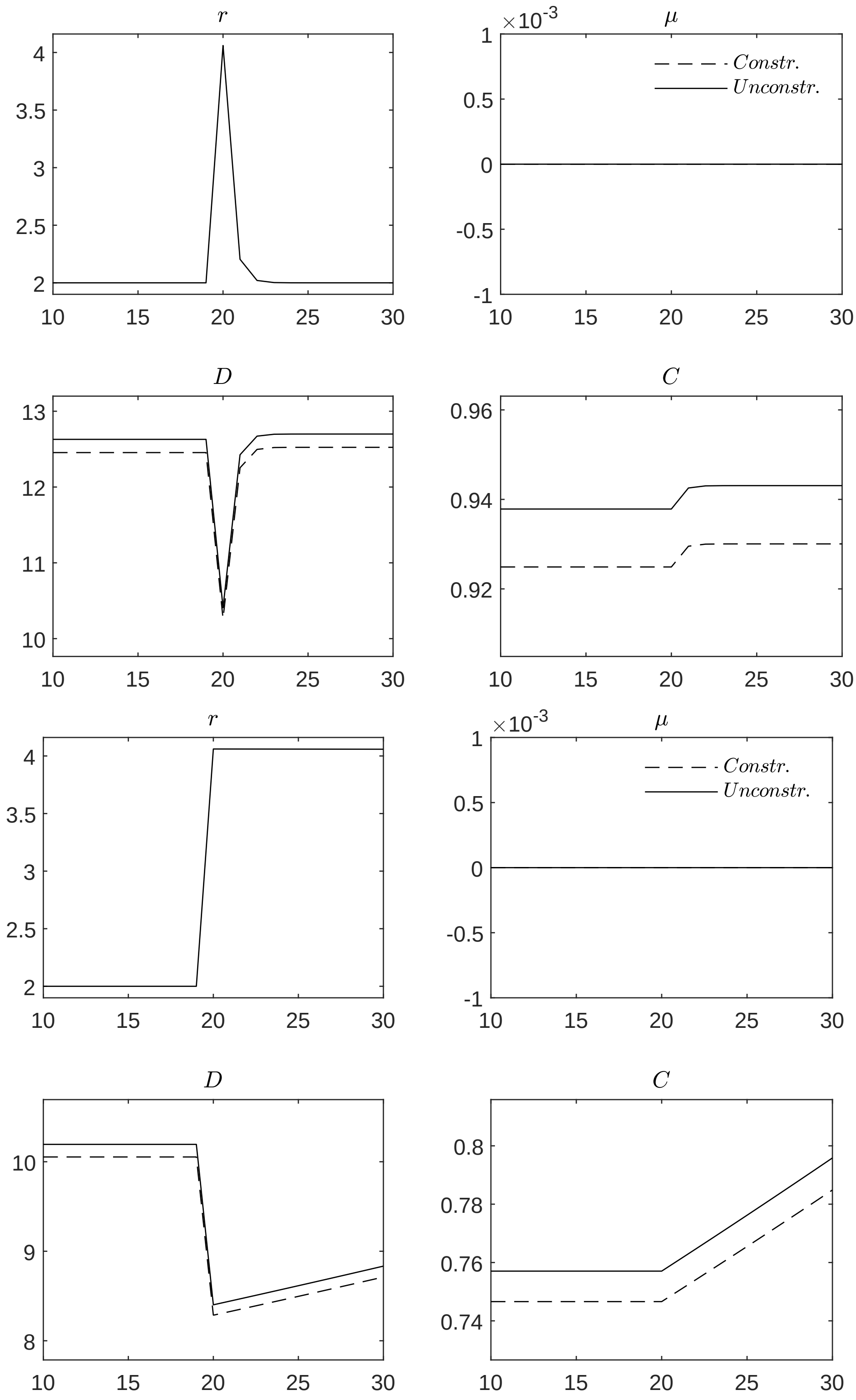


Figure D.6: Temporary and permanent increase in the interest rate r



D.3 Data description and sources

The empirical model is estimated on quarterly data available for 1996Q1-2018Q3 (in levels) as of 30 January 2019. For the euro area member states we take the series for nominal and real D and C from Eurostat, and we compute P^d and P. We construct our euro area series as a bottom-up aggregation of country-level data for the 19 individual member states. The series for R are provided by National Central Banks and collected in the *MIR – MFI Interest Rate Statistics* database managed by the European Central Bank Statistical Data Warehouse. Monthly series of recession and expansion periods for euro area countries are published by the Economic Cycle Research Institute (ECRI); the Center for Economic Policy Research (CEPR) publishes a quarterly series for the euro area aggregate.

All the data on the US are taken from Haver Analytics. The original source for nominal and real series for D and C and the corresponding deflators is the Bureau of Economic Analysis. R is published by the Federal Reserve Board. Chronologies of recessions and expansions are published by the National Bureau of Economic Research (NBER).

Measures on excess financial assets are computed based on data published by the European Central Bank in the Household Finance and Consumption Survey (HFCS) for EA countries and the euro area aggregate. Analogous data for the US are published by the Federal Reserve Board in the Survey of Consumer Finances (SCF).

D, C, P^d, and P are in logs and the deflators are rebased. All series are differenced accordingly, to obtain year-on-year percent changes.

(1) D - Individual consumption expenditure of durable goods in chain linked volume, millions of euro, calendar and seasonally adjusted data.

(2) C - Individual consumption expenditure of semi-durable and nondurable goods and services in chain linked volume, millions of euro, calendar and seasonally adjusted data.

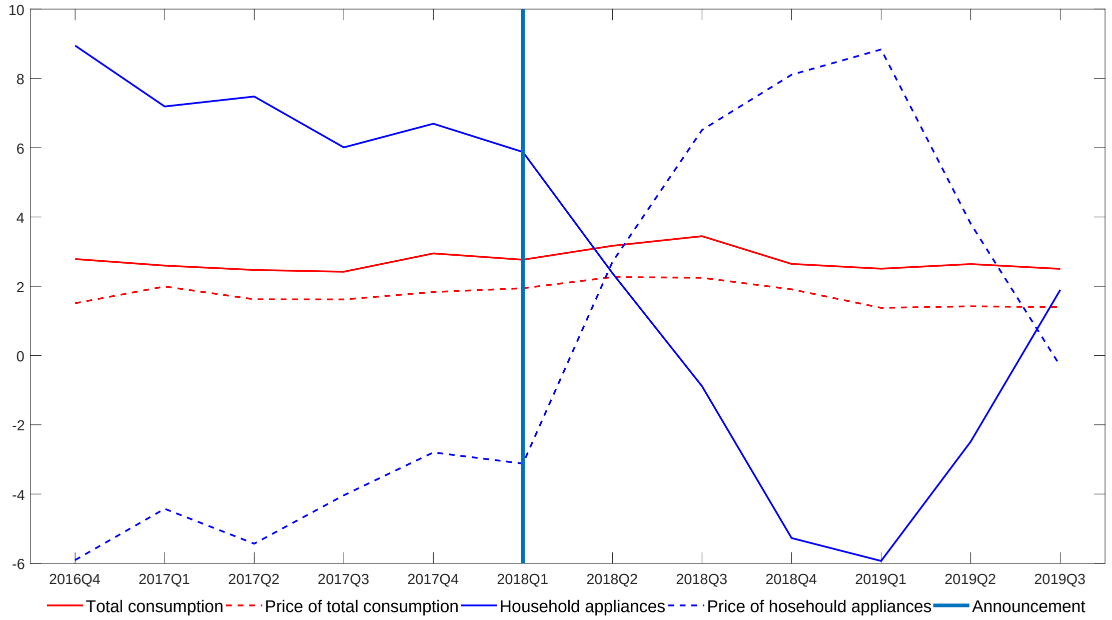
(3) P^d - Implicit deflator for D, computed using D and the individual consumption expenditure of durable goods in current prices.

(4) P - Implicit deflator for C, computed using D and the individual consumption expenditure of semi-durable and nondurable goods and services in current prices.

(5) R - Composite lending rate to consumer credit in nominal terms.

D.4 Real world example of a durable-specific supply shock

Figure D.7: Real world supply shock example



Source: Bureau of Economic Analysis.
Note: Quantity and prices of total consumption and household appliance (belonging to durables) consumption. On 22 January 2018, a hike on the tariffs of imported washing machines was announced, leading to a sharp increase in their prices and a corresponding decline in quantities. In our framework, this is a clear durable(subsector)-specific negative supply shock, with aggregate consumption and prices not reacting.

D.5 Optimal lag selection and parameter stability tests

D.5.1 Optimal lag selection

Table D.1: Optimal VAR order

	US		EA		DE		FR		IT		ES	
	L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4
Akaike	1	4	4	4	2	4	4	3	3	2	4	4
Schwarz Bayesian	1	1	1	2	1	1	1	1	1	1	3	3
Hannan-Quinn	1	1	1	2	1	1	1	2	1	2	3	3

Note: Optimal lag order of a VAR fitted on quarterly data in levels (L) and year-on-year (Δ_4) according to different criteria. Maximum lag order is set to 4.

D.5.2 Parameter stability tests

Table D.2: Chow test - standard version

			US		EA		DE		FR		IT		ES	
T_B/T			L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4
		p	1	1	1	2	1	1	1	1	1	1	3	3
35%	λ_{ss}	1%	R	R	R	R	R	R	R	R	R	R	R	R
		5%	R	R	R	R	R	R	R	R	R	R	R	R
		10%	R	R	R	R	R	R	R	R	R	R	R	R
	λ_{bp}	1%	R	R	R	R	R	R	R	R	R	R	R	R
		5%	R	R	R	R	R	R	R	R	R	R	R	R
		10%	R	R	R	R	R	R	R	R	R	R	R	R
50%	λ_{ss}	1%	R	R	R	R	R	R	R	R	R	R	R	R
		5%	R	R	R	R	R	R	R	R	R	R	R	R
		10%	R	R	R	R	R	R	R	R	R	R	R	R
	λ_{bp}	1%	R	R	R	R	R	R	R	R	R	R	R	R
		5%	R	R	R	R	R	R	R	R	R	R	R	R
		10%	R	R	R	R	R	R	R	R	R	R	R	R
65%	λ_{ss}	1%	R	R	R		R		R	R	R	R	R	R
		5%	R	R	R		R		R	R	R	R	R	R
		10%	R	R	R		R		R	R	R	R	R	R
	λ_{bp}	1%	R	R	R	R	R	R	R	R	R	R	R	R
		5%	R	R	R	R	R	R	R	R	R	R	R	R
		10%	R	R	R	R	R	R	R	R	R	R	R	R

Note: Chow test for parameter stability of a VAR(p) where the lag order p is based on the Schwarz Bayesian criterion. R stands for rejection of the null hypothesis of parameter stability at different confidence levels (1%, 5%, 10%). Both the *split sample* and the *breaking point* version of the test, as described in Lütkepohl and Krätzig (2004), are performed on data in levels and in year-on-year growth rates. The breaking point is assumed to be at 35%, 50%, and 65% of the sample, corresponding to 2003Q4, 2007Q2, 2010Q3 for the series in levels and 2004Q2, 2007Q4, and 2011Q1 for the ones in year-on-year growth rates.

Table D.3: Chow test - bootstrapped version

			US		EA		DE		FR		IT		ES	
T_B/T			L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4
		p	1	1	1	2	1	1	1	1	1	1	3	3
35%	λ_{ss}	1%			R	R	R	R	R	R	R	R	R	R
		5%	R	R	R	R	R	R	R	R	R	R	R	R
		10%	R	R	R	R	R	R	R	R	R	R	R	R
	λ_{bp}	1%				R	R	R	R	R	R	R	R	R
		5%		R	R	R	R	R	R	R	R	R	R	R
		10%	R	R	R	R	R	R	R	R	R	R	R	R
50%	λ_{ss}	1%	R	R	R	R	R	R	R	R	R	R	R	R
		5%	R	R	R	R	R	R	R	R	R	R	R	R
		10%	R	R	R	R	R	R	R	R	R	R	R	R
	λ_{bp}	1%	R	R	R	R	R	R	R	R		R	R	R
		5%	R	R	R	R	R	R	R	R	R	R	R	R
		10%	R	R	R	R	R	R	R	R	R	R	R	R
65%	λ_{ss}	1%										R		
		5%					R			R	R	R		
		10%					R			R	R	R		
	λ_{bp}	1%										R	R	R
		5%		R	R		R	R			R	R	R	R
		10%		R	R		R	R			R	R	R	R

Note: Chow test for parameter stability of a VAR(p) where the lag order p is based on the Schwarz Bayesian criterion. R stands for rejection of the null hypothesis of parameter stability at different confidence levels (1%, 5%, 10%). Both the *split sample* and the *breaking point* version of the test, as described in Lütkepohl and Krätzig (2004), are performed on data in levels and in year-on-year growth rates. To avoid small sample distortions, we follow Candelon and Lütkepohl (2001) and use a bootstrap correction with 100,000. The breaking point is assumed to be at 35%, 50%, and 65% of the sample, corresponding to 2003Q4, 2007Q2, 2010Q3 for the series in levels and 2004Q2, 2007Q4, and 2011Q1 for the ones in year-on-year growth rates.

Table D.4: Nyblom-Hansen parameter stability test

		US		EA		DE		FR		IT		ES	
		L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4	L	Δ_4
BIC	p	1	1	1	2	1	1	1	1	1	1	3	3
	L_c	2.18**	2.32**	2.59***	2.96**	2.02**	1.85*	2.41***	1.87*	2.23**	2.87***	3.84*	3.75*
AIC	p	1	4	4	4	2	4	4	3	3	2	4	4
	L_c	2.18**	3.89	4.76**	4.47*	3.13**	4.93**	4.57*	3.39	3.34	3.86***	4.79**	4.54*

Note: Nyblom-Hansen test for parameter stability of a VAR(p), where the lag order p is based on either the Schwarz Bayesian (BIC) or the Akaike (AIC) criterion. We report the statistic for joint stability of all parameters (L_c). Stars indicate the confidence level for rejecting the null hypothesis of parameter stability: 1%***, 5%**, 10%*. Critical values are tabulated in Nyblom (1989) and Hansen (1990, 1992).

D.6 Priors and empirical model estimation

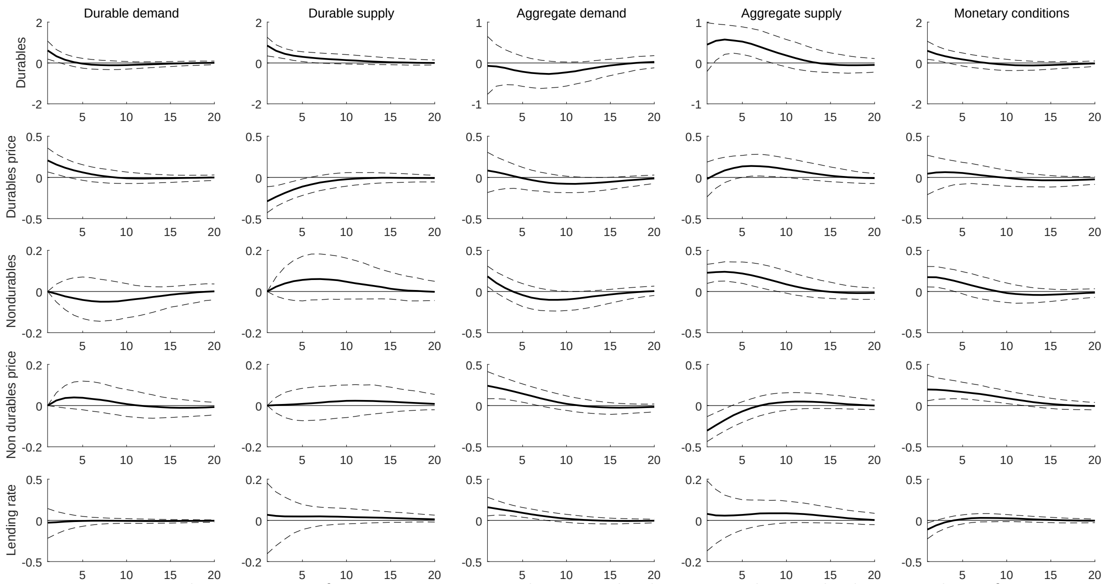
The model estimation relies on Bayesian methods: we perform $3,000$ iterations of the Gibbs sampler and discard the first 1500. The objects of interest to be estimated are β (Equation 4.8), $\mathbf{\Omega}$ (Equation 4.11), $\mathbf{Z}^{-1}$ (Equation 4.13), $\mathbf{H}$ (Equation 4.15), and $\mathbf{\Phi}_i$ (Equation 4.16).

The prior distribution for β, $\mathbf{Z}^{-1}$, and $\mathbf{H}$ is assumed to be normal, while the priors for $\mathbf{\Omega}$ and $\mathbf{\Phi}_i$ take the form of an inverse Gamma distribution. The parametrization and the calibration of hyperparameters are as in Dieppe et al. (2016), who rely on Chan and Jeliazkov (2009), and Legrand (2018). We set the autoregressive coefficient on the residual variance γ in Equation 4.16 to 0.85.

D.7 Additional tables and figures - Baseline specification

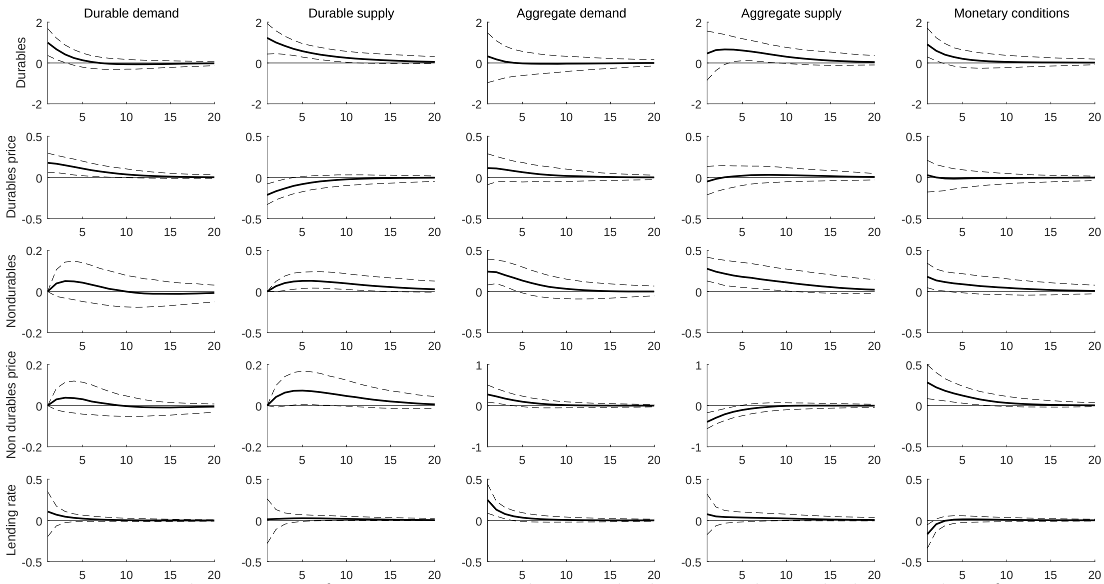
D.7.1 Impulse response functions computed using the long-run value of $\mathbf{\Sigma}_t$

Figure D.8: Euro area impulse response functions



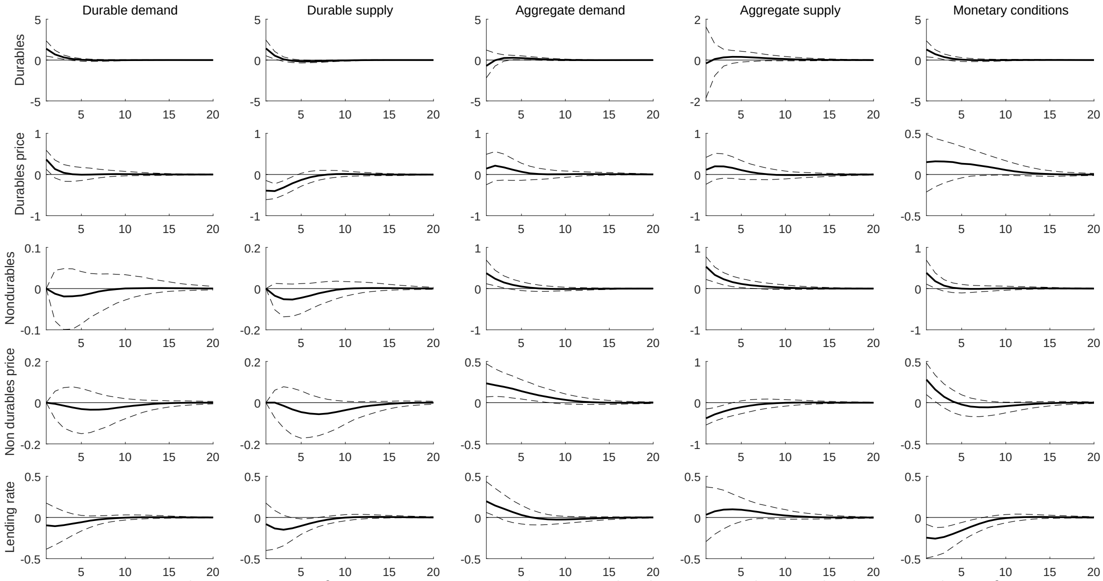
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$.

Figure D.9: United States impulse response functions



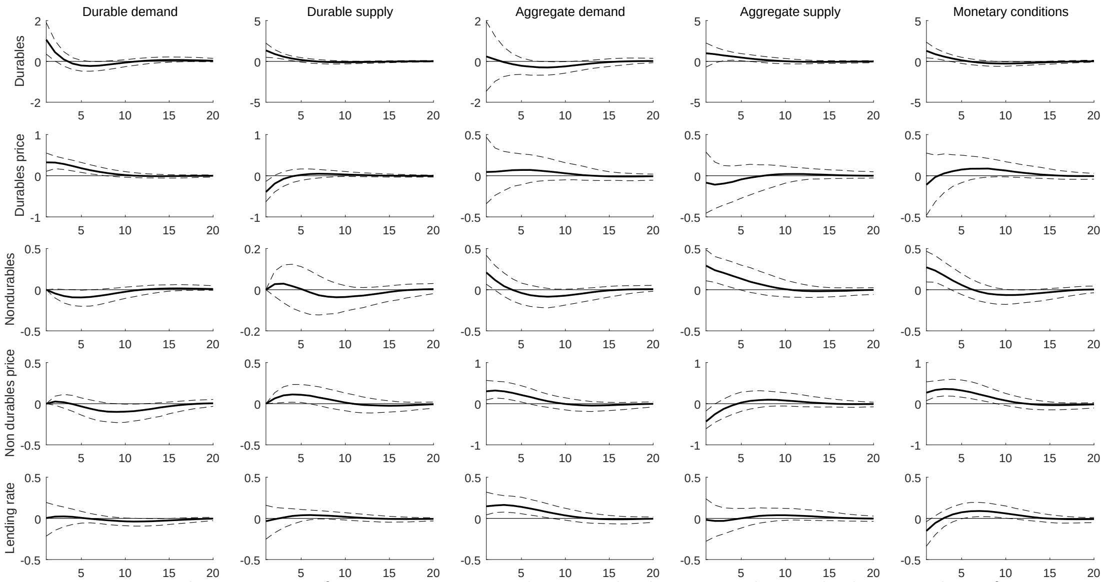
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$.

Figure D.10: Germany impulse response functions



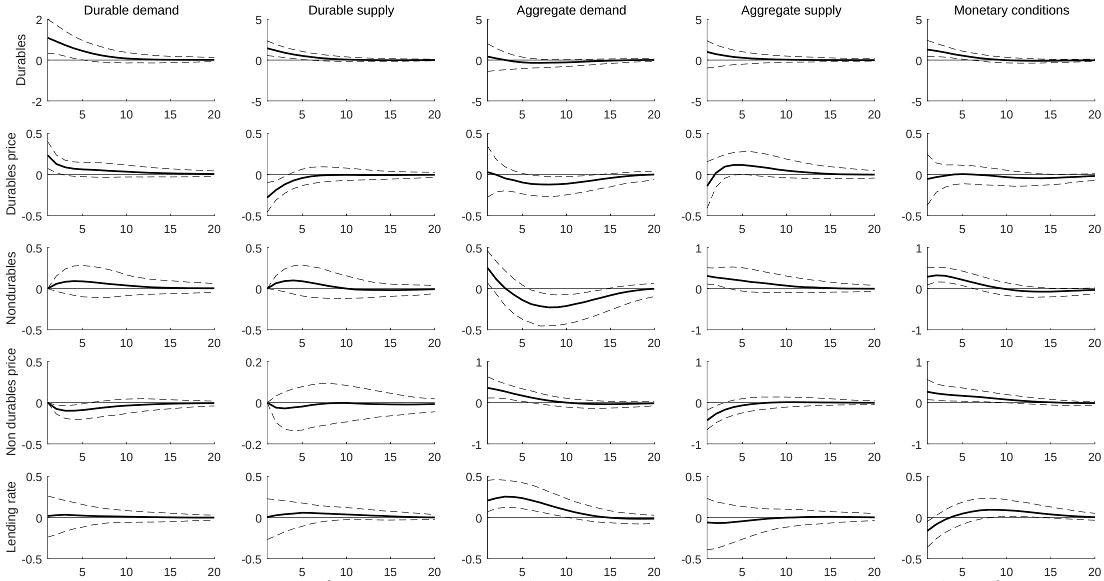
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$.

Figure D.11: France impulse response functions



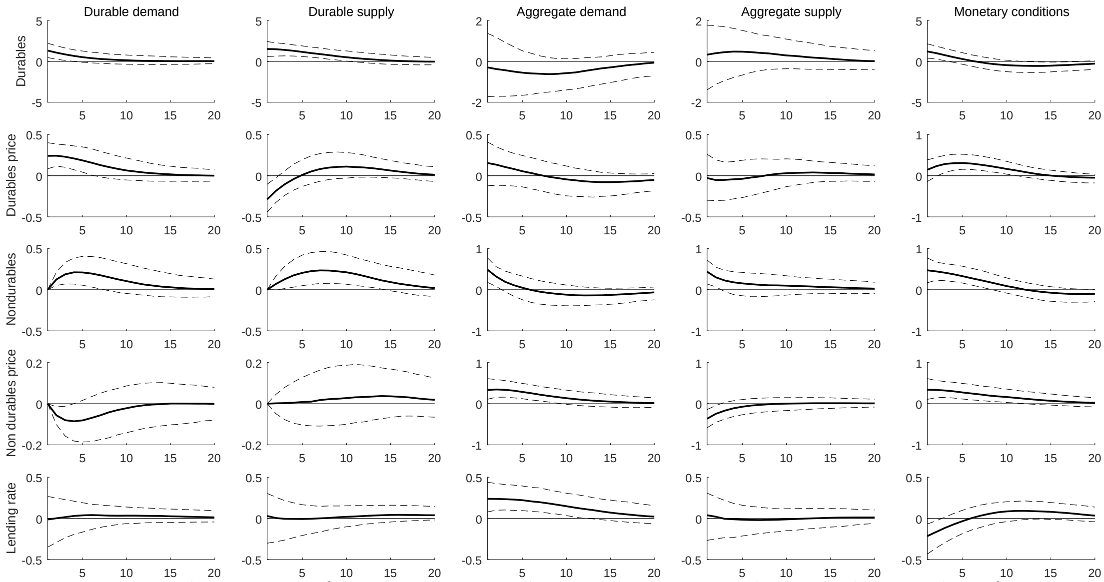
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$.

Figure D.12: Italy impulse response functions



Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$.

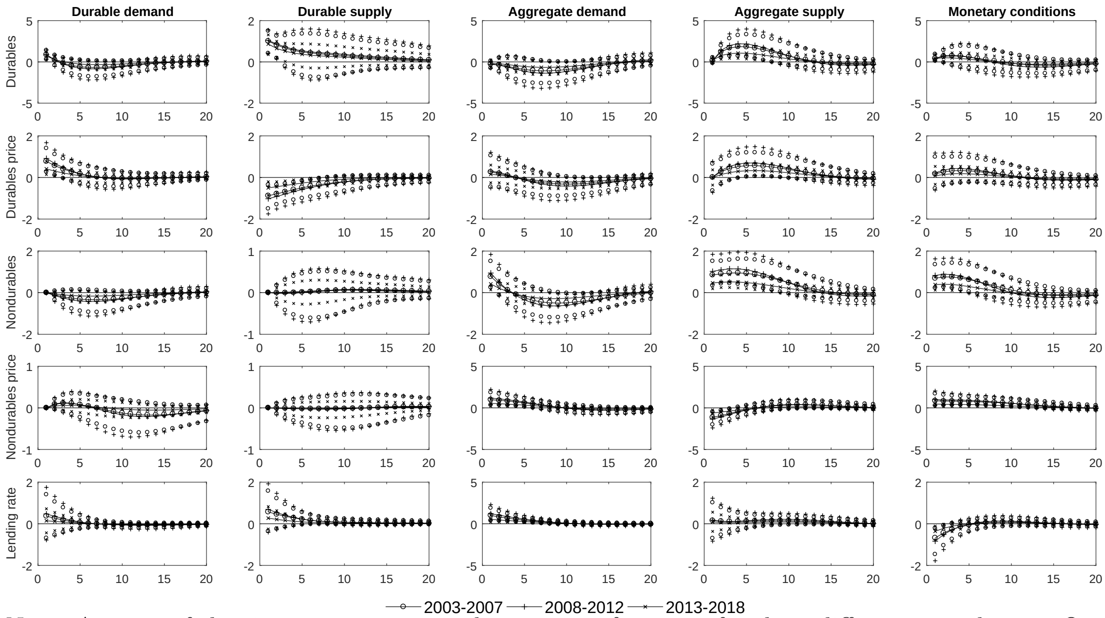
Figure D.13: Spain impulse response functions



Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$.

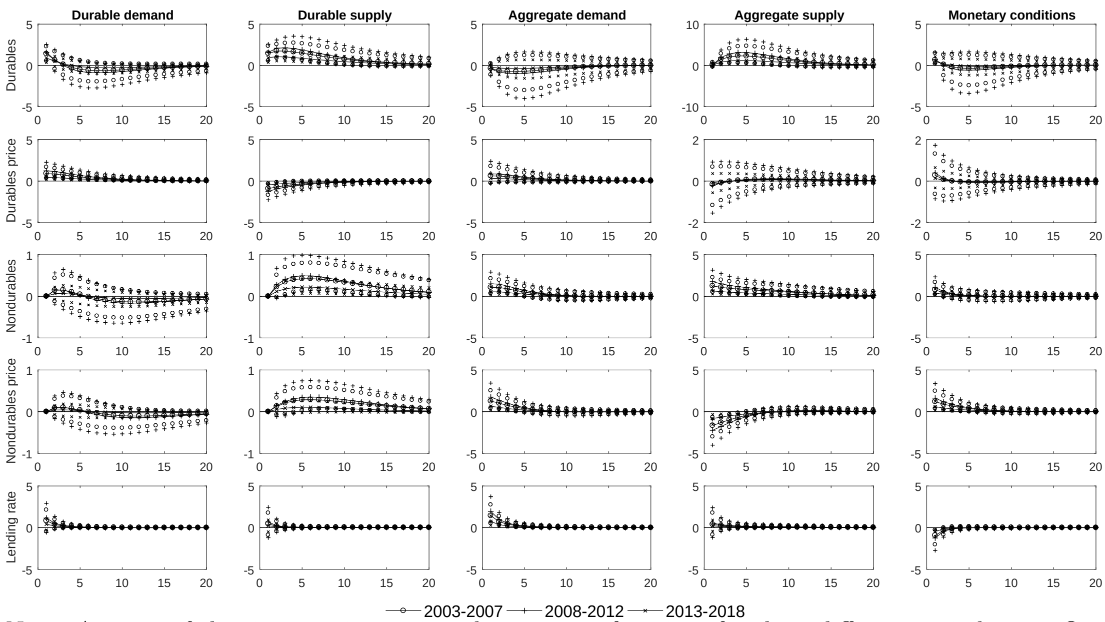
D.7.2 Impulse response functions computed with time-varying Σ_t, averaged over pre-crisis, crisis, and post-crisis periods.

Figure D.14: Euro area impulse response functions



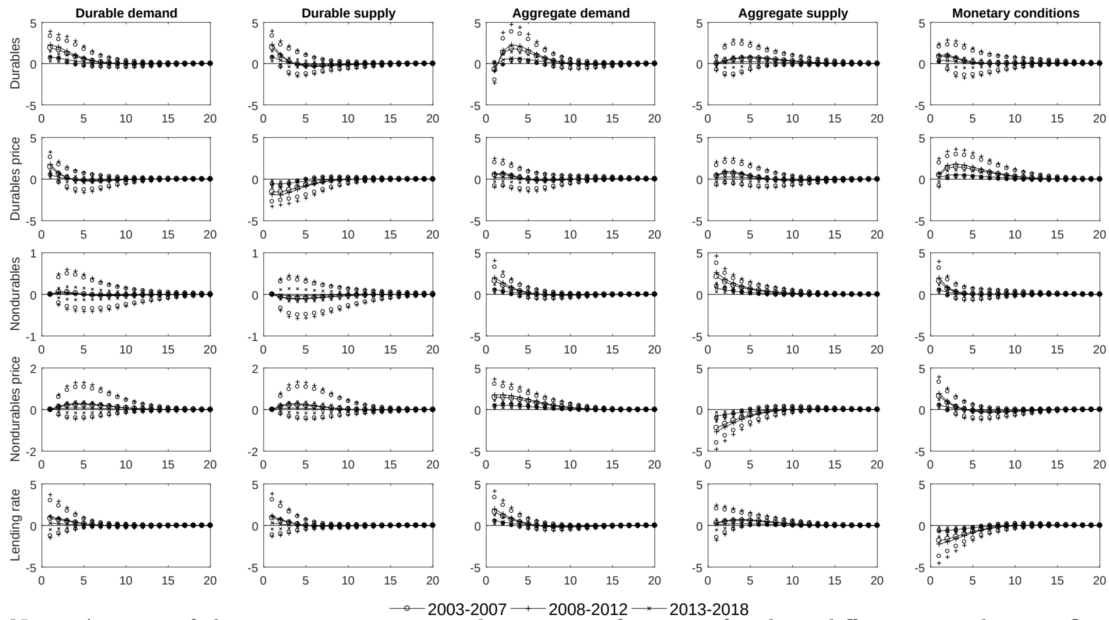
Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis), and 2013Q1-2018Q3 (post-crisis recovery).

Figure D.15: United States impulse response functions



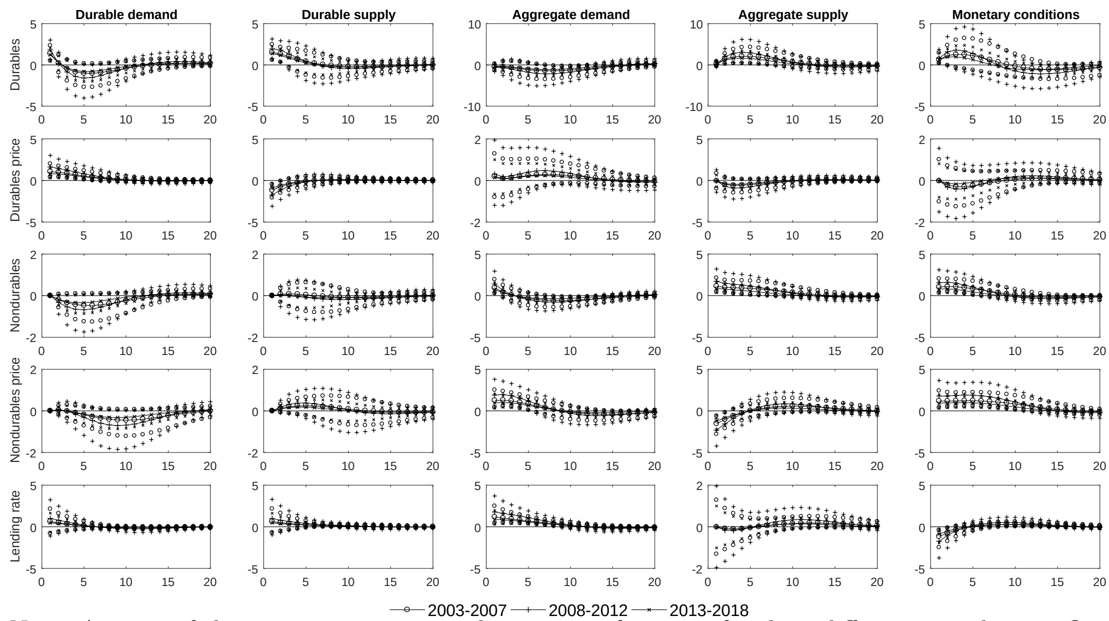
Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis), and 2013Q1-2018Q3 (post-crisis recovery).

Figure D.16: Germany impulse response functions



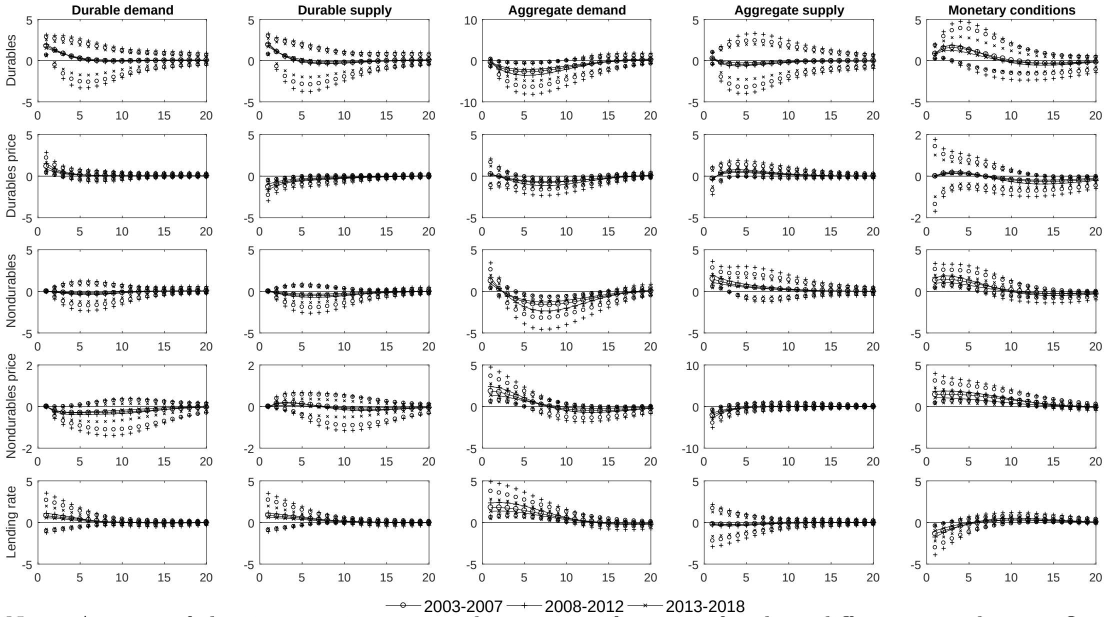
Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis), and 2013Q1-2018Q3 (post-crisis recovery).

Figure D.17: France impulse response functions



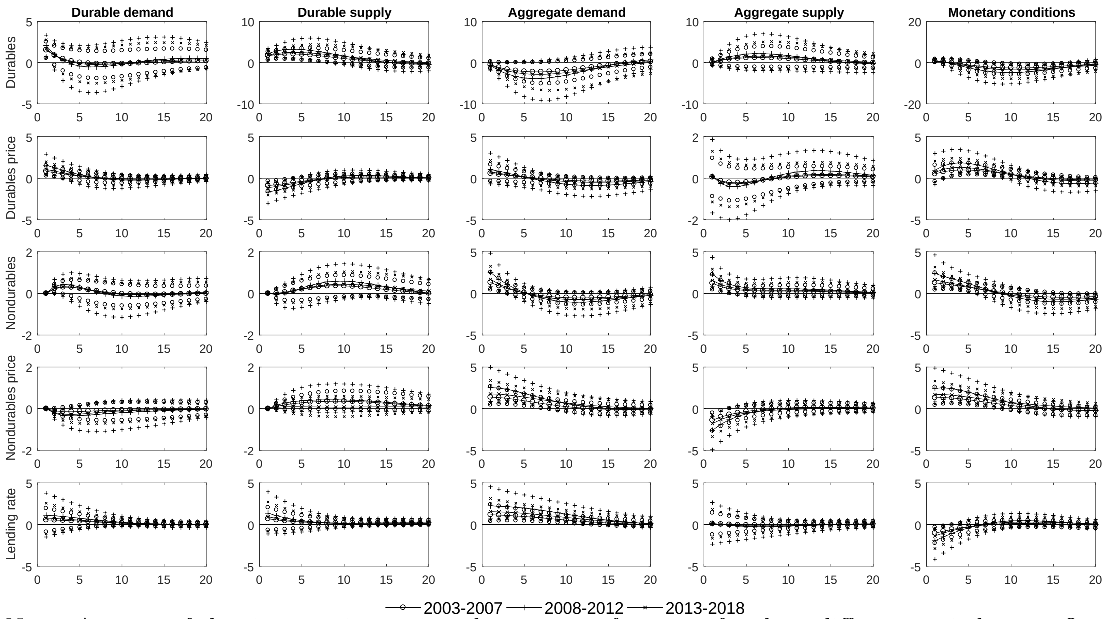
Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis) and 2013Q1-2018Q3 (post-crisis recovery).

Figure D.18: Italy impulse response functions



Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis), and 2013Q1-2018Q3 (post-crisis recovery).

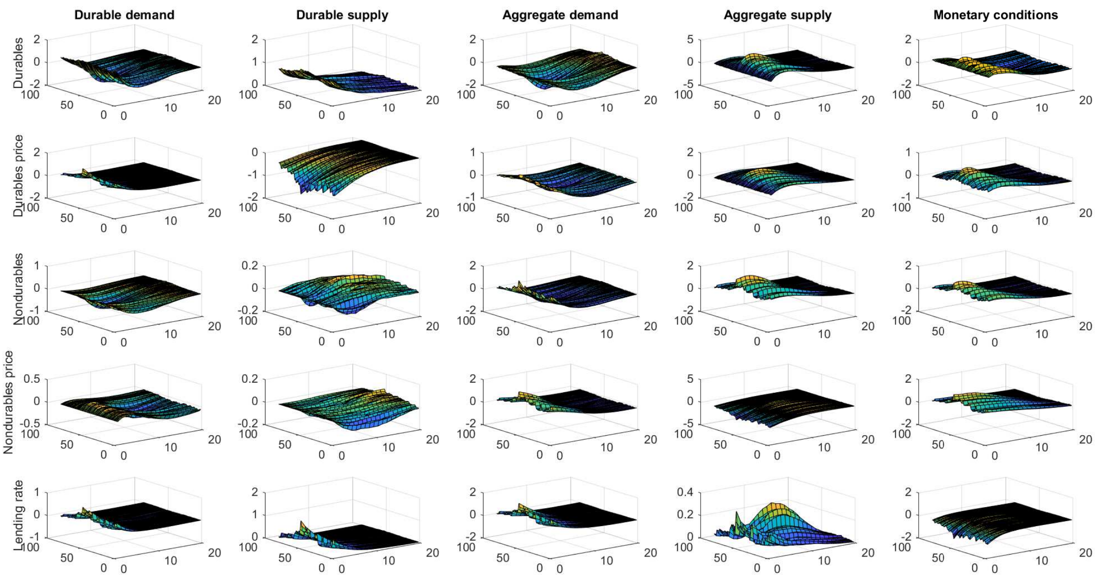
Figure D.19: Spain impulse response functions



Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis), and 2013Q1-2018Q3 (post-crisis recovery).

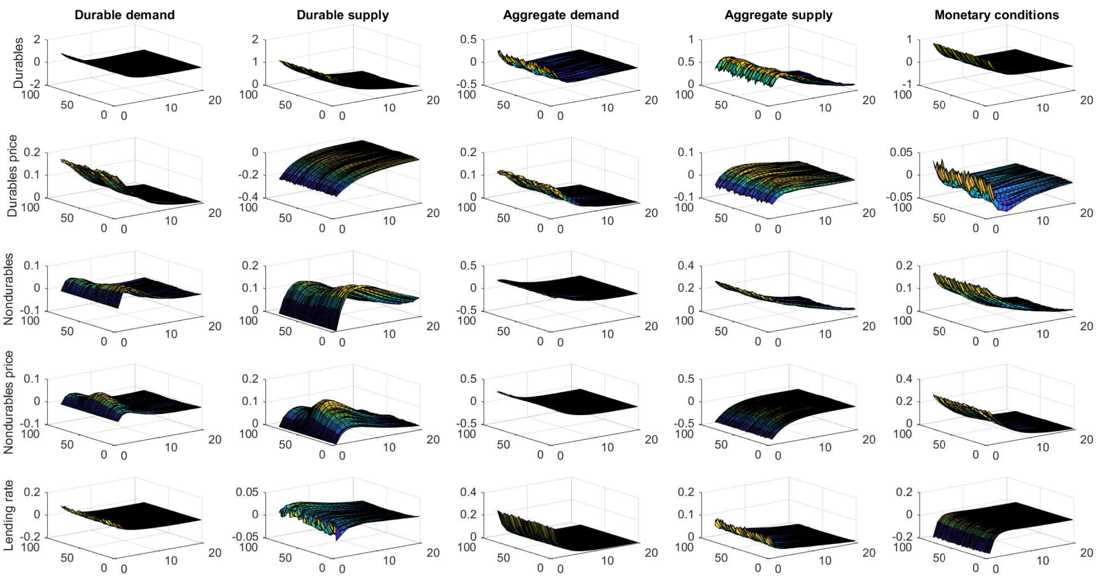
D.7.3 Impulse response functions over time

Figure D.20: Euro area impulse response functions



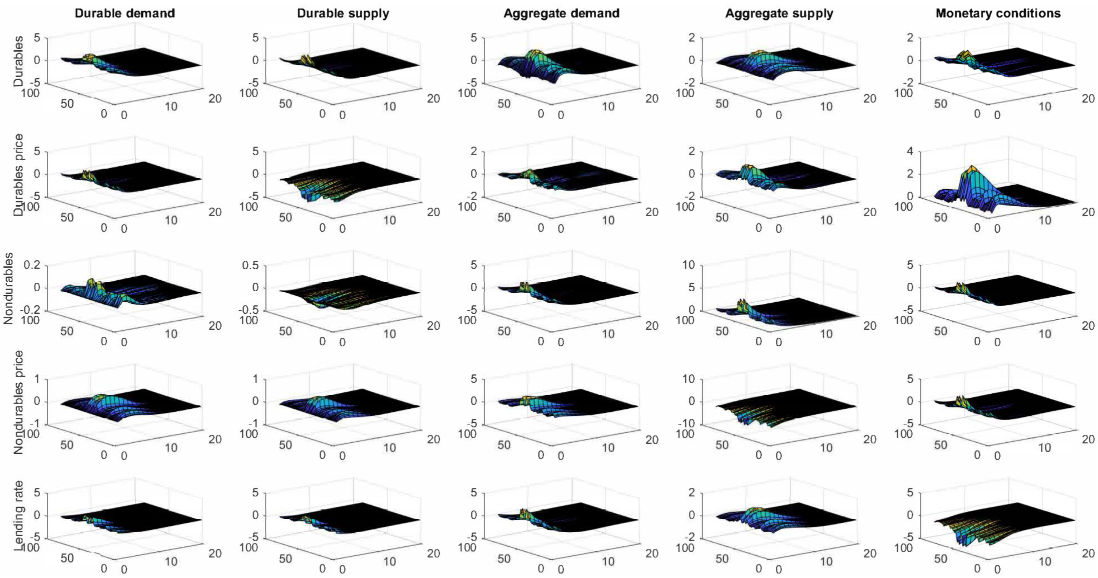
Note: Impulse response functions for each quarter in the sample.

Figure D.21: United States impulse response functions



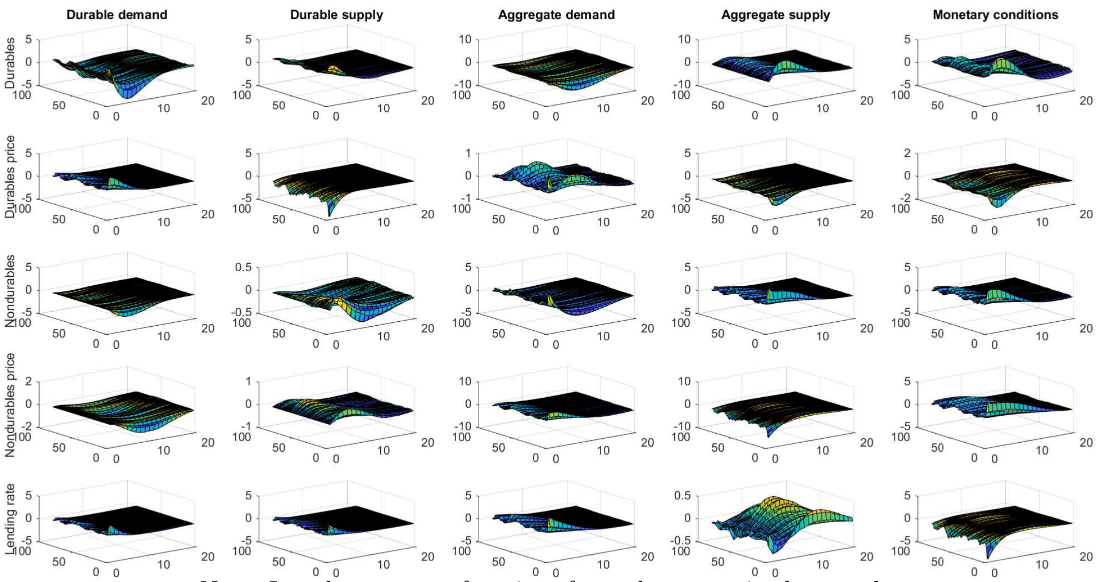
Note: Impulse response functions for each quarter in the sample.

Figure D.22: Germany impulse response functions



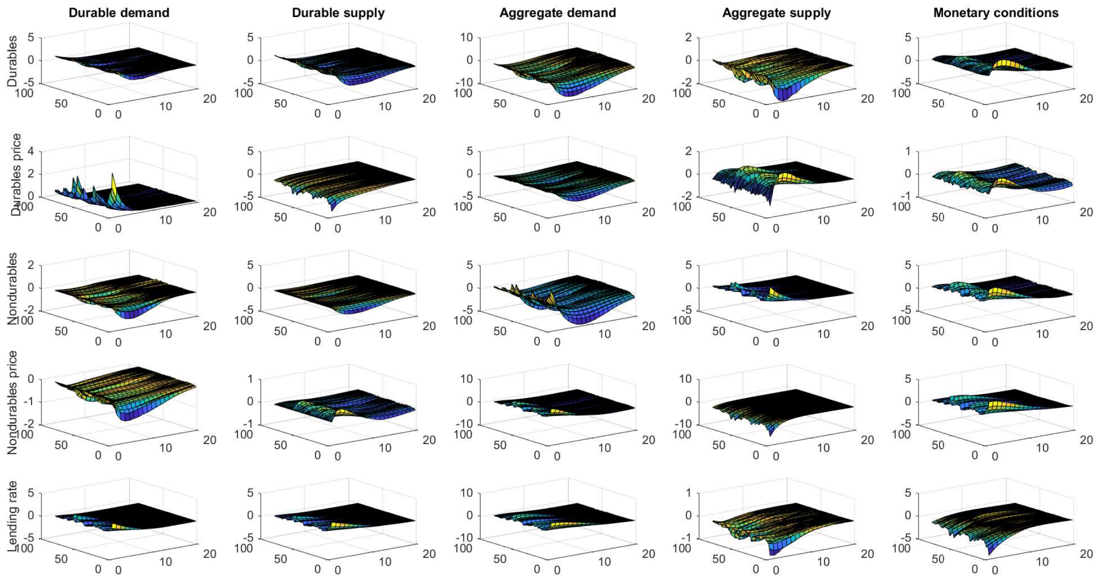
Note: Impulse response functions for each quarter in the sample.

Figure D.23: France impulse response functions



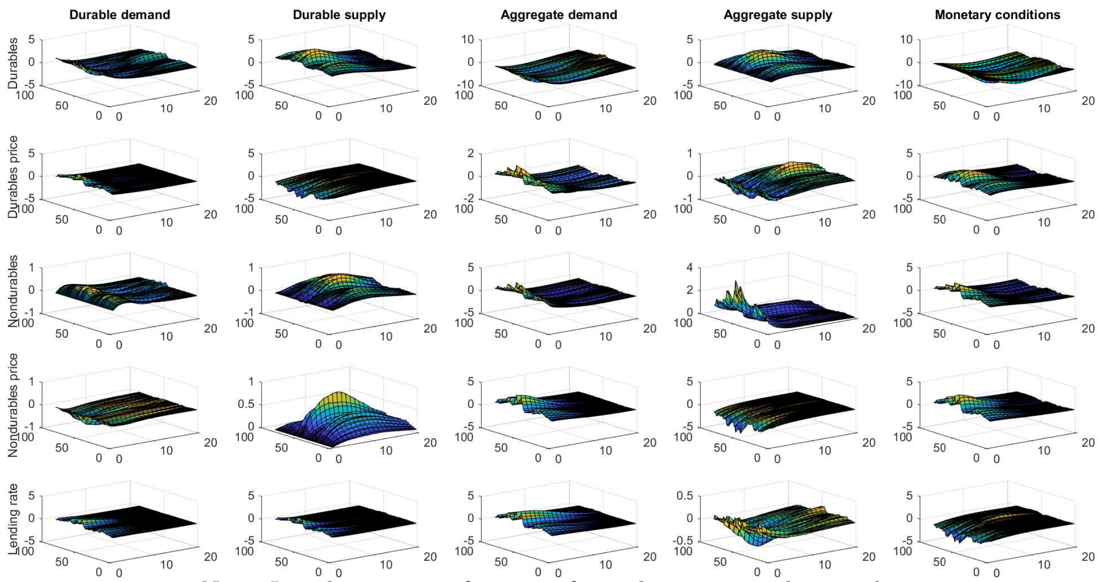
Note: Impulse response functions for each quarter in the sample.

Figure D.24: Italy impulse response functions



Note: Impulse response functions for each quarter in the sample.

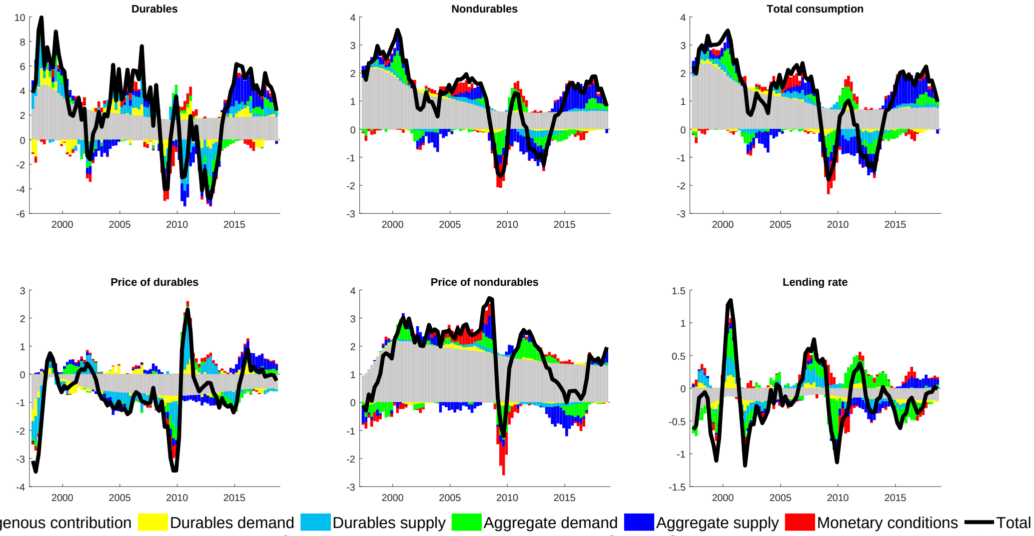
Figure D.25: Spain impulse response functions



Note: Impulse response functions for each quarter in the sample.

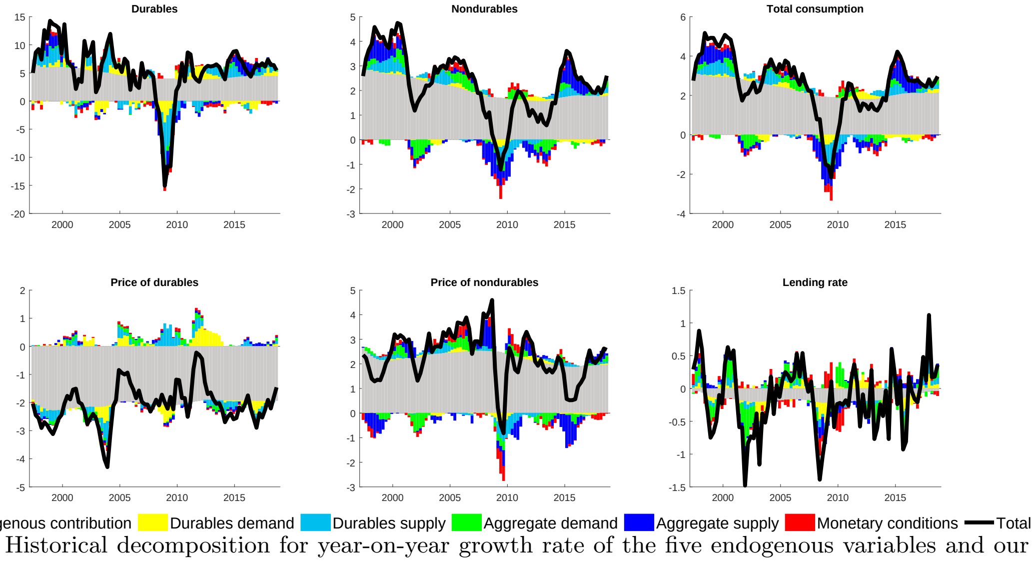
D.7.4 Historical decomposition

Figure D.26: Euro area historical decomposition



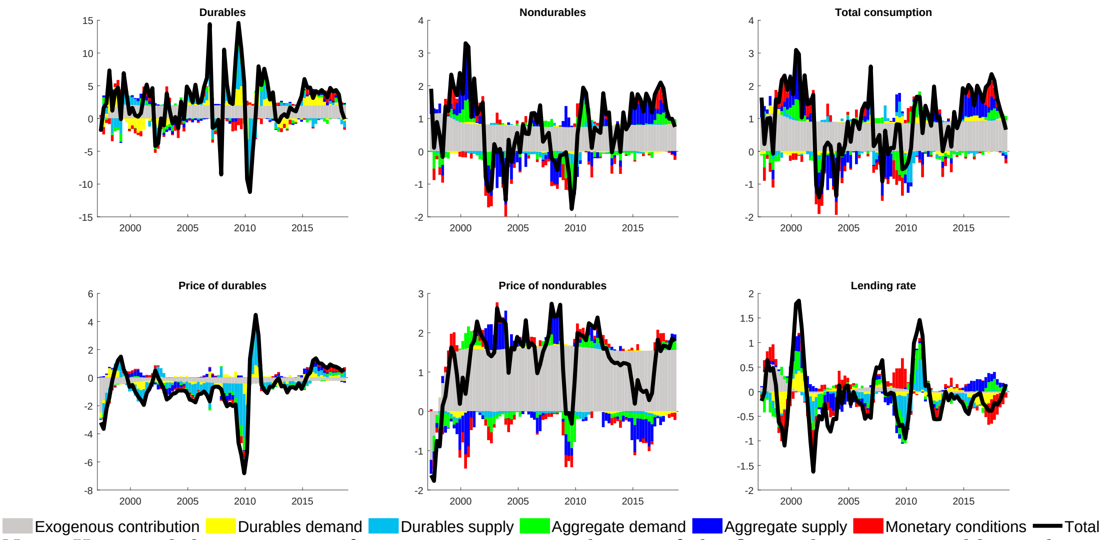
Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

Figure D.27: United States historical decomposition



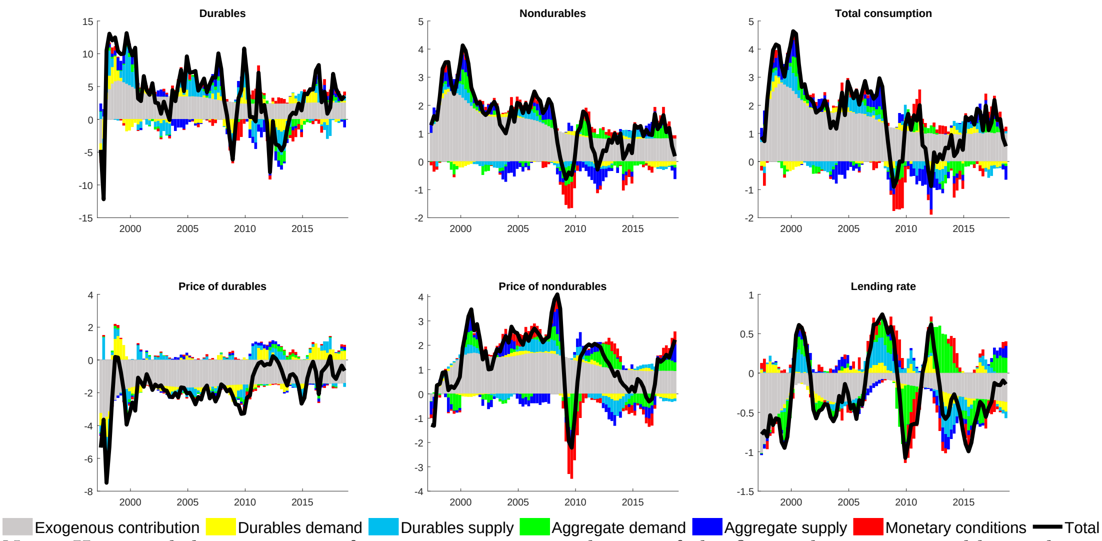
Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

Figure D.28: Germany historical decomposition



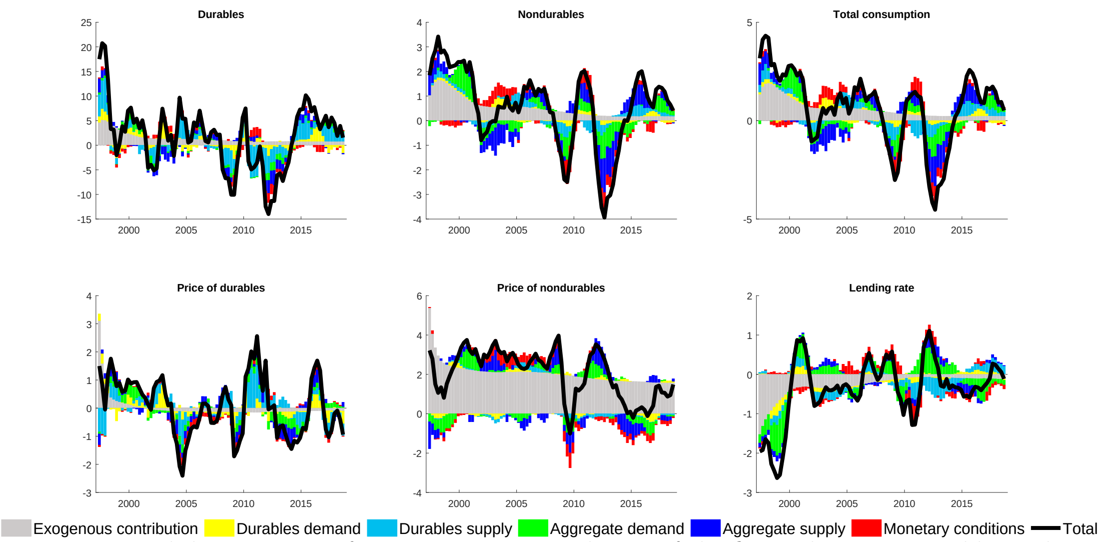
Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

Figure D.29: France historical decomposition



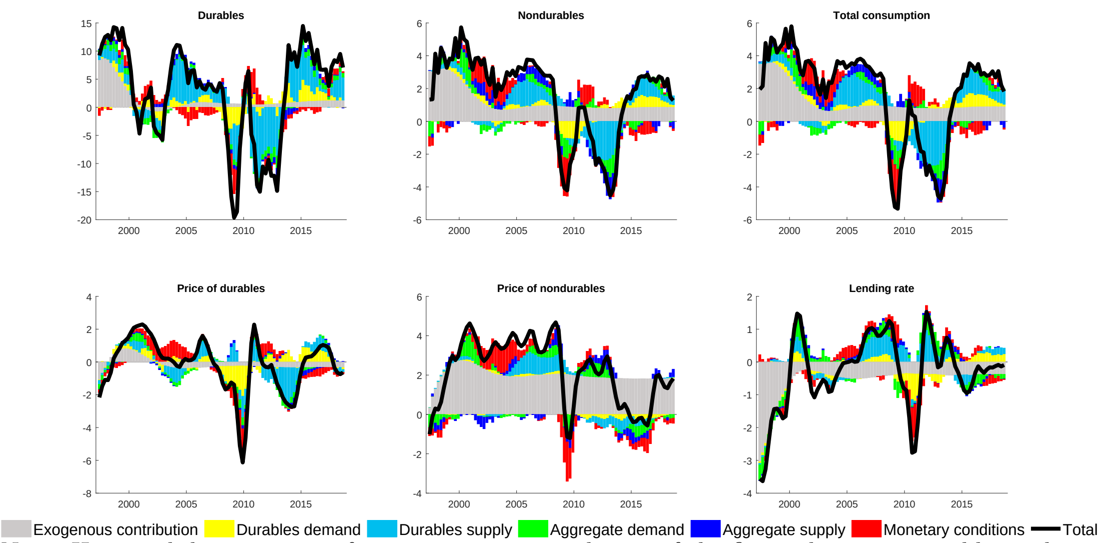
Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

Figure D.30: Italy historical decomposition



Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

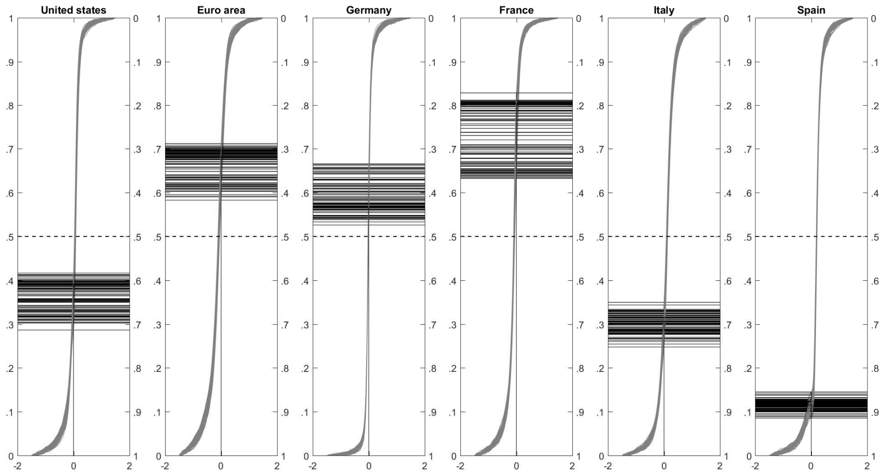
Figure D.31: Spain historical decomposition



Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

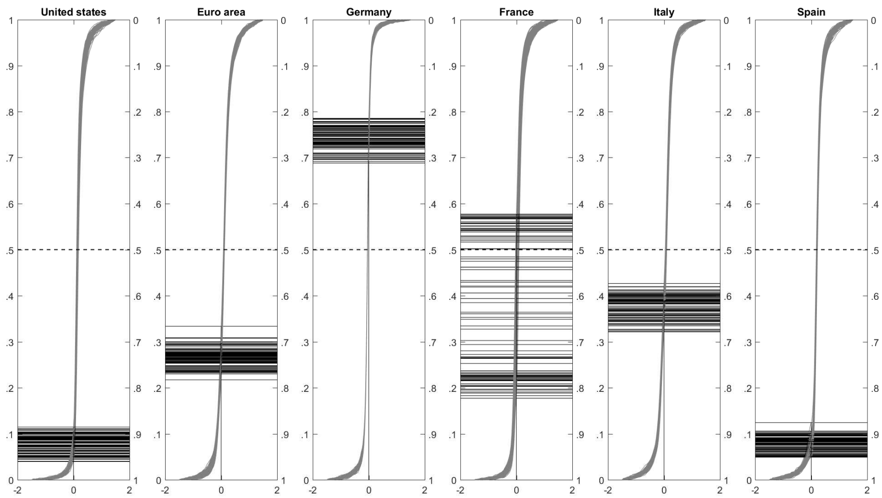
D.7.5 Spillovers: distributions of maxima over time

Figure D.32: Cumulative distribution function of peak spillover for each quarter - demand



Note: Kernel estimation of the cumulative distribution function of peak reaction of nondurable consumption to a durable-specific demand shock, as identified in Section 4.4.2. Each grey line represents the cumulative distribution for a given quarter, generated by $1,500$ extractions via Gibbs sampling. The support is limited to the interval $[-2, 2]$ to cut off outliers and the magnitude of the peak is rescaled by the impact value of the shock for durables to make it comparable across time and countries. Vertical line is on zero, horizontal lines indicate how much of the density function cumulates before (after) zero, on the left (right) scale.

Figure D.33: Cumulative distribution function of peak spillover for each quarter - supply



Note: Kernel estimation of the cumulative distribution function of peak reaction of nondurable consumption to a durable-specific supply shock, as identified in Section 4.4.2. Each grey line represents the cumulative distribution for a given quarter, generated by $1,500$ extractions via Gibbs sampling. The support is limited to the interval $[-2, 2]$ to cut off outliers and the magnitude of the peak is rescaled by the impact value of the shock for durables to make it comparable across time and countries. Vertical line is on zero, horizontal lines indicate how much of the density function cumulates before (after) zero, on the left (right) scale.

D.7.6 Forecast Error Variance Decomposition

Table D.5: Forecast Error Variance Decomposition and share of total variance explained by the model

		Shares of explained variance (sum equals 100)						Total variance
	Horizon\Shock	ε_{DD}	ε_{DS}	ε_{DD+DS}	ε_{AD}	ε_{AS}	ε_{M}	explained
US	1	1.7	2.4	4.1	30.4	47.1	18.3	78.9
	4	3.5	8.3	11.8	30.2	43.3	14.7	76.8
	8	4.4	13.3	17.7	26.3	41.6	14.4	75.9
	20	5.6	15.7	21.3	24.4	39.7	14.6	76.8
EA	1	1.5	2.8	4.3	28.8	41.5	25.4	78.0
	4	2.4	4.4	6.8	16.0	51.5	25.8	80.5
	8	4.1	6.4	10.5	18.3	49.7	21.5	82.7
	20	5.7	8.3	14.0	20.9	43.4	21.7	83.3
DE	1	2.0	2.1	4.1	25.7	45.3	24.9	76.5
	4	2.7	2.8	5.5	26.2	47.1	21.1	77.2
	8	3.1	3.6	6.6	25.7	46.0	21.7	78.2
	20	3.3	3.9	7.1	25.5	45.2	22.2	78.6
FR	1	1.0	1.7	2.7	21.7	41.4	34.2	76.6
	4	2.6	4.4	7.0	14.9	42.6	35.5	77.6
	8	5.0	5.9	10.8	18.2	41.5	29.4	78.4
	20	5.9	7.0	12.9	20.5	37.4	29.2	79.5
IT	1	1.0	1.7	2.7	24.6	39.9	32.7	75.8
	4	4.4	5.1	9.5	17.4	34.9	38.3	76.2
	8	6.9	7.4	14.3	23.2	32.2	30.2	74.1
	20	7.7	8.4	16.1	28.2	28.8	27.0	75.8
ES	1	1.3	1.8	3.0	35.0	27.8	34.2	77.7
	4	6.3	5.8	12.1	24.2	22.3	41.4	79.9
	8	8.8	12.3	21.1	22.7	21.2	35.0	79.1
	20	9.2	15.5	24.6	25.0	20.3	30.0	80.0

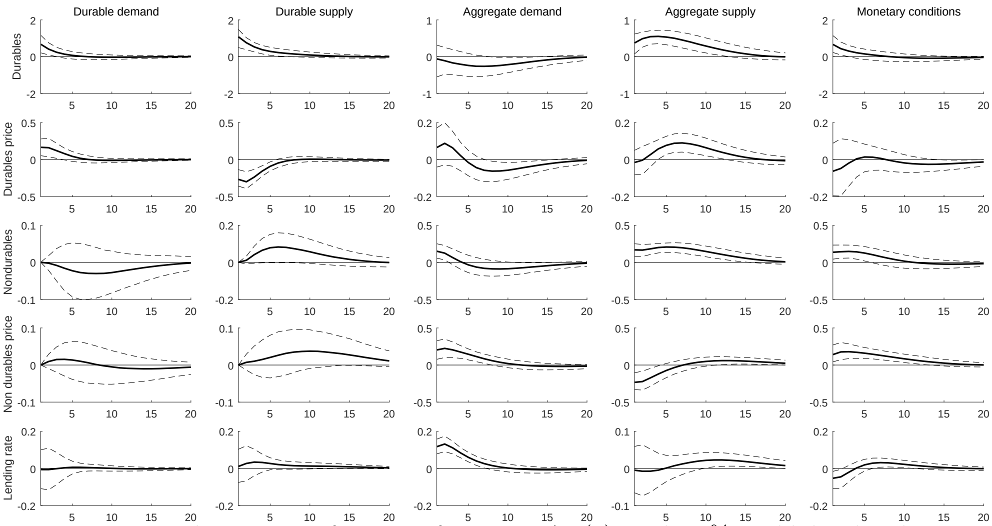
Note: Average percentage of the explained variance of the error made in forecasting total consumption, at horizons of 1, 4, 8, and 20 quarters, due to a specific shock. Last column is the total share of forecast error variance explained.

D.8 Robustness

In this section we present results for some alternative specifications: a BVAR(p) with constant parameters estimated both in levels and in year-on-year differences, where the optimal lag order p is based on the Bayesian Schwarz information criterion as reported in Appendix D.5.1, and a TVP-SVAR(1) as in the baseline, but replacing the nondurable consumption variable with real GDP excluding durable consumption expenditures.

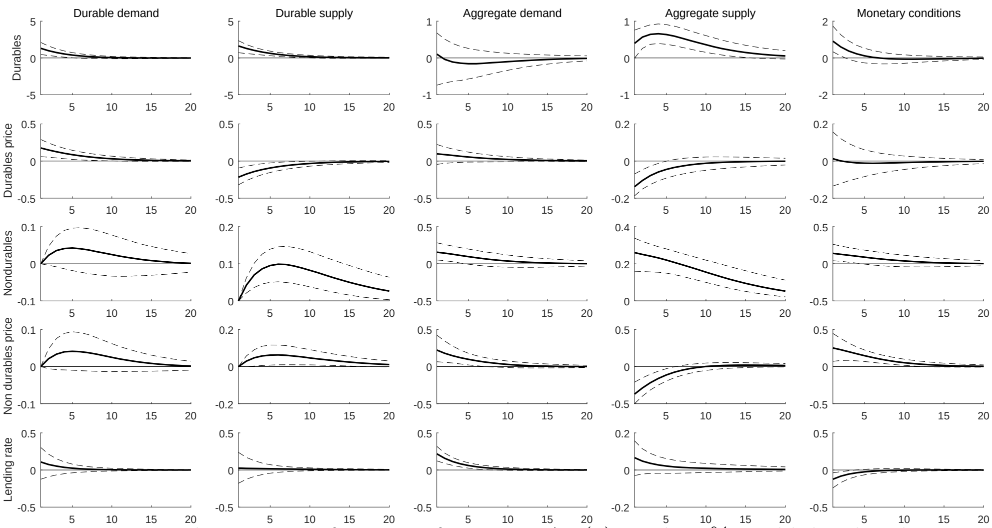
D.8.1 BVAR(p): Specification in year-on-year changes, constant parameters

Figure D.34: Euro area impulse response functions



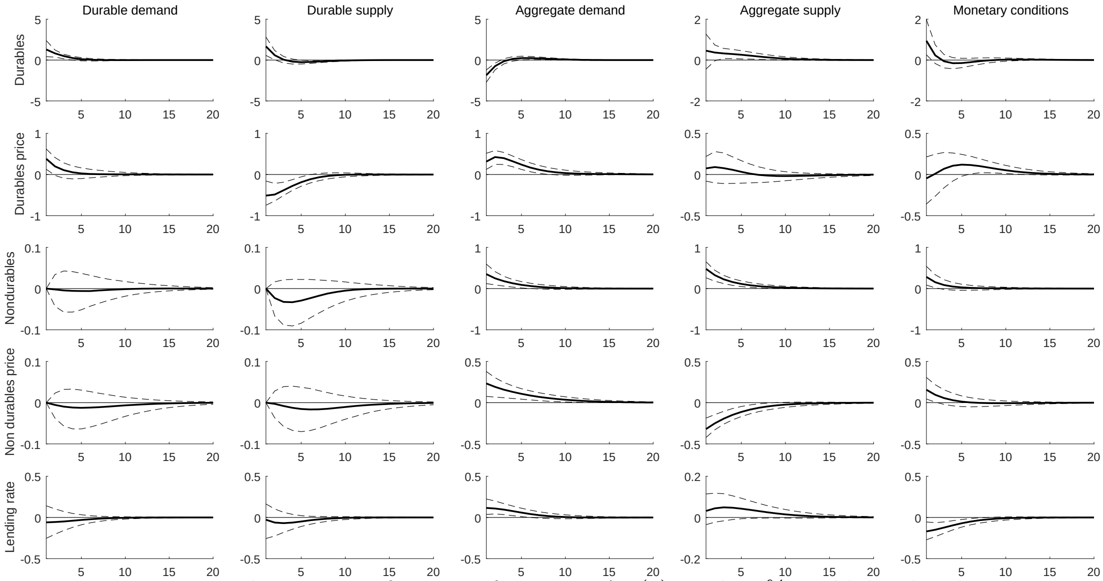
Note: Impulse response functions from a BVAR(2), with 68% credibility bands.

Figure D.35: United States impulse response functions



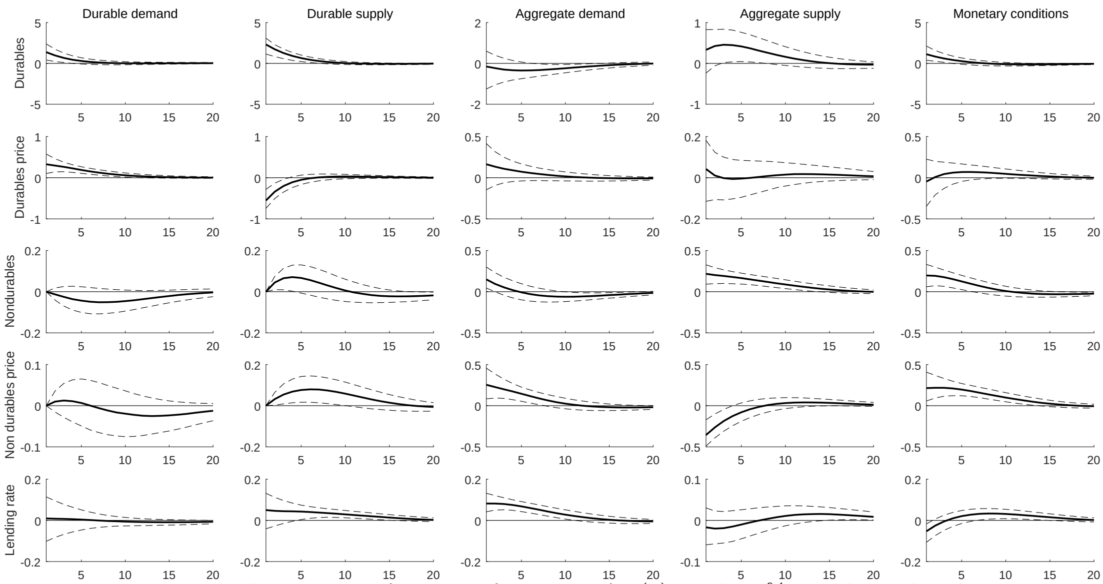
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure D.36: Germany impulse response functions



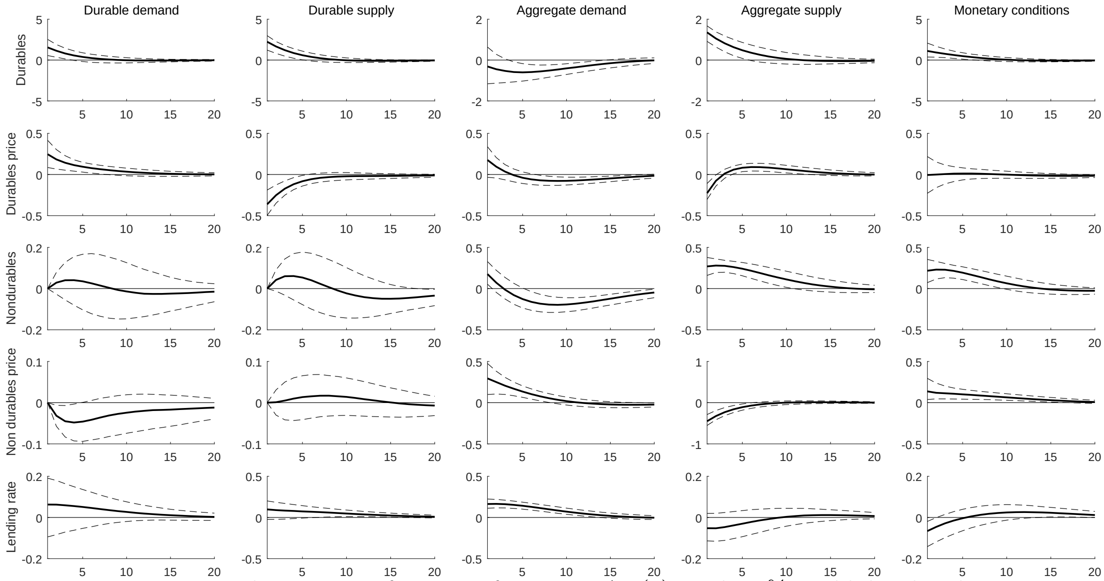
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure D.37: France impulse response functions



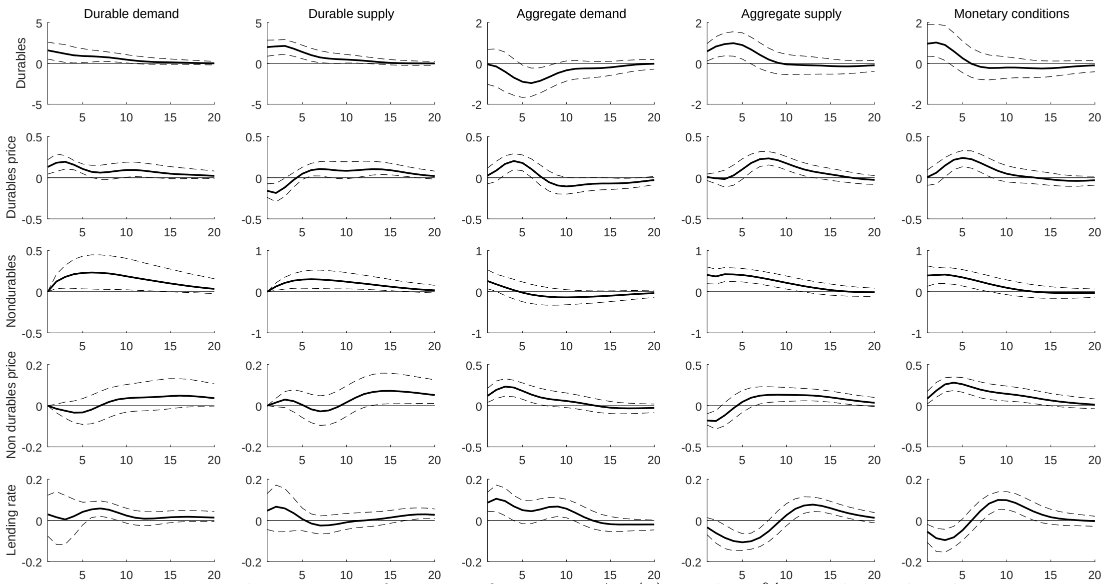
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure D.38: Italy impulse response functions



Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

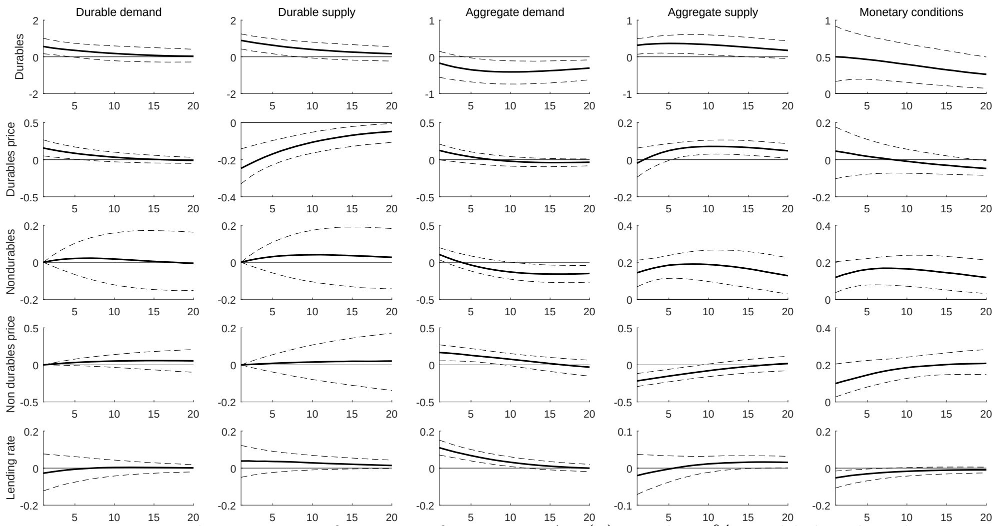
Figure D.39: Spain impulse response functions



Note:Impulse response functions from a BVAR(3), with 68% credibility bands.

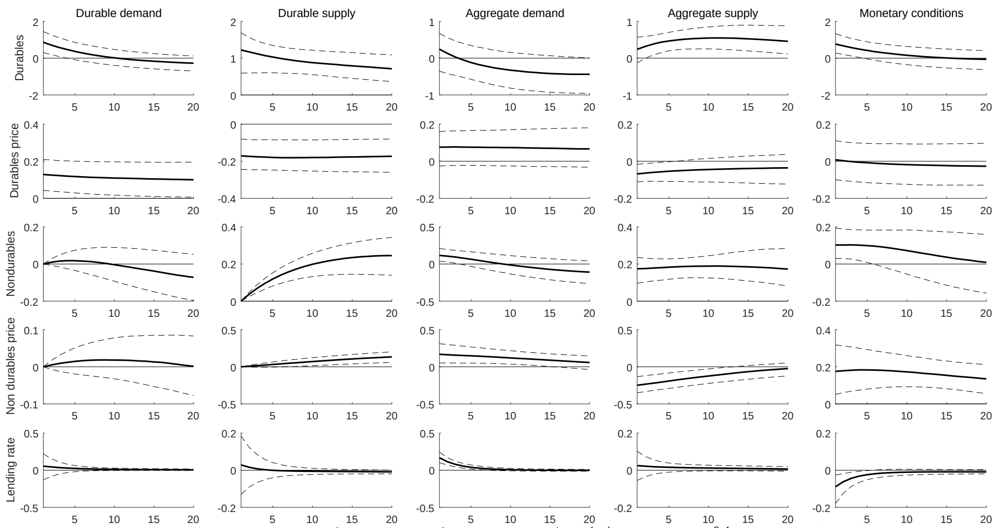
D.8.2 BVAR(p): Specification in levels, constant parameters

Figure D.40: Euro area impulse response functions



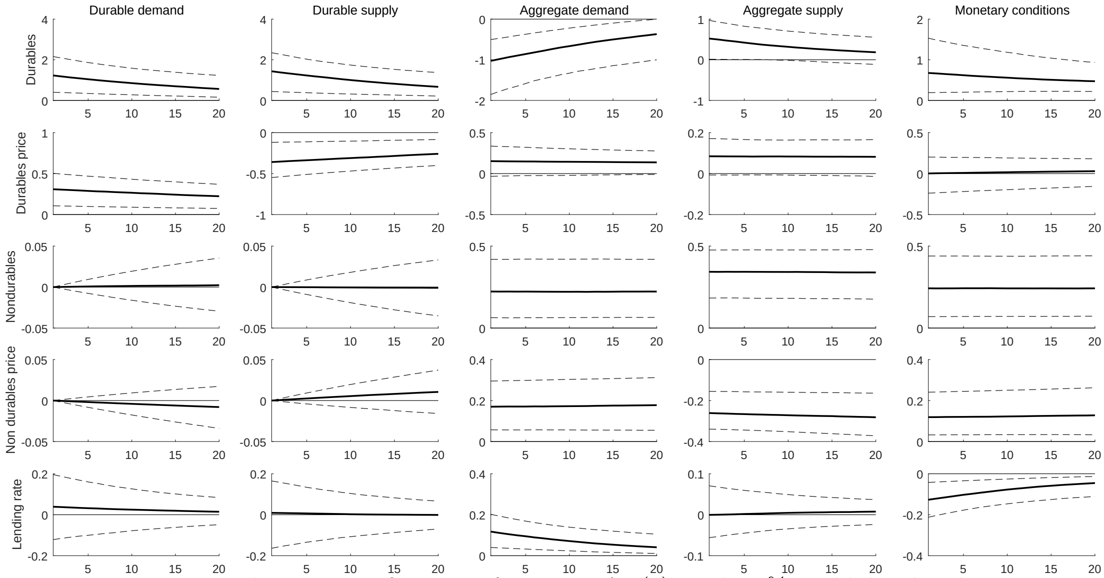
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure D.41: United States impulse response functions



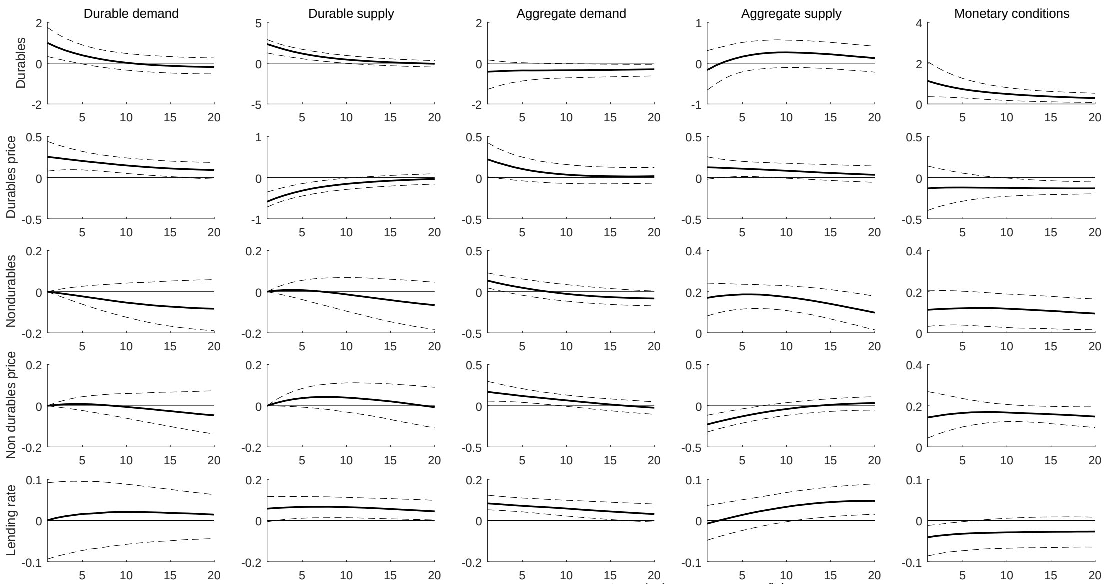
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure D.42: Germany impulse response functions



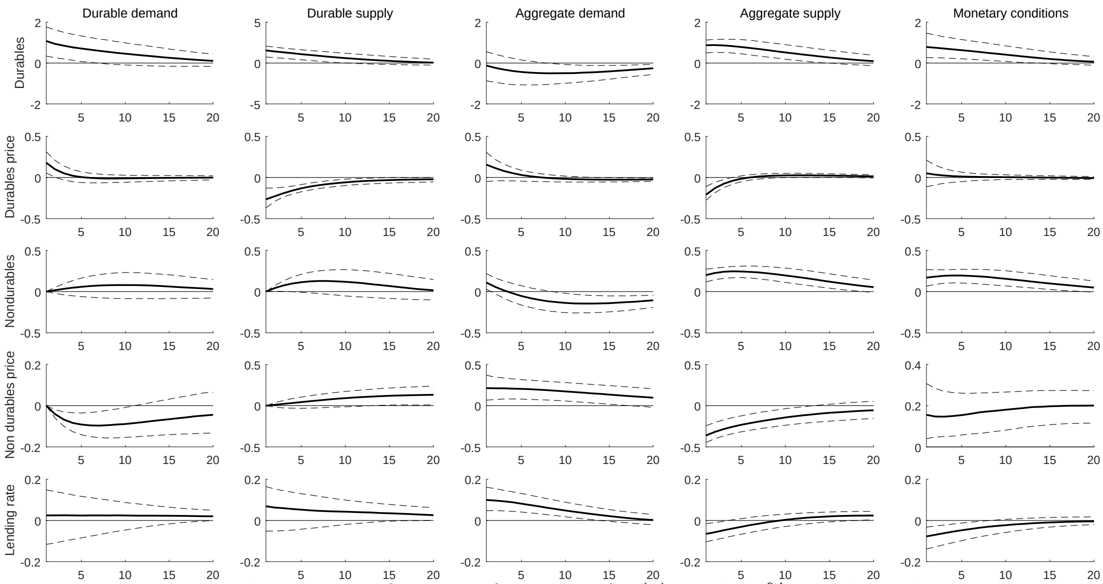
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure D.43: France impulse response functions



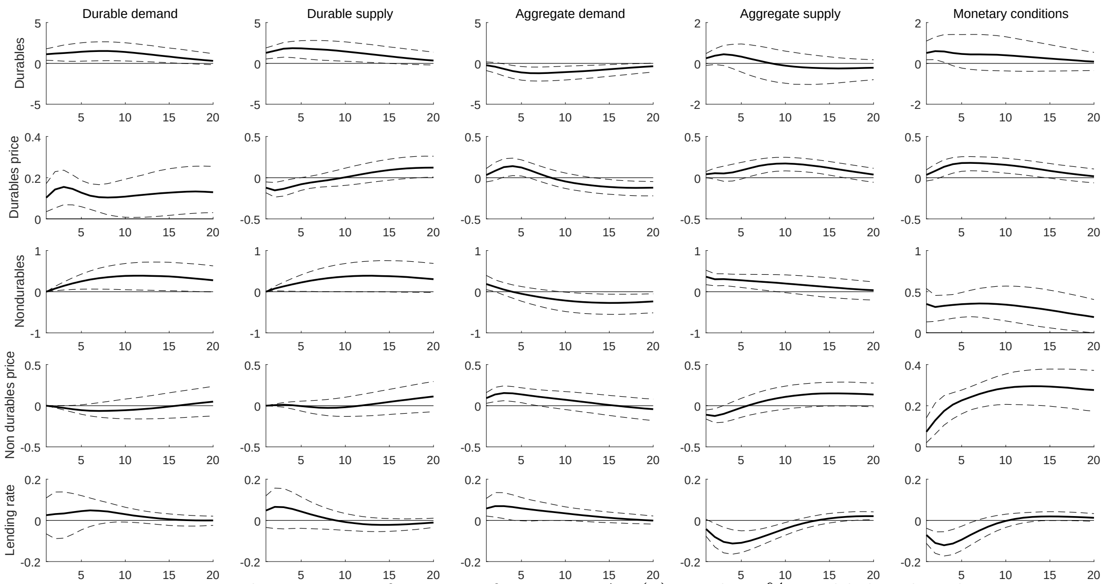
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure D.44: Italy impulse response functions



Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

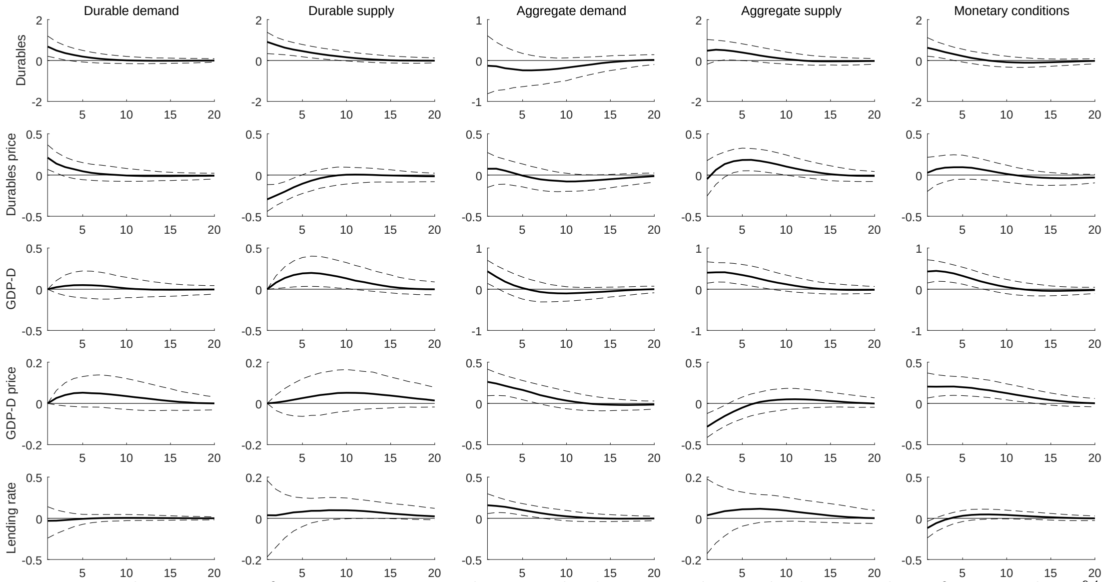
Figure D.45: Spain impulse response functions



Note: Impulse response functions from a BVAR(3), with 68% credibility bands.

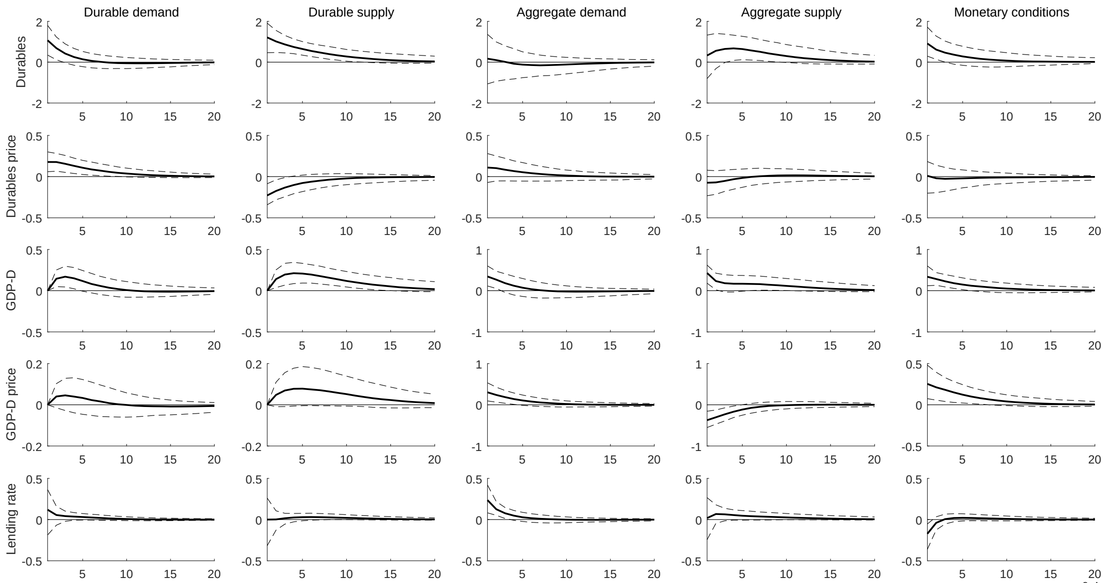
D.8.3 TVP-SVAR(1): Using GDP ex-durables, instead of nondurables

Figure D.46: Euro area impulse response functions



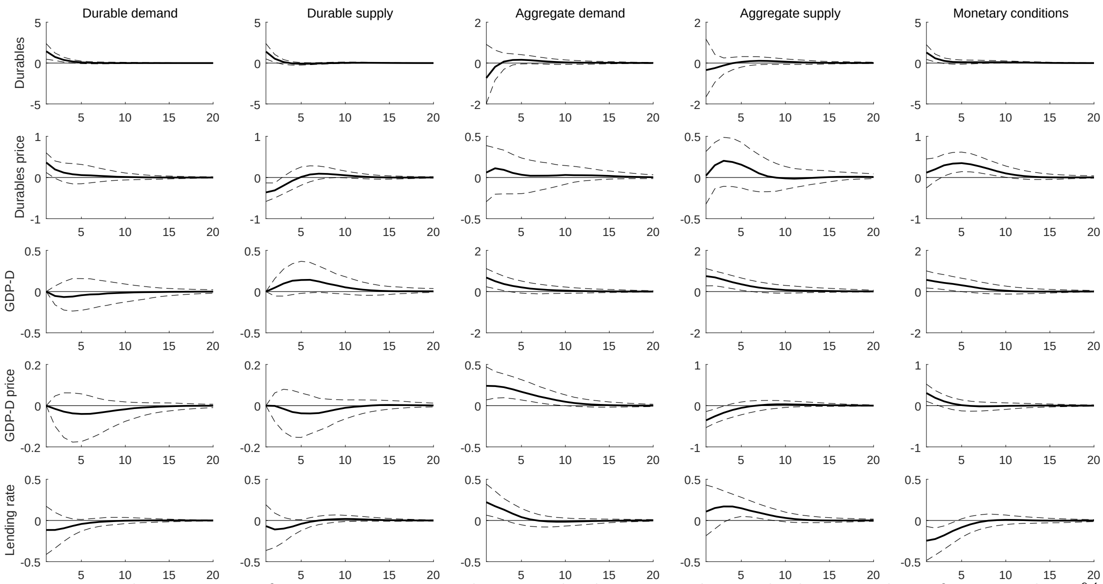
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure D.47: United States impulse response functions



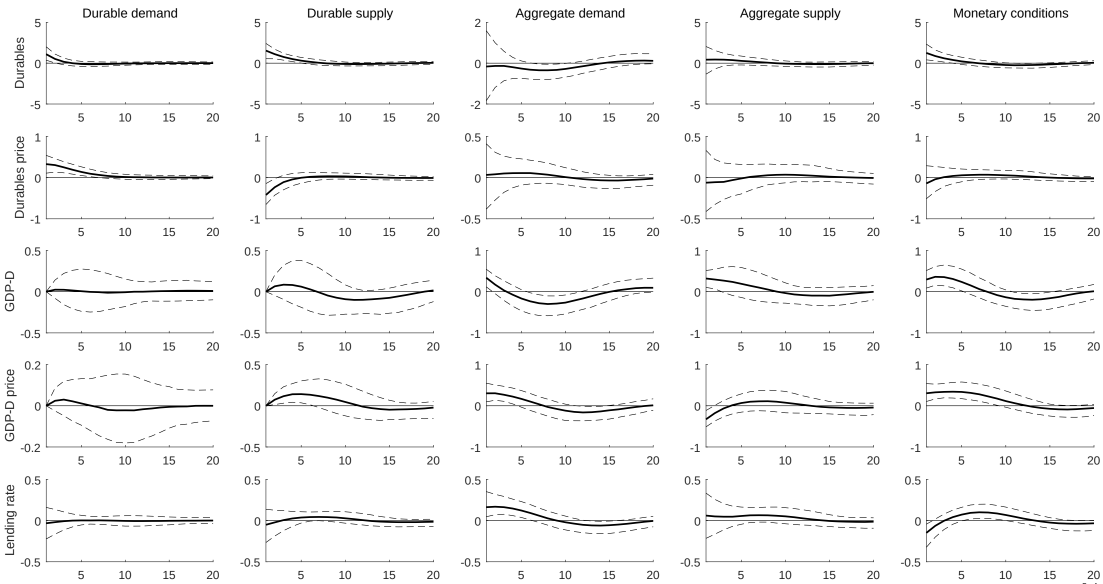
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure D.48: Germany impulse response functions



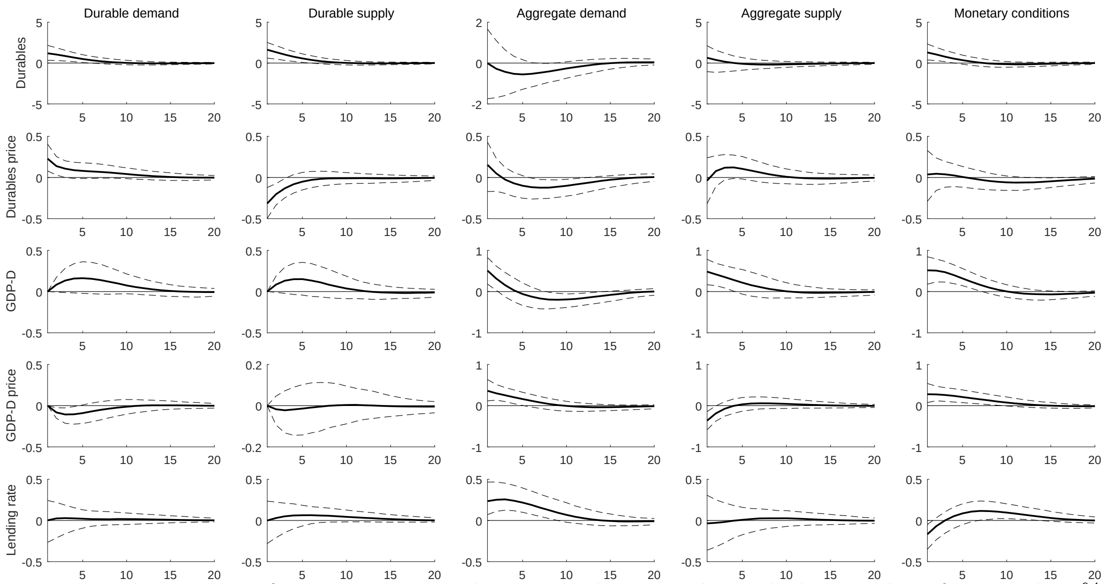
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure D.49: France impulse response functions



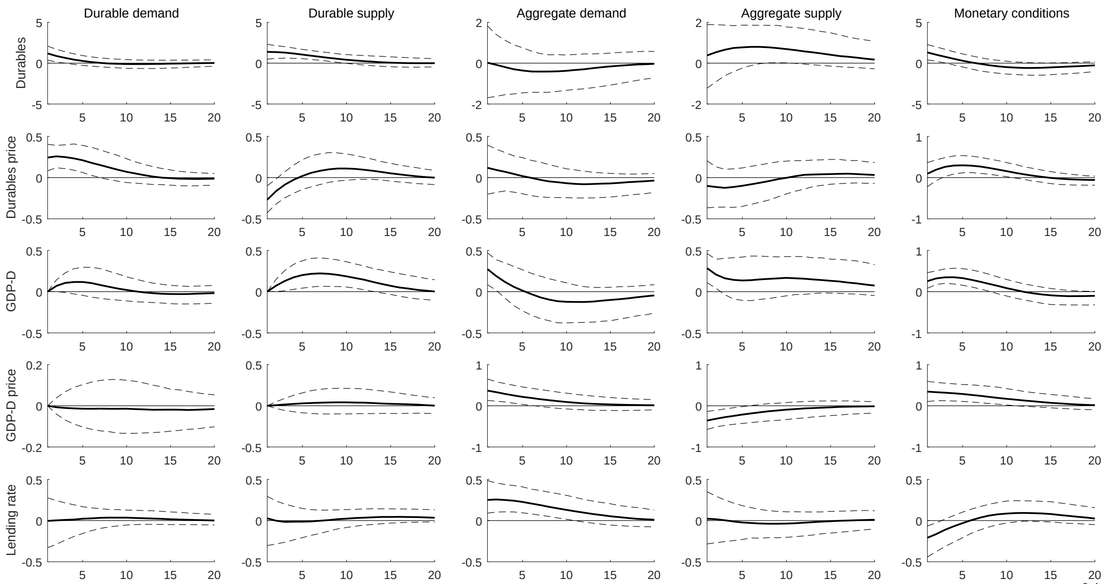
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure D.50: Italy impulse response functions



Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

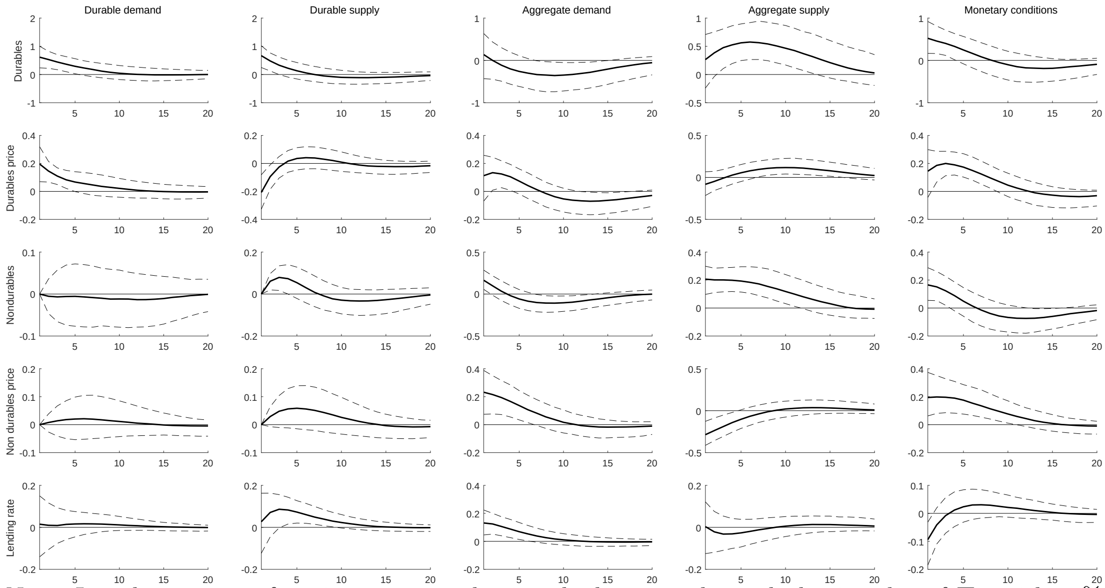
Figure D.51: Spain impulse response functions



Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

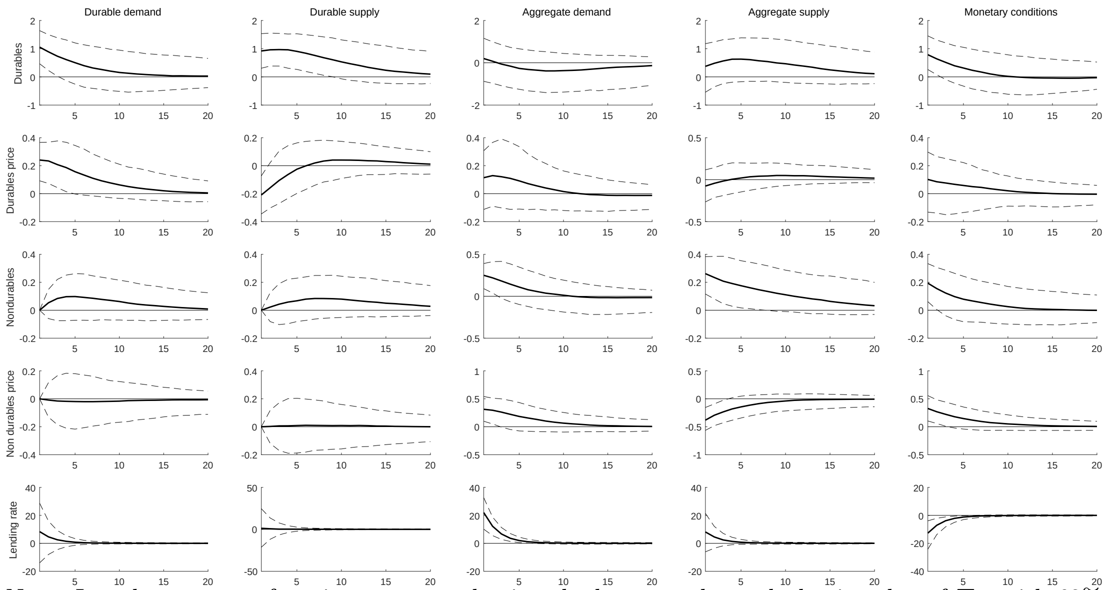
D.8.4 TVP-SVAR(1): Using durables together with housing

Figure D.52: Euro area impulse response functions



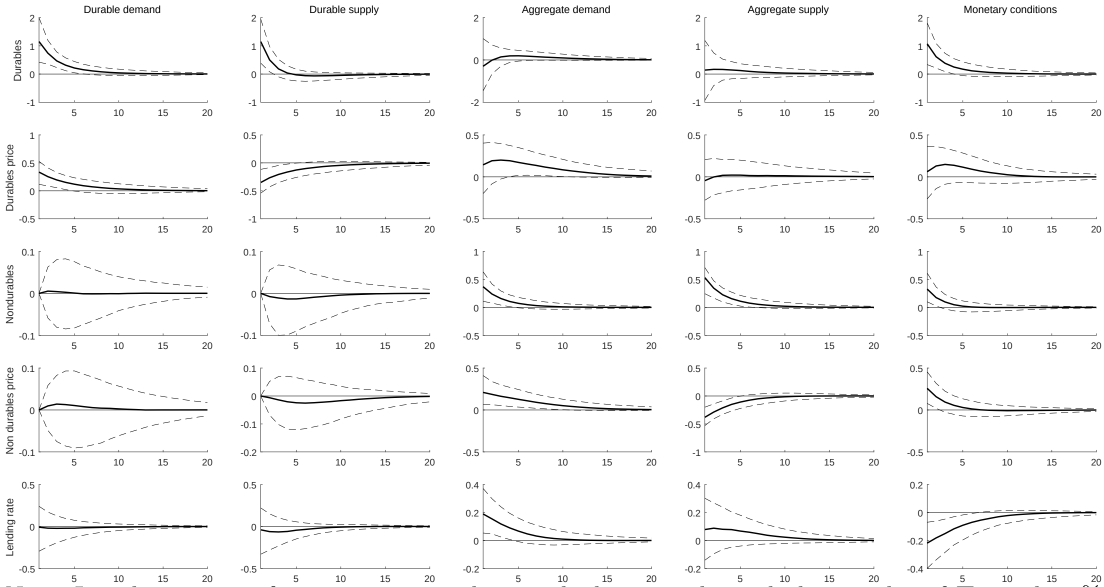
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure D.53: United States impulse response functions



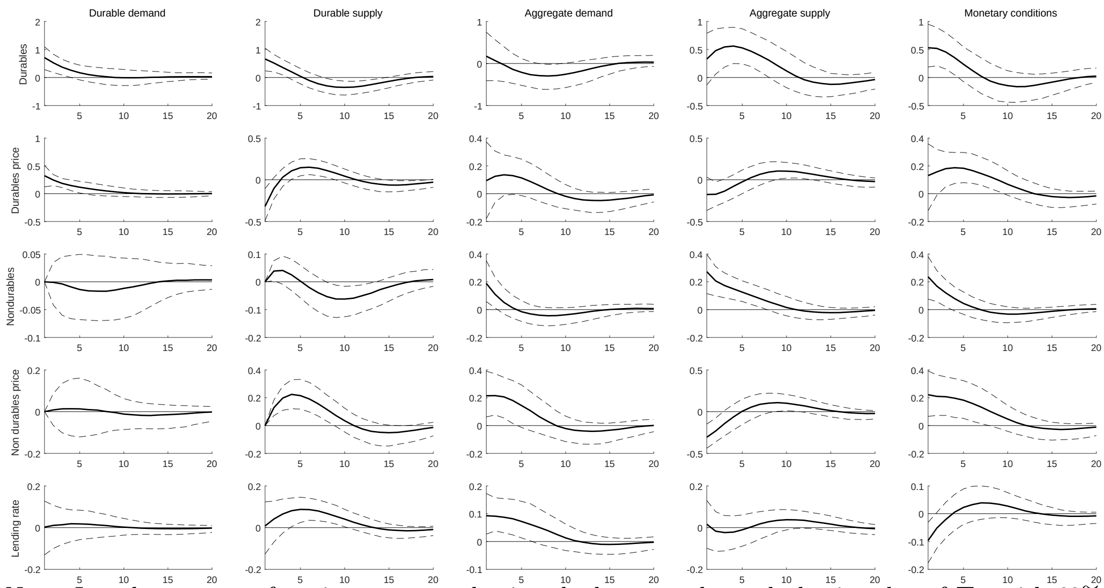
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure D.54: Germany impulse response functions



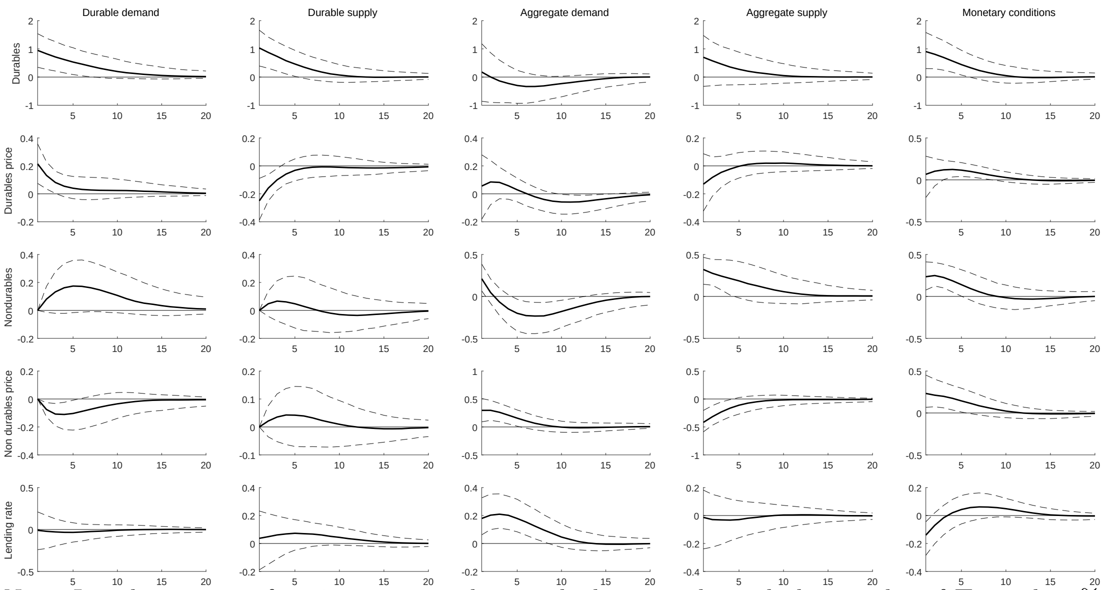
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure D.55: France impulse response functions



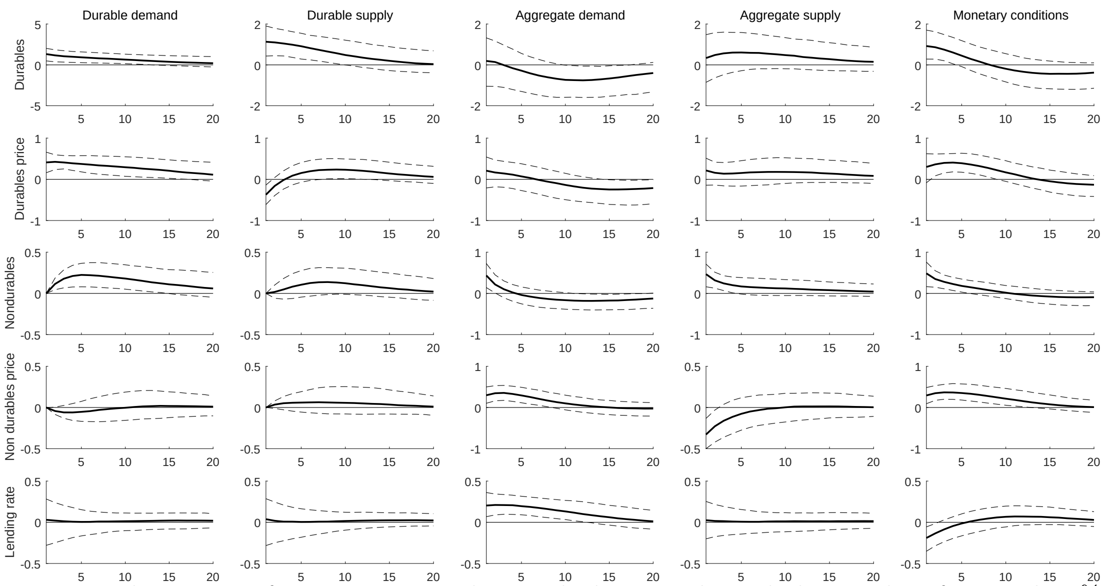
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure D.56: Italy impulse response functions



Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure D.57: Spain impulse response functions



Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.