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André Casalis, Georgi Krustev

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

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Abstract

We study the cyclical dynamics of consumption in the euro area (EA) and the large EA countries by distinguishing durable from 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, a confirmation of an outcome commonly reported for the US; (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 how much households across countries are likely to be liquidity constrained.

Keywords: consumption; durable goods; SVARs; sign restrictions.
JEL Classification: C11, C32, D11, E21, E32

Non-technical summary

We study the cyclical dynamics of consumption in the euro area (EA) and the large EA countries by distinguishing durable from nondurable expenditures. The task of modelling consumption becomes substantially more challenging when one accounts for consumer durables like cars, furniture and electronics. Goods of this type provide utility over multiple periods and at the same time they depreciate. Moreover, they are frequently financed with credit and may be subject to adjustment costs. These specific characteristics make expenditures on consumer durables exposed to credit conditions and, despite their small share in total consumption, lead them to account for a disproportionately large fraction of overall economic fluctuations.

Few studies in the literature distinguish between durable and nondurable consumption. In particular, due to data limitations, model-based analyses exploring the factors that drive durable goods expenditures in the euro area, and how they relate to the rest of consumption, are virtually non-existent at the time of writing. The main contribution of this paper is to zoom in on this important component of demand.

We start by setting up a theoretical model of durable and nondurable consumption featuring nonlinear dynamics and occasionally binding borrowing constraints. One interesting prediction from the theoretical model is that liquidity constrained agents will experience spillovers from durables-specific shocks to nondurable consumption. The results stress the need to model durable and nondurable consumption separately and in a time-contingent manner, in order to allow for asynchronous and nonlinear adjustments in the presence of borrowing constraints.

Following these insights, in a second step we employ a time-varying parameter structural vector autoregressive model (TVP-SVAR) that allows for non-linearities. We estimate it over the period from 1997Q1 to 2018Q3 to study durable and non-durable consumption in the US, the euro area and the four largest EA countries – Germany, France, Italy and Spain. We construct our euro area sample as a bottom-up aggregation of country-level data for the 19 individual member states. Our identification strategy is based on a combination of zero and sign restrictions and distinguishes aggregate, from durable-specific, supply and demand shocks, accounting for monetary and credit conditions (defined in a way to encompass together the monetary policy and the idiosyncratic country-level credit environment).

Our main findings can be summarised as follows: (i) durables react faster and more strongly than nondurables after monetary shocks in the euro area and in the largest euro area countries, a confirmation of 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 how much 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.

1 Introduction

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

Expenditures on consumer durables – like cars, furniture and electronics – make up a small share of total consumption, but account for a disproportionately large fraction of its overall fluctuation. Durable goods feature specific characteristics which complicate substantially the task of a modeller when they enter into a consumption function. First, a durable good provides utility over multiple periods and (similarly to capital) is subject to depreciation. This allows consumers to postpone purchases of durables in times of economic duress, while still benefiting from the service flow coming from the accumulated stock, and 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 expenditures to monetary shocks is larger than the one of 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 expenditures, 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 nonlinear dynamics and occasionally binding liquidity constraints.[1] When they bind, consumers are not fully able to smooth consumption and the path of durables becomes informative about future expenditures on nondurables. This result, derived in Chah et al. (1995), represents a deviation from the standard random walk model of consumption by Hall (1978) and provides a strong justification to model separately these two components of consumption. 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 non-durable 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.

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

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 assets 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 indeed 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) about 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 affecting in particular the behaviour of low income households.

Following a shock to monetary conditions (defined such that they encompass together 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 by 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 a key role of monetary condition factors 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 played a key role behind the deep contraction in consumption, alongside aggregate demand factors. The heterogeneous evolution of consumption carried on 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 paper is organised as follows. Section 2 sketches a theoretical model of consumption with durable and nondurable expenditures and shows their simulated path under occasionally binding liquidity constraints. Section 3 describes the data and shows some stylised facts. Section 4 discusses our empirical framework, identification strategy, and results. The heterogeneity of the results for the biggest four euro area countries is examined in Section 5. Section 6 concludes.

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

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

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

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

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

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

$$U_d(t) = P^d \left[U_c(t) - \frac{1-\delta}{1+r} E_t U_c(t+1) \right] - \varphi P^d \mu_t \tag{2}$$

with supplementary slackness conditions

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

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

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

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

$$U_c(t) = \underbrace{\frac{R}{R-(1-\delta)}}_{\Omega^{-1}} \frac{1}{P^d} U_d(t) + \frac{\varphi R - (1-\delta)}{R-(1-\delta)} \mu_t \tag{5}$$

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. 1) it follows that, under perfect foresight, the path of nondurables is smoothed over time. Eq. 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 such 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, in contrast to the random walk model of Hall (1978) derived under the standard life cycle-permanent income hypothesis with rational expectations and thus recovering the argument of Mankiw (1982).

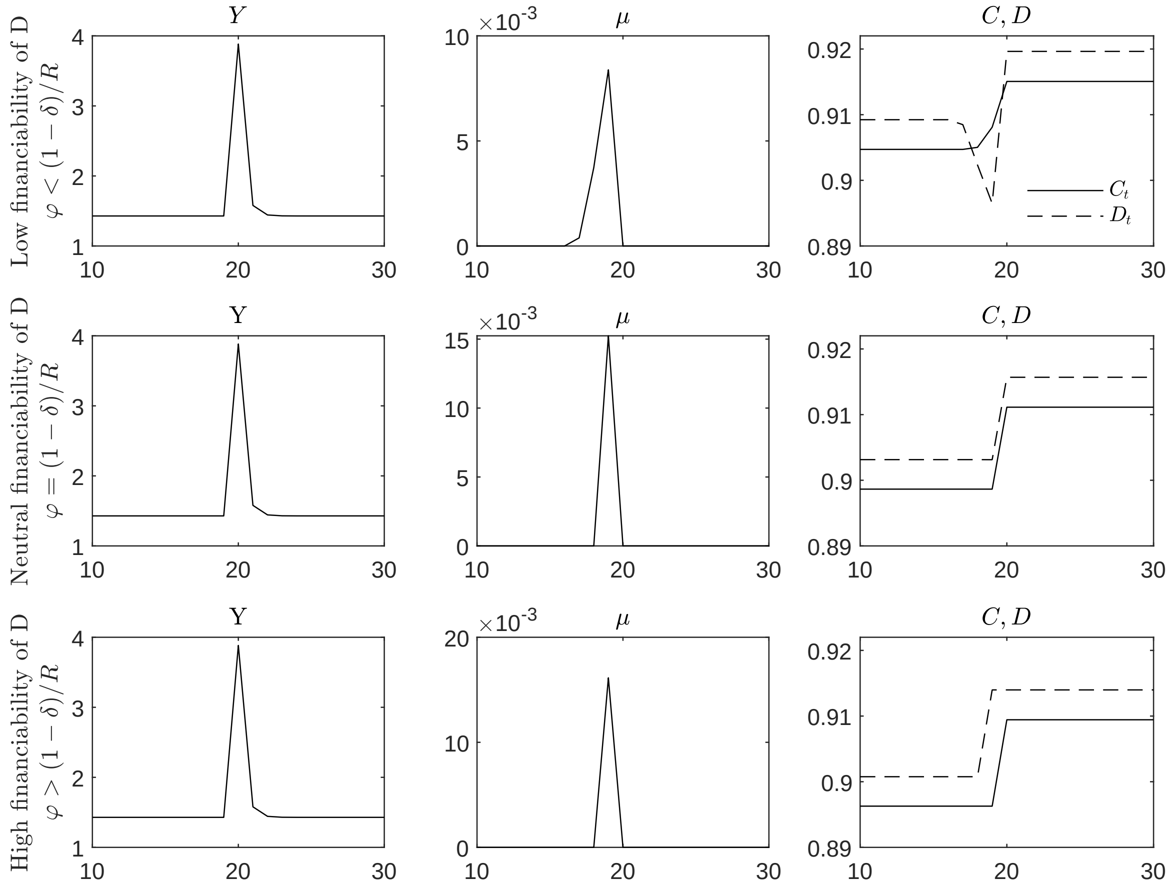
Figure 1 shows simulations under perfect foresight of a known increase in income occurring in period $t = 20$ under the assumption that $\gamma = 0.6$ in the utility function. As the predicted variation in income makes the liquidity constraint binding one or more periods ahead of the time when it occurs, 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, just 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 separately from the rest to allow for asynchronous adjustment in the presence of borrowing constraints. The occasionally binding constraints induce nonlinearities that may be further reinforced by changes in the degree of financiability of durables φ over time. Overall, the

[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.

results hint that it would be wise to model the relationship between durable and nondurable consumption in a time-contingent manner.

Figure 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.

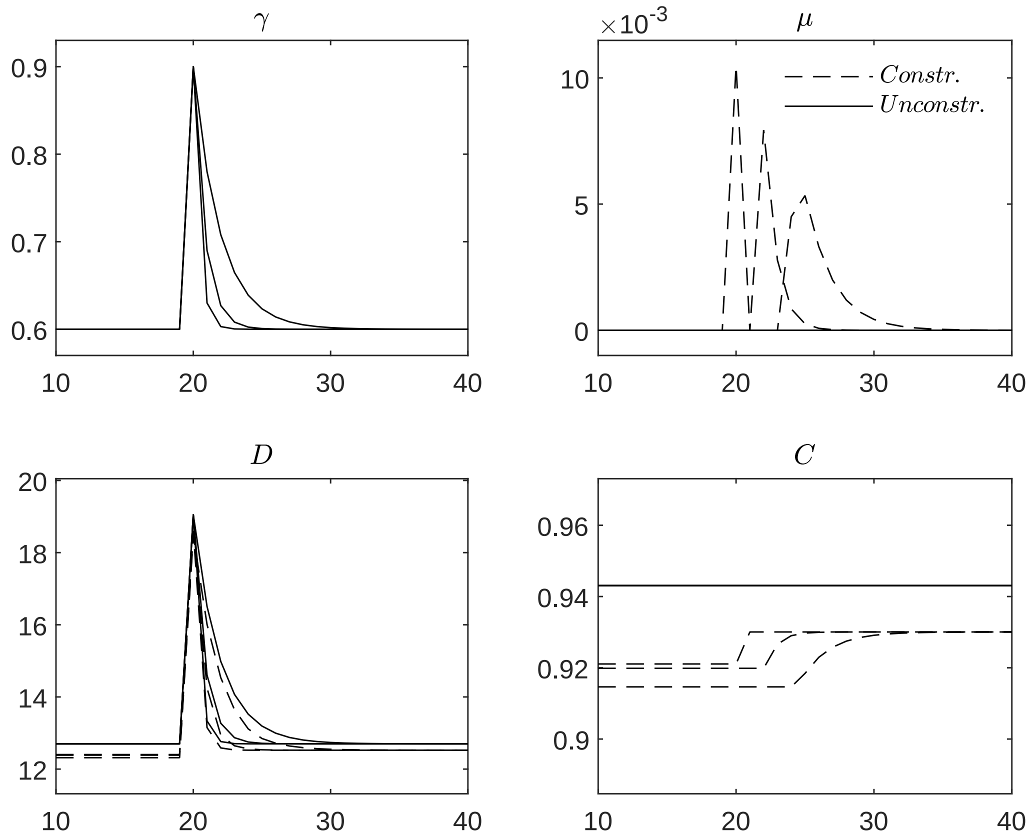
In a next step (described in Appendix A) we extend our model to allow for time variation in relative prices, preferences and the interest rate.[4] Simulation results from shocks to these variables show important lagged interactions from durable to nondurable consumption. Figure 2 illustrates the case 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]

Appendix B 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 noting 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.

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

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

Figure 2: Effects from a temporary increase in the preference parameter γ for durables



Note: The figures display a temporary increase in the preference paramater 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.

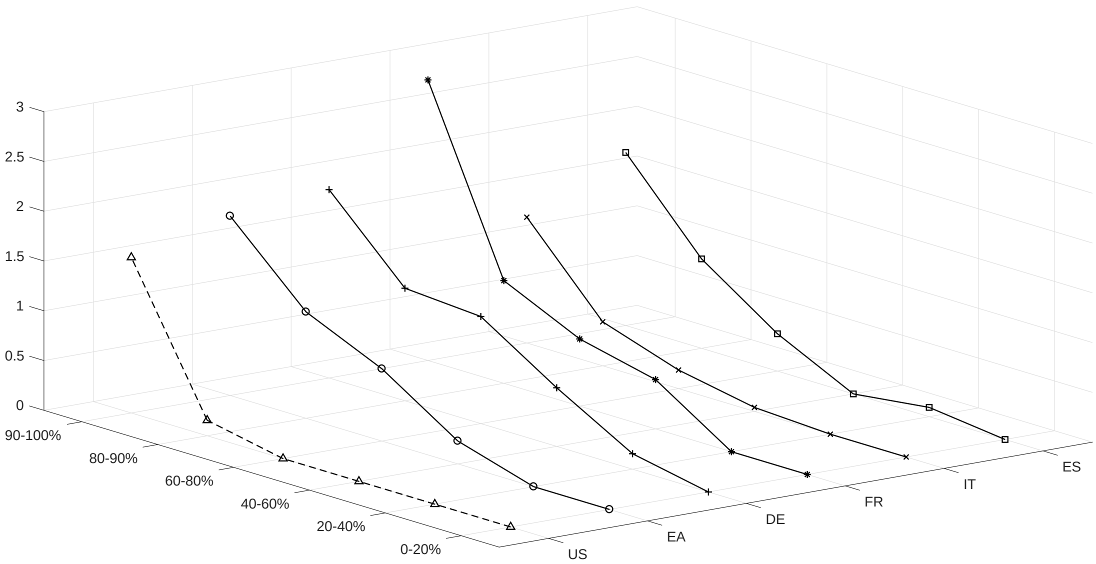
In our framework, occasionally binding constraints – expected to affect only households with little liquid wealth – in conjunction with the assumption of separability of durables from non-durables in the utility function, are the key ingredients to generate lagged spillovers from durable-specific shocks to nondurable consumption. This mechanism differs from the one in Bernanke (1985) where durables and nondurables are nonseparable in the utility function and furthermore there are adjustment costs. In that case, durables and nondurables are either complements or substitutes depending on the parameterisation and moreover spillovers, if they occur, are contemporaneous.

Before proceeding, two caveats are worthwhile mentioning. First, 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 – 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 second 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), José Luengo-Prado (2006).

Here, we limit ourselves to note 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 3 show that a larger fraction of housheholds 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 5 indeed support this intuition.

Figure 3: Distribution of financial assets across households by income quintiles



Source: Authors' 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.

[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).

3 Data and stylised facts

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

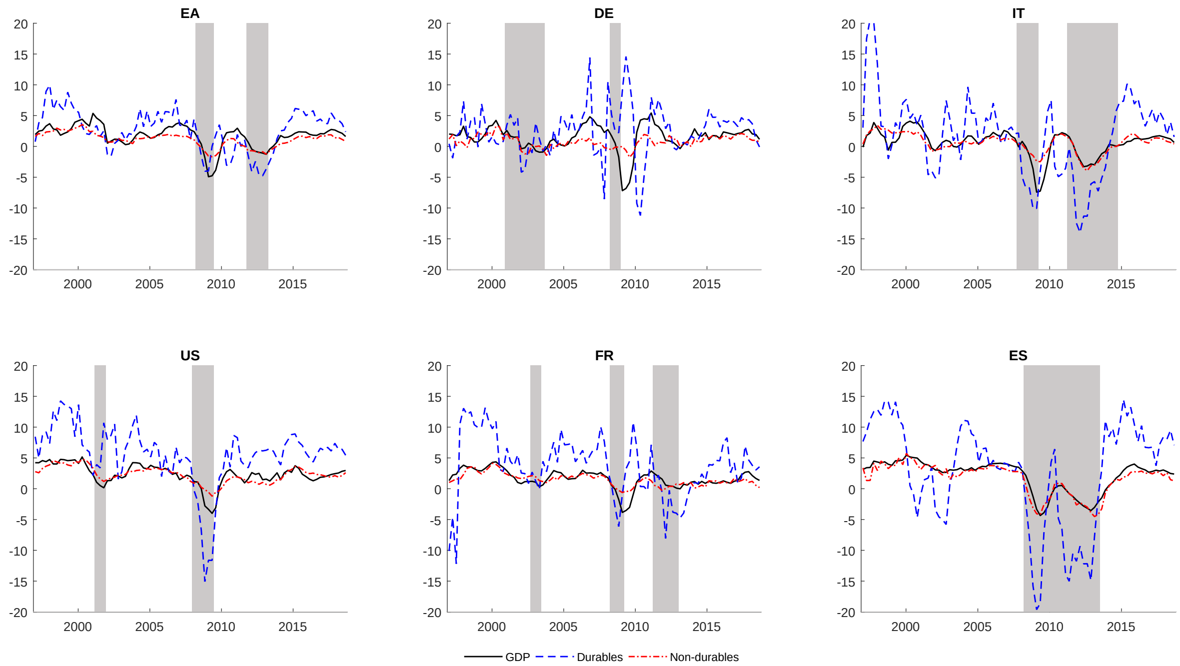
3.1 Data

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 expenditures 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 as 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 C.

3.2 Stylised facts

In our empirical application, we use real expenditures 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 shows, the annual growth rates of nondurable consumption and GDP are highly correlated.[7]

Figure 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).

[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.

One feature evident in Figure 4 is the volatility of durables compared to GDP. In particular, expenditures on durables tend to grow faster during periods of economic expansion, and contract more strongly during recessions. Table 1 provides a breakdown of consumption components in terms of GDP shares and shares of GDP variance explained. Durable expenditures are able to explain a more than proportional fraction of the variance of GDP, further justifying the interest in treating durables as a separate variable in the model.[8]

Table 1: Cyclical properties of consumption and its components

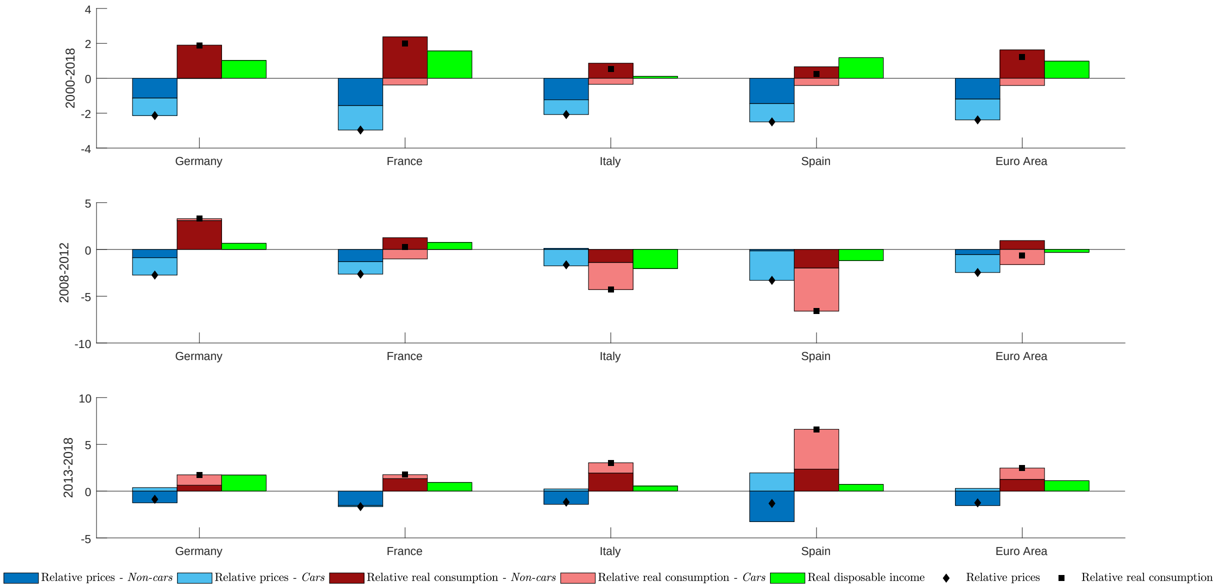
	US		**EA**		**DE**		**FR**		**IT**		**ES**	
	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$	%Y	$\%\sigma^2$
Consumption	67.4	54.7	55.4	33.7	52.6	9.7	53.2	34.0	60.8	43.9	59.6	62.6
Dur	7.8	13.1	5.2	5.1	6.1	-2.6	4.8	5.8	5.2	8.8	4.3	9.0
Cars	*36.2*	*5.3*	*42.2*	*1.4*	*42.2*	*-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 percentage of durables.

Figure 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 expenditures in total consumption. However, such 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 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.

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

Figure 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 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 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 E.2 generally reject the null hypothesis of parameter stability and support the use of a time-varying parameter model.

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 expenditures 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 E.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 up 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 F.

The baseline model can then be written as in Equation 6:

$$\mathbf{A}_0 X_t = \mathbf{A}_{i,t}(L) X_{t-1} + \varepsilon_t \tag{6}$$

$\mathbf{A}_0$ 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

$$\eta_t = \mathbf{A}_0^{-1} \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \mathbf{\Sigma}_t) \tag{7}$$

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

$$X_t = \beta_t \overline{X}_{t-1} + \eta_t \tag{8}$$

where

$$\overline{X}_{t-1} = \mathbf{I}_n \otimes (L) X_{t-1} \tag{9}$$

and

$$\beta_t = \text{vec}(\mathbf{B}_t), \qquad \mathbf{B}_t = \begin{pmatrix} \mathbf{A}_0^{-1}\mathbf{A}_{1,t} \\ \mathbf{A}_0^{-1}\mathbf{A}_{2,t} \\ \vdots \\ \mathbf{A}_0^{-1}\mathbf{A}_{p,t} \end{pmatrix} \tag{10}$$

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

$$\beta_t = \beta_{t-1} + \nu_t, \qquad \nu_t \sim \mathcal{N}(0, \mathbf{\Omega}) \tag{11}$$

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 generalize to the multivariate case the stochastic volatility model of Jacquier et al. (1994). Specifically, we assume that $\mathbf{\Sigma_t}$ can be written as

$$\mathbf{\Sigma}_t = \mathbf{Z}^{-1} \mathbf{H}_t \mathbf{Z}^{-1\prime} \tag{12}$$

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

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:

$$\mathbf{H}_t = \begin{pmatrix} \lambda_1 h_{1t} & 0 & 0 \\ 0 & \lambda_2 h_{2t} & 0 \\ 0 & 0 & \lambda_3 h_{3t} \end{pmatrix}, \qquad \mathbf{Z} = \begin{pmatrix} 1 & 0 & 0 \\ \zeta_{21} & 1 & 0 \\ \zeta_{31} & \zeta_{32} & 1 \end{pmatrix} \tag{13}$$

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:

$$\ln h_{it} = \ln h_{it-1} + \upsilon_{it}, \qquad \upsilon_{it} \sim \mathcal{N}(0, \mathbf{\Phi}_i) \tag{14}$$

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

$$\mathbf{H}_t = \begin{pmatrix} \lambda_1 \exp(h_{1t}) & 0 & 0 \\ 0 & \lambda_2 \exp(h_{2t}) & 0 \\ 0 & 0 & \lambda_3 \exp(h_{3t}) \end{pmatrix} \tag{15}$$

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

$$h_{it} = \gamma h_{it-1} + \upsilon_{it}, \qquad \upsilon_{it} \sim \mathcal{N}(0, \mathbf{\Phi}_i) \tag{16}$$

4.2 Identification strategy

We use a combination of sign and zero restrictions à la Arias et al. (2018), as reported in Table 2.

Table 2: Sign restrictions

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

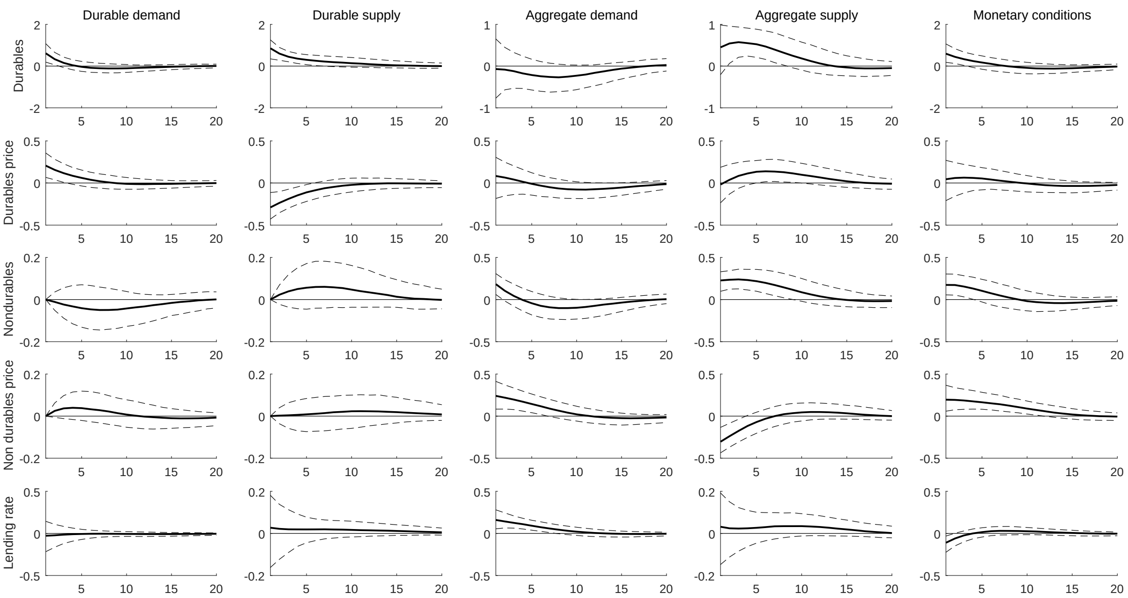
Our modelling strategy rests on two main choices: to model separately durables and nondurables, and to use nondurables as a proxy for GDP. We include in the model both durable and nondurable consumption expenditures so that we are able to aggregate them to total consumption.

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 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 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.

4.3 Results

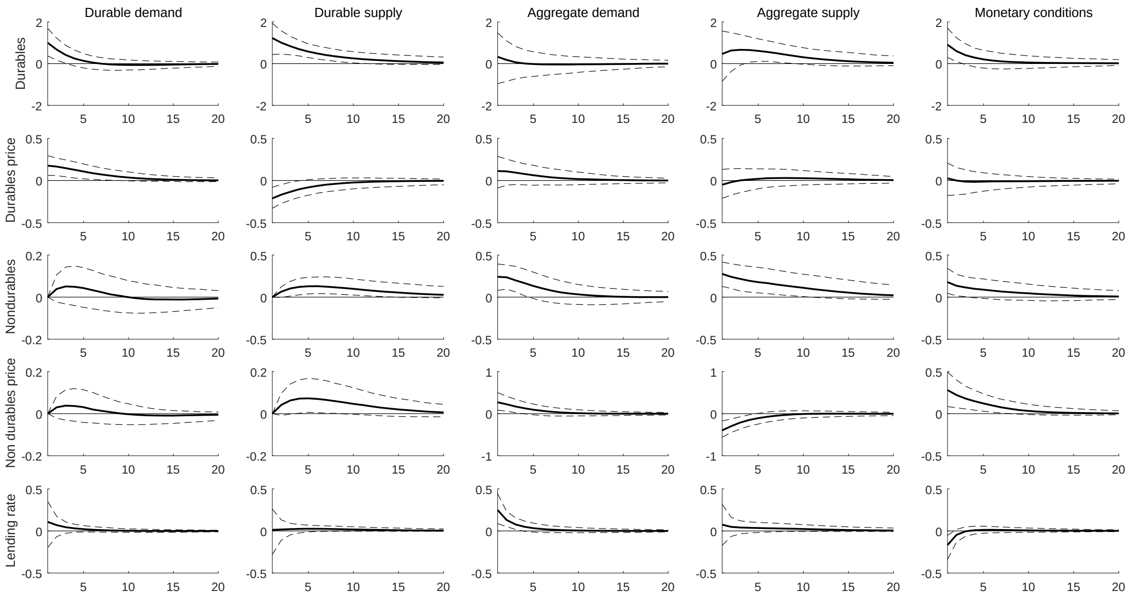
In what follows we present a selection of results. Impulse response functions displayed in Figures 6 and 7 represent the expected response of the model to the identified structural shocks and are therefore computed using the long term, homoskedastic value for the variance-covariance matrix $\mathbf{\Sigma}_t$. 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 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 7: United States: impulse responses



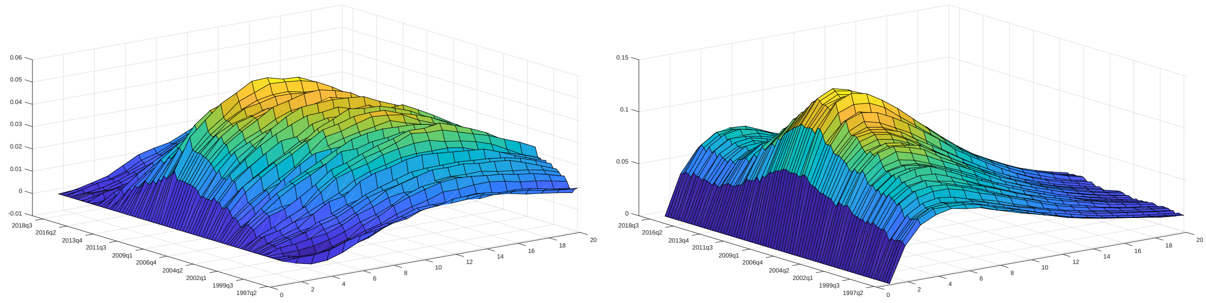
Note: Impulse response functions to a one standard deviation shock computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

In Appendix G.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 6 and 7, some regularities are visible between the euro area and the US. The reaction of durables to a monetary condition shock is larger than the one 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). This result, however, looks heavily influenced by the assumption of homoskedasticity: once relaxed, the difference in the magnitude of reactions wanes out. At the same time, some differences arise as well: 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 begs for caution, as they also reflect differences in the size of the structural shocks. However, if we look at the evolution over time of the impulse response functions, 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 8, the effect of the shock reaches faster its peak 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, to then settle down at lower values in the post-crisis period.

Figure 8: Reaction of the price of nondurables to a durable-specific supply shock

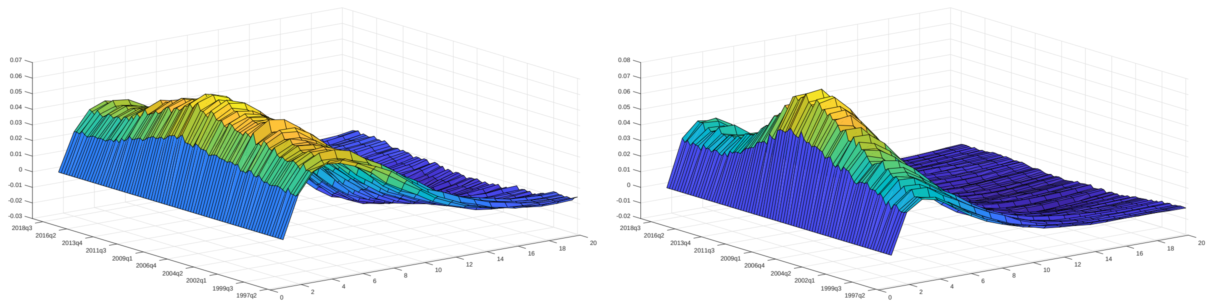


(a) Euro area (b) United States

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 9.

Figure 9: Reaction of the price of nondurables to a durable-specific demand shock

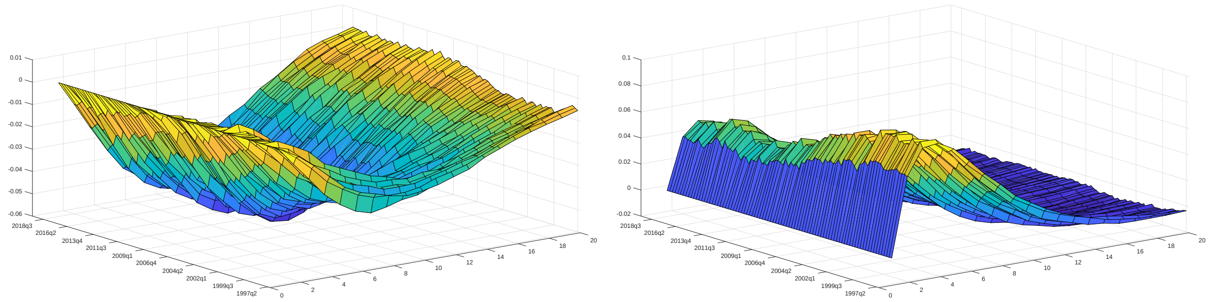


(a) Euro area (b) United States

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 United States 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 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 10: Reaction of nondurable consumption to a durable-specific demand shock

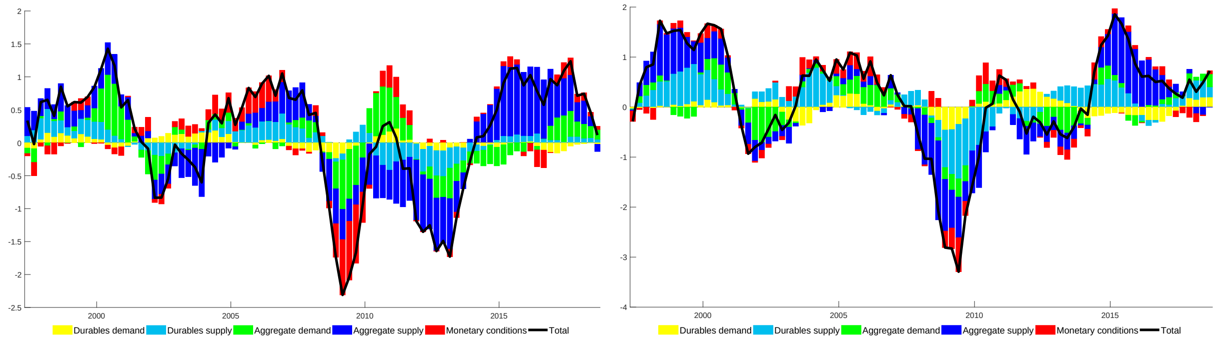


(a) Euro area (b) United States

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 United States. As Figure 11 shows, the 2008-09 crisis was strongly driven by both supply and demand in the US, while the main contributors of 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 starting 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 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 durables and nondurables consumption. Data for (a) euro area and (b) United States.

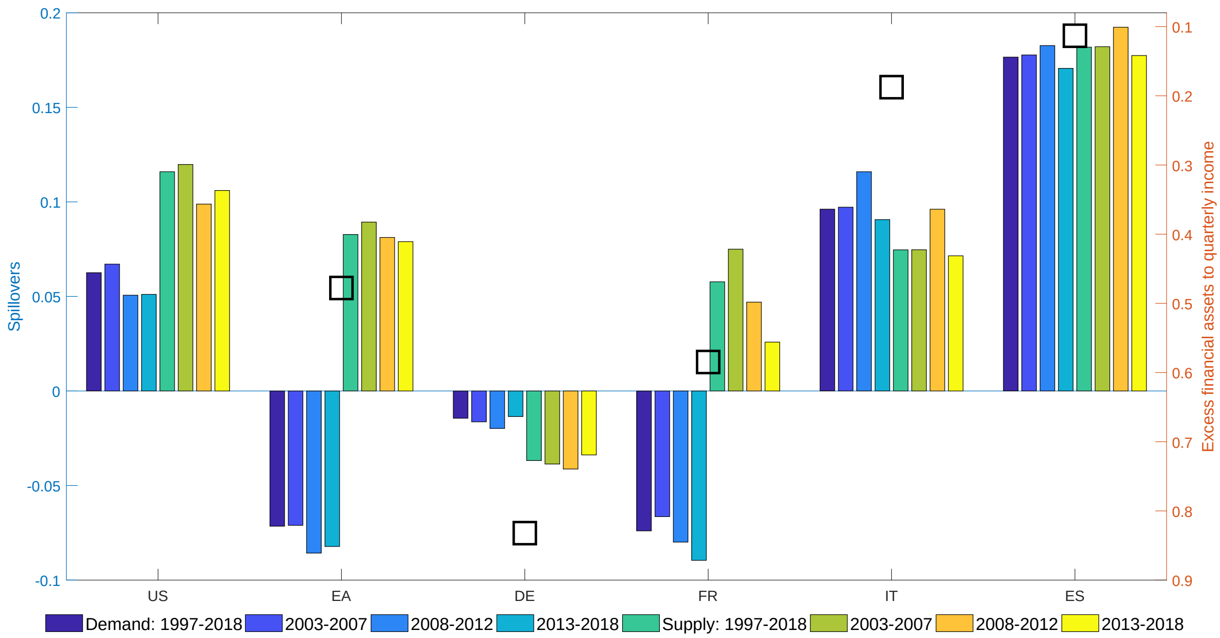
In Appendix H, we present results for both a SVAR estimated in levels, and a TVP-SVAR as in the baseline specification but using GDP excluding durables, instead of nondurable consumption, as a sensitivity check. The results are broadly comparable in qualitative terms.

5 Heterogeneity among countries

The theoretical model predicts spillovers between durables and nondurables when agents suffer from liquidity constraints. As discussed in Section 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 3 we showed important differences across countries in the likelihood of household becoming affected by liquidity constraints and therefore in the likelihood to observe 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 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 have 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 G.5.

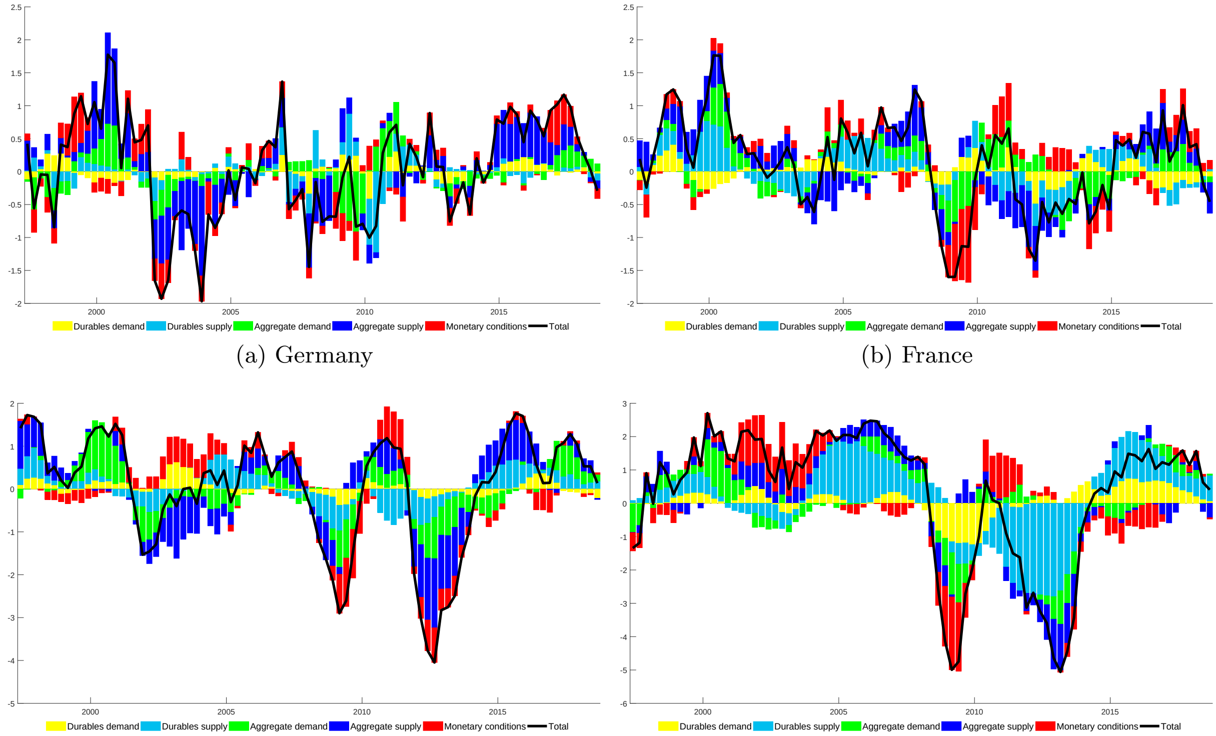
Figure 12: Spillovers from durable-specific shocks to nondurable consumption



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 it is computed from HFCS data, as in Figure 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 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 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 durables and nondurables consumption.

The so-called Great Recession of 2008-09 and the following sovereign debt crisis is specifically evident in France, Italy and Spain and much less pronounced in Germany. Moreover, Figure 13(a) shows how the relatively small contraction in consumption growth is due to supply side factors, specifically of durables. Such contribution can be found also for France and Italy, while in Spain the demand side, both durable-specific and aggregate, appears to be among the main drivers. Figures 13(b), 13(c) and 13(d) also suggest a key role of monetary conditions (which captures both common monetary policy and the country-idiosyncratic consumer credit environment) 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 one in Italy and Spain, and more contained in France. In Italy and Spain durable-specific factors seems 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.

6 Concluding remarks

We use a theoretical partial equilibrium model to inform a structural TVP-SVAR where the structural shocks are 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 durables-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 expenditures react more 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.

Appendix

A 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

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

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

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

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

with supplementary slackness conditions

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

$$\mu_t \left(A_t + \varphi P_t^d D_t \right) = 0 \tag{A.4}$$

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

$$U_c(t) = \underbrace{\frac{R_t}{R_t - (1-\delta)\left(1+\pi_t^d\right)}}_{\Omega_t^{-1}} \frac{1}{P_t^d} U_d(t) + \frac{\varphi R_t - (1-\delta)\left(1+\pi_t^d\right)}{R_t - (1-\delta)\left(1+\pi_t^d\right)} \mu_t \tag{A.5}$$

where $\Omega_t = \frac{R_t - (1-\delta)\left(1+\pi_t^d\right)}{R_t}$ 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. A.5 becomes

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

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

$$\frac{D_t}{C_t} = \gamma_t \frac{1}{\Omega_t} \frac{1}{P_t^d}$$

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

$$P_t^d = P^{d*} \exp(u_t^p)$$
$$u_t^p = \rho^p u_{t-1}^p + \varepsilon_t^p$$

for preferences for durables in the utility function γ

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

and for the compound interest rate R

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

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

Appendix B shows results from 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 the cases of both temporary and permanent shocks and show adjustment paths for a consumer that becomes, or alternatively does not become, liquidity constrained as a result of the shock.

In particular, Figures B.1 and B.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 B.3, B.4, B.5 and B.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 $\rho^R = 0.1$.

B Dynamic responses to shocks in the theoretical model

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

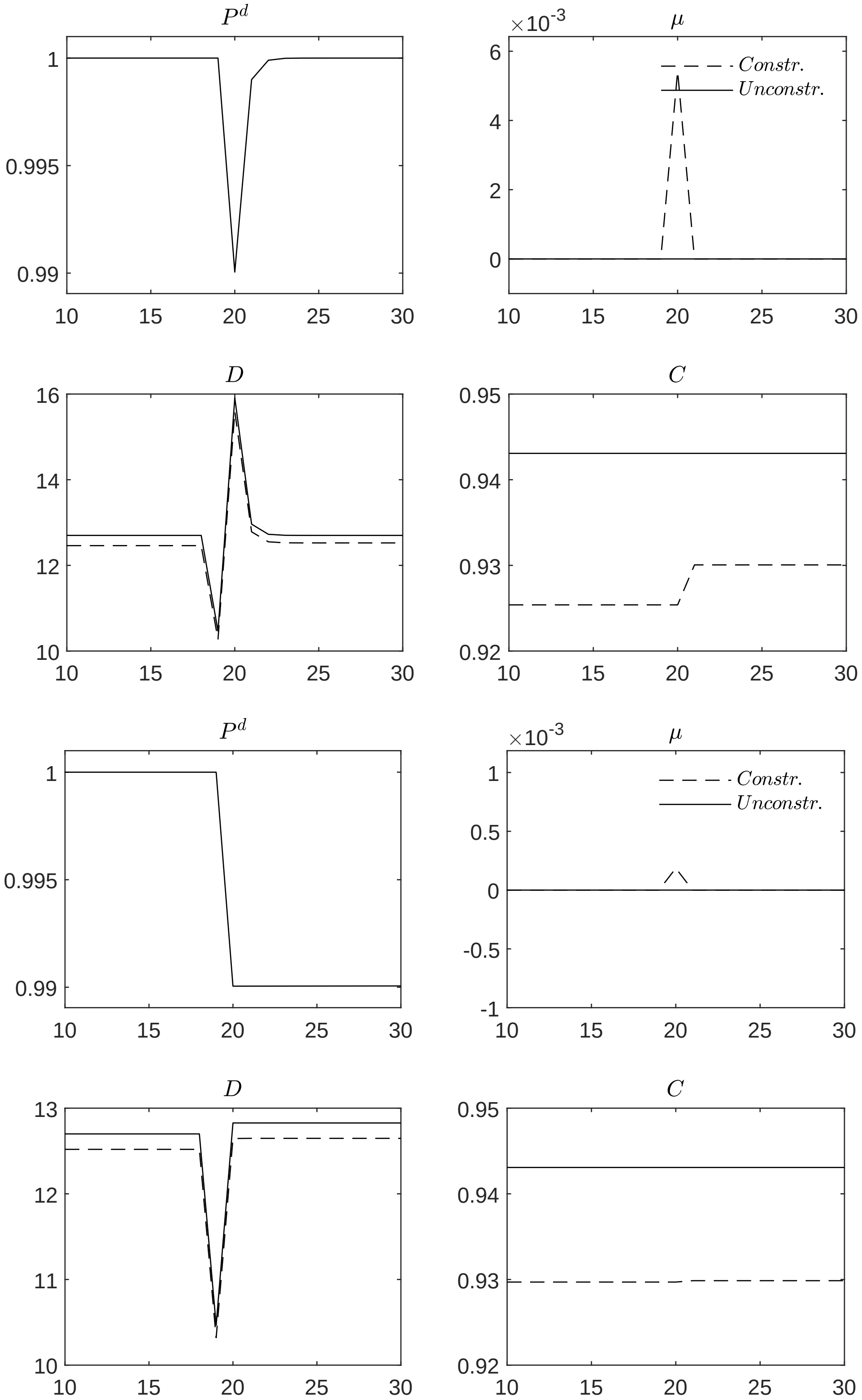


Figure B.2: Temporary and permanent increase of 1% in relative durable prices P^d

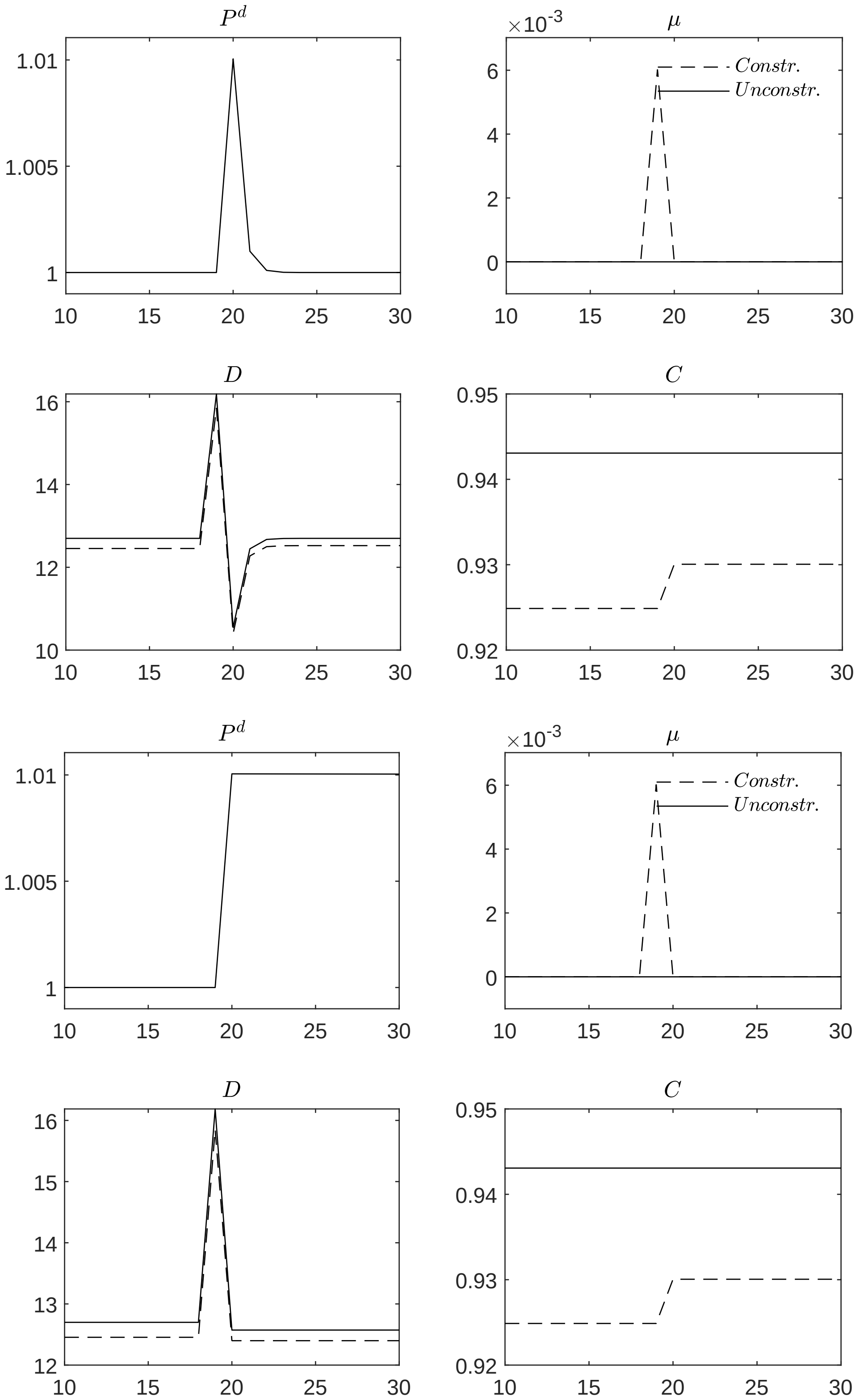


Figure B.3: Temporary and permanent increase in the preference parameter γ for durables

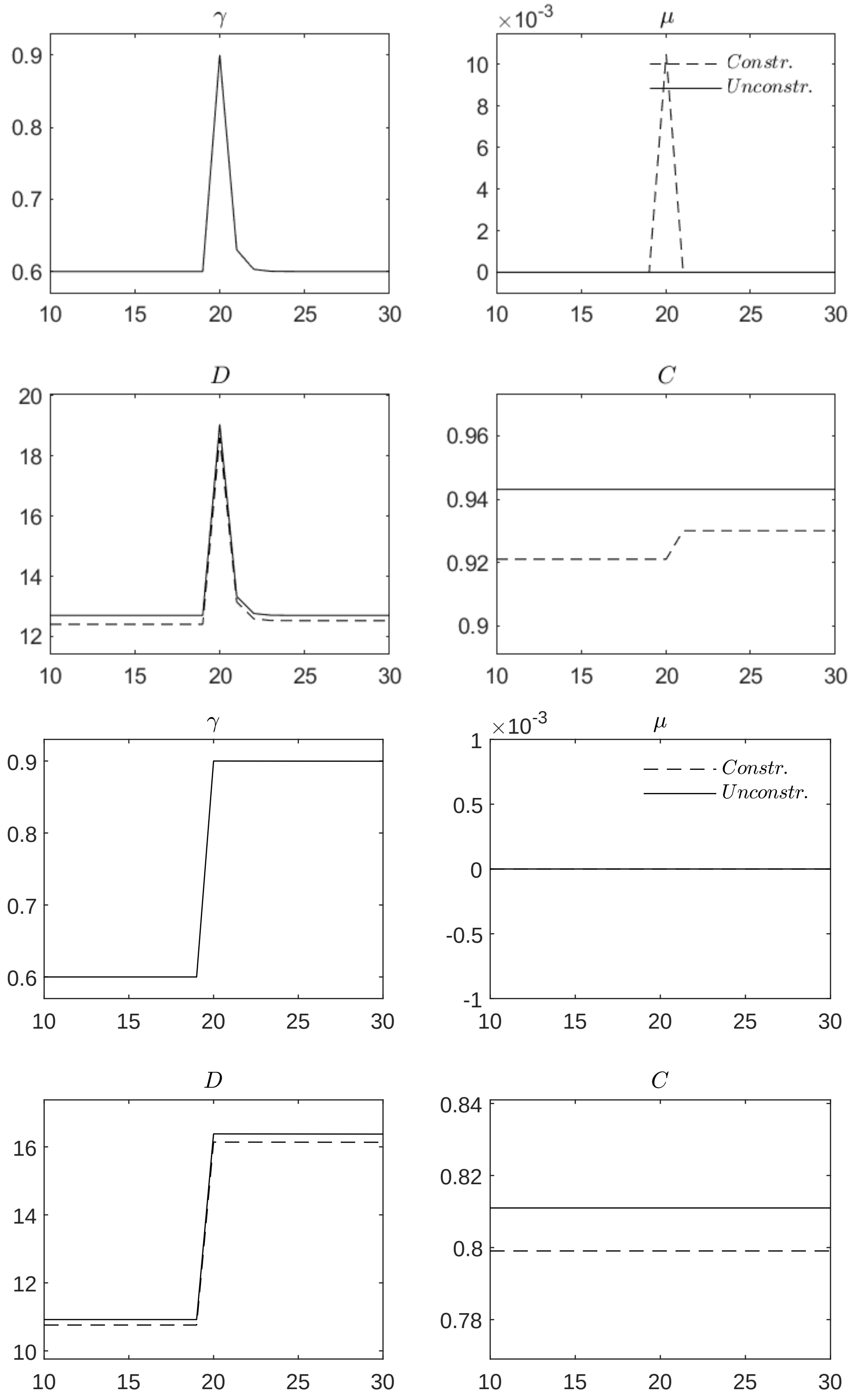


Figure B.4: Temporary and permanent decline in the preference parameter γ for durables

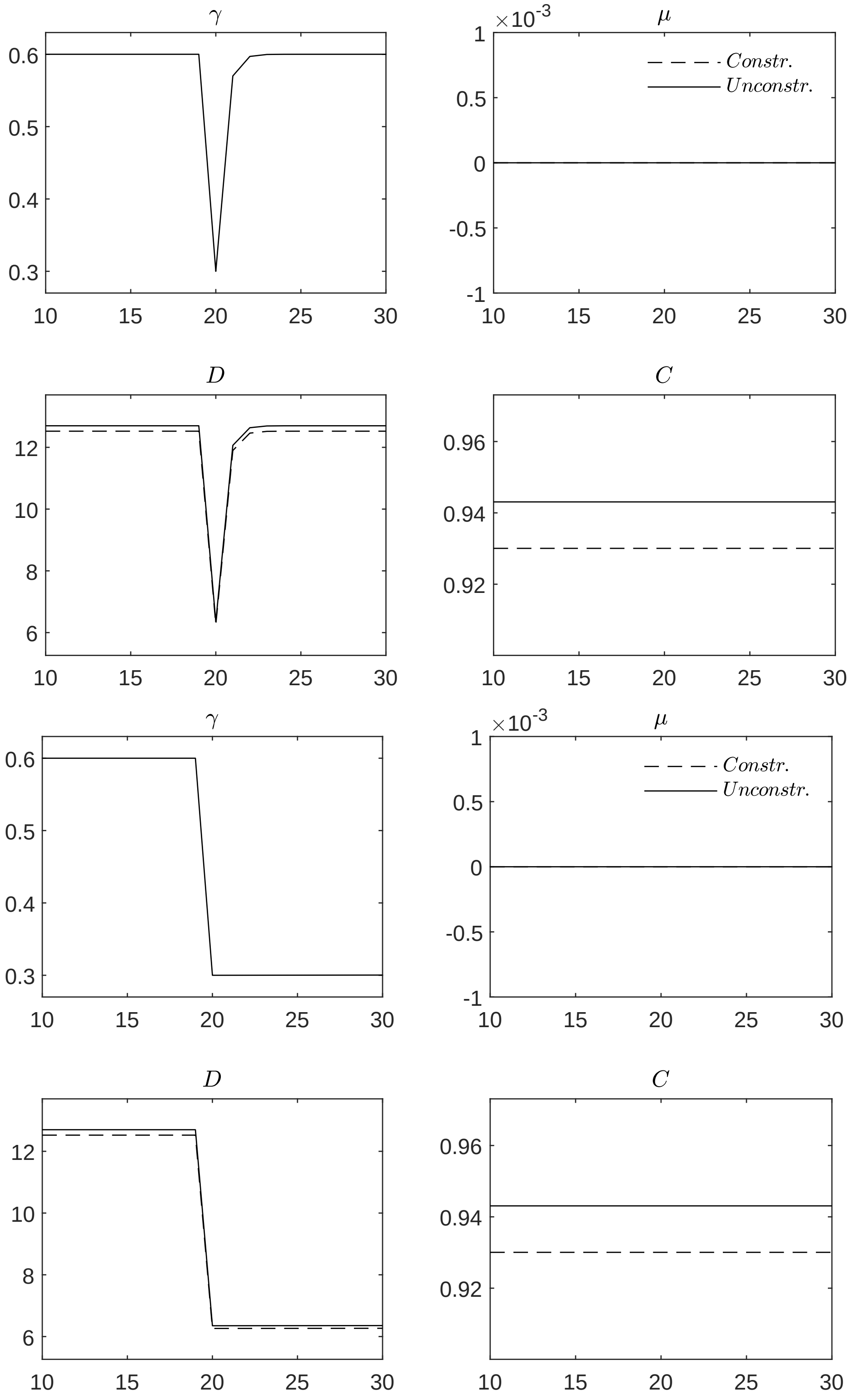


Figure B.5: Temporary and permanent decline in the interest rate r

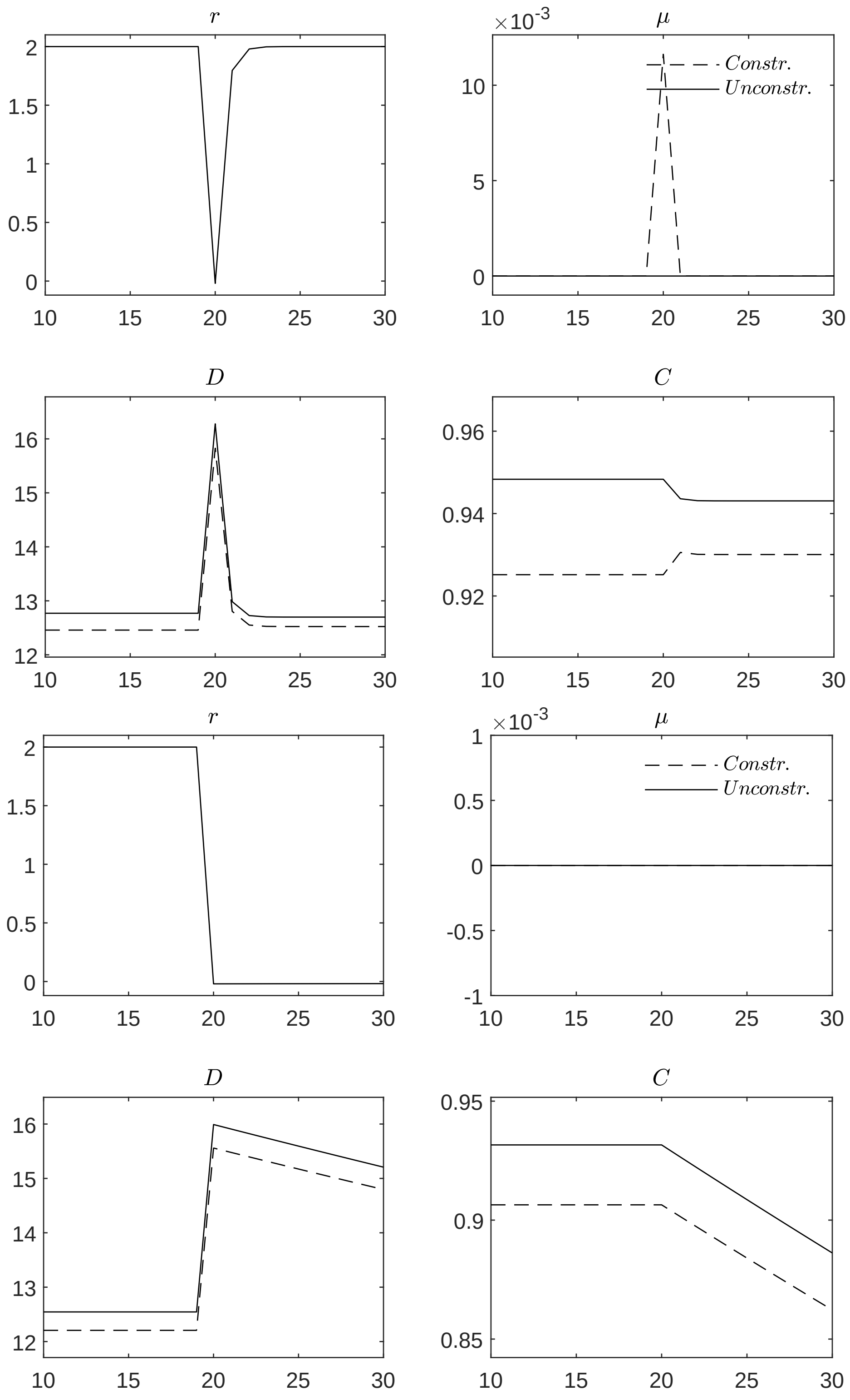
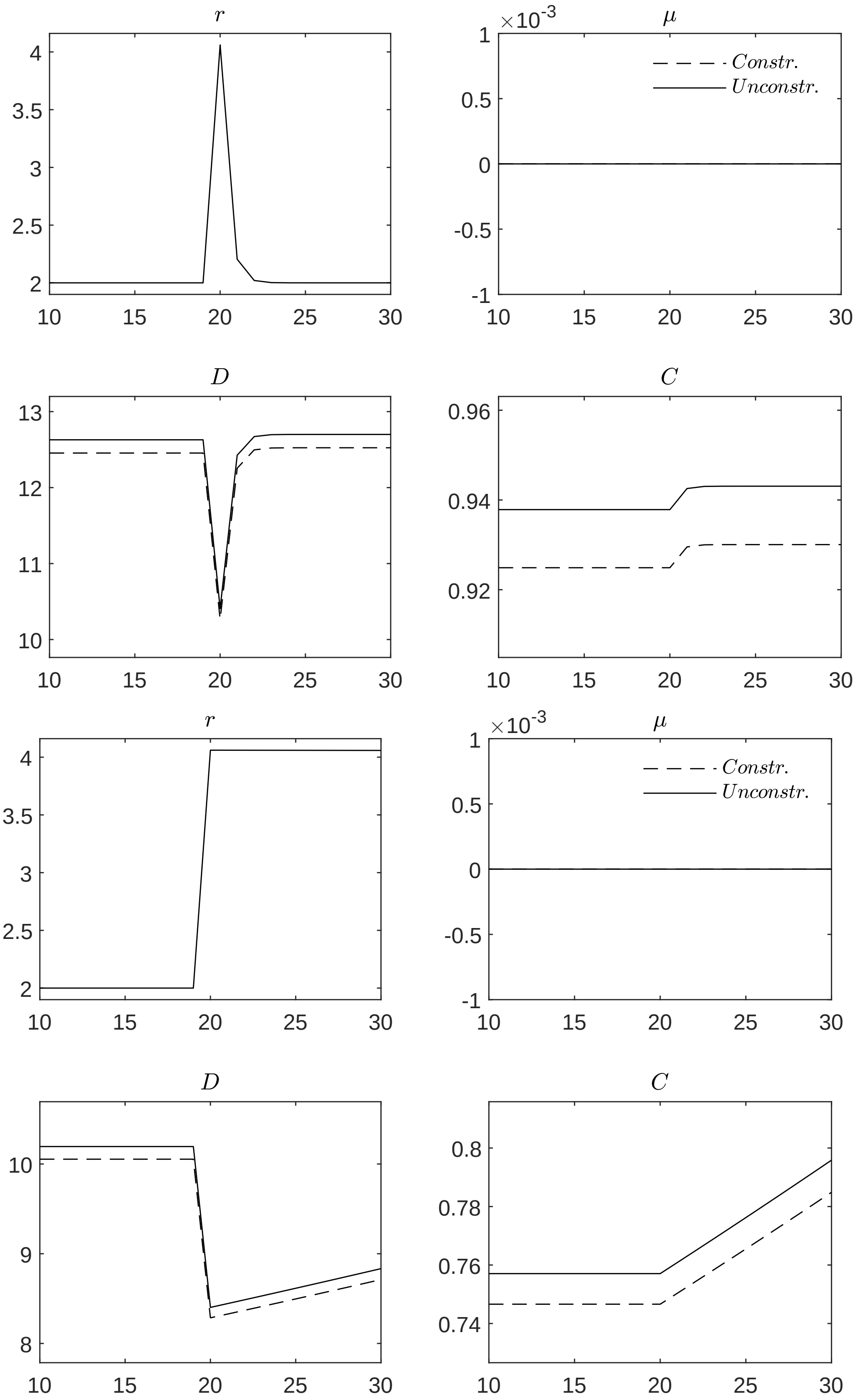


Figure B.6: Temporary and permanent increase in the interest rate r



C 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 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.

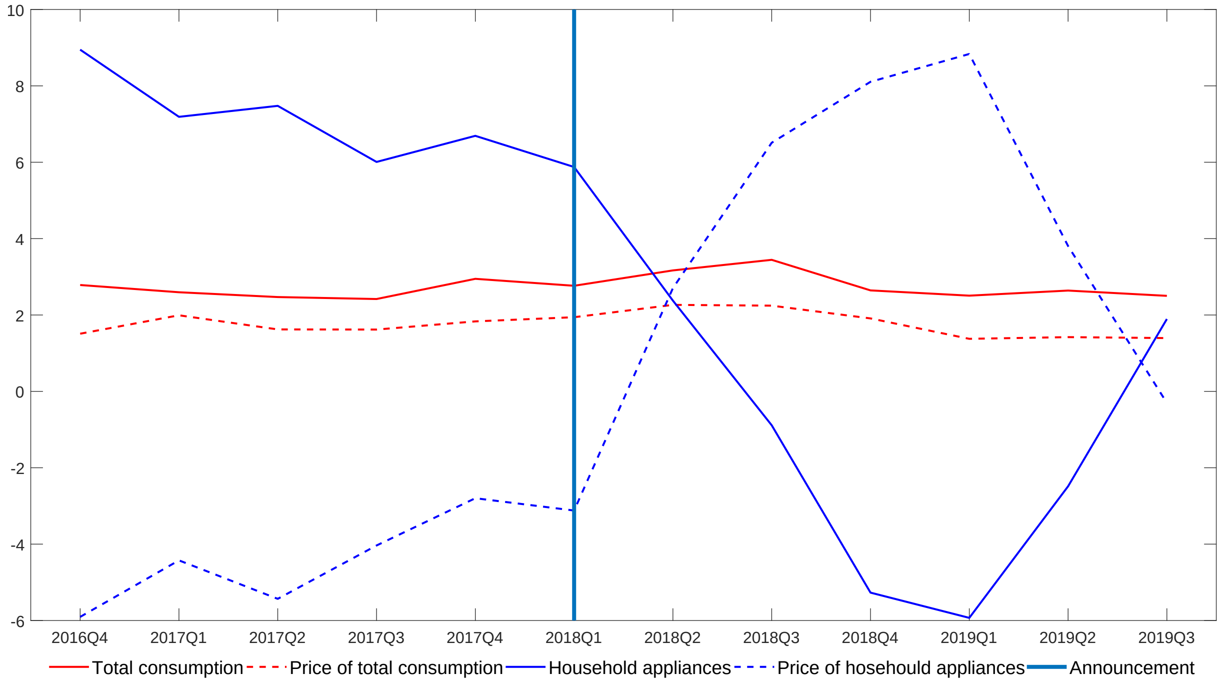
(3) P^d - Implicit deflator for D, computed using D and the individual consumption expenditure of durable goods in current prices.

(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 Real world example of a durable-specific supply shock

Figure D.1: Real world supply shock example



Source: Bureau of Economic Analysis.
Note: Quantity and prices of total consumption and household appliances (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.

E Optimal lag selection and parameter stability tests

E.1 Optimal lag selection

Table E.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.

E.2 Parameter stability tests

Table E.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 y-o-y 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 y-o-y growth rates.

Table E.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 y-o-y 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 y-o-y growth rates.

Table E.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).

F Priors and empirical model estimation

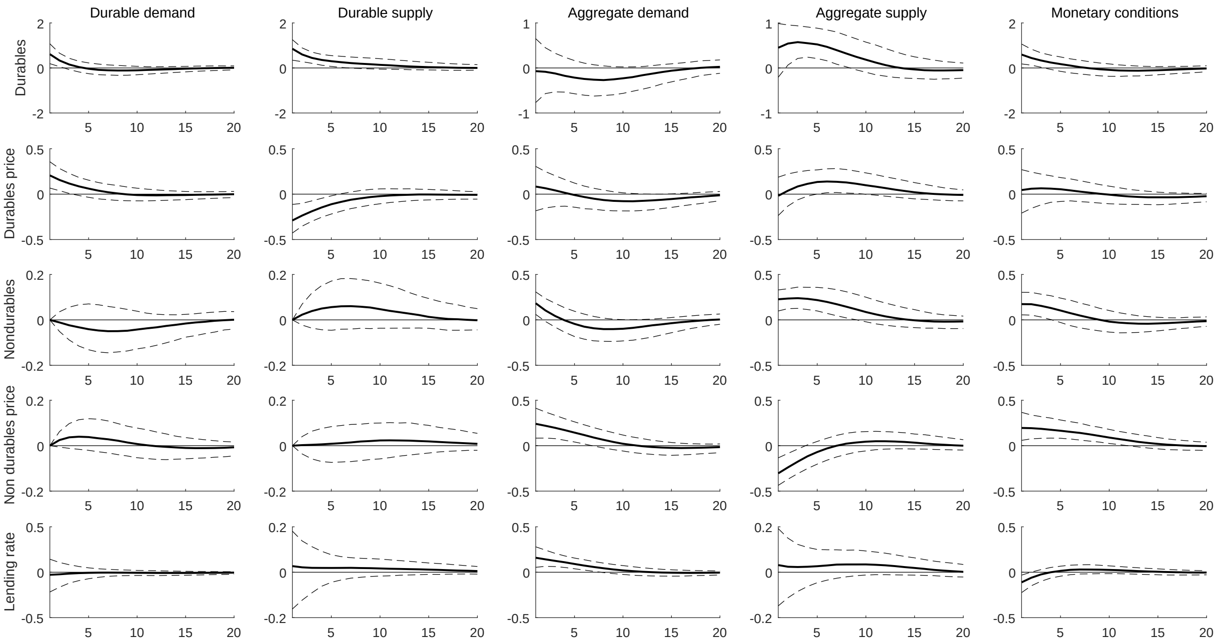
The model estimation relies on Bayesian methods: we perform 3000 iterations of the Gibbs sampler and discard the first 1500. The objects of interest to be estimated are β (Equation 8), $\mathbf{\Omega}$ (Equation 11), $\mathbf{Z}^{-1}$ (Equation 13), $\mathbf{H}$ (Equation 15) and $\mathbf{\Phi}_i$ (Equation 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 16 to 0.85.

G Additional tables and figures - Baseline specification

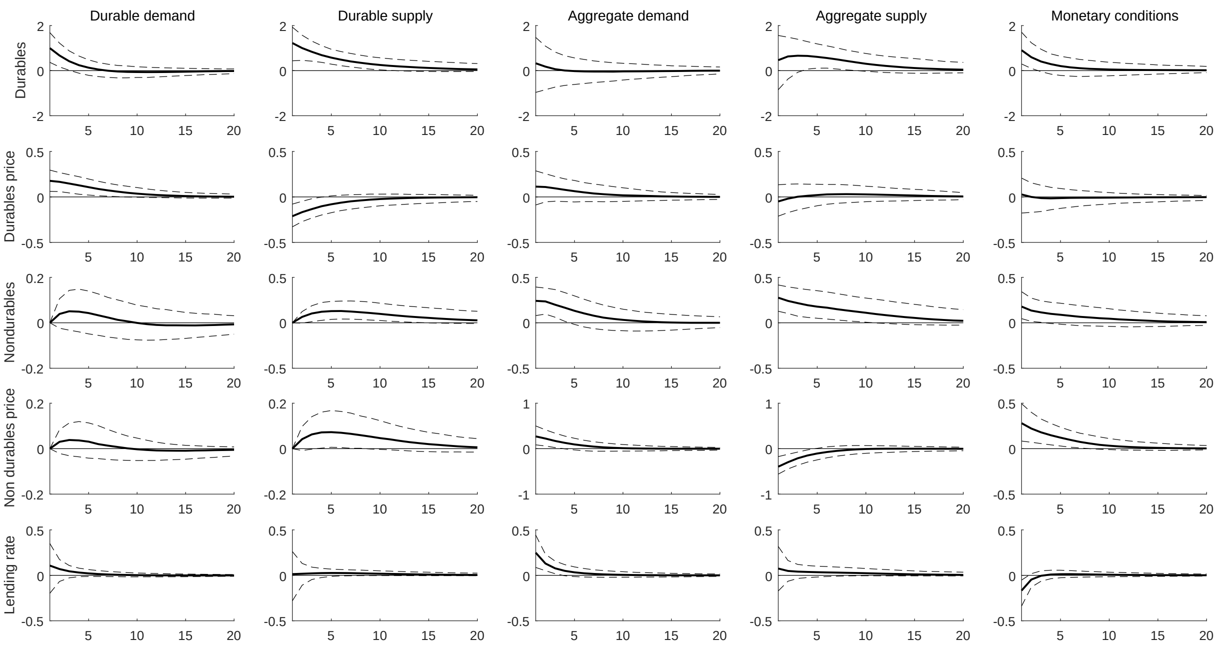
G.1 Impulse response functions computed using the long run value of $\boldsymbol{\Sigma}_t$

Figure G.1: Euro area impulse response functions



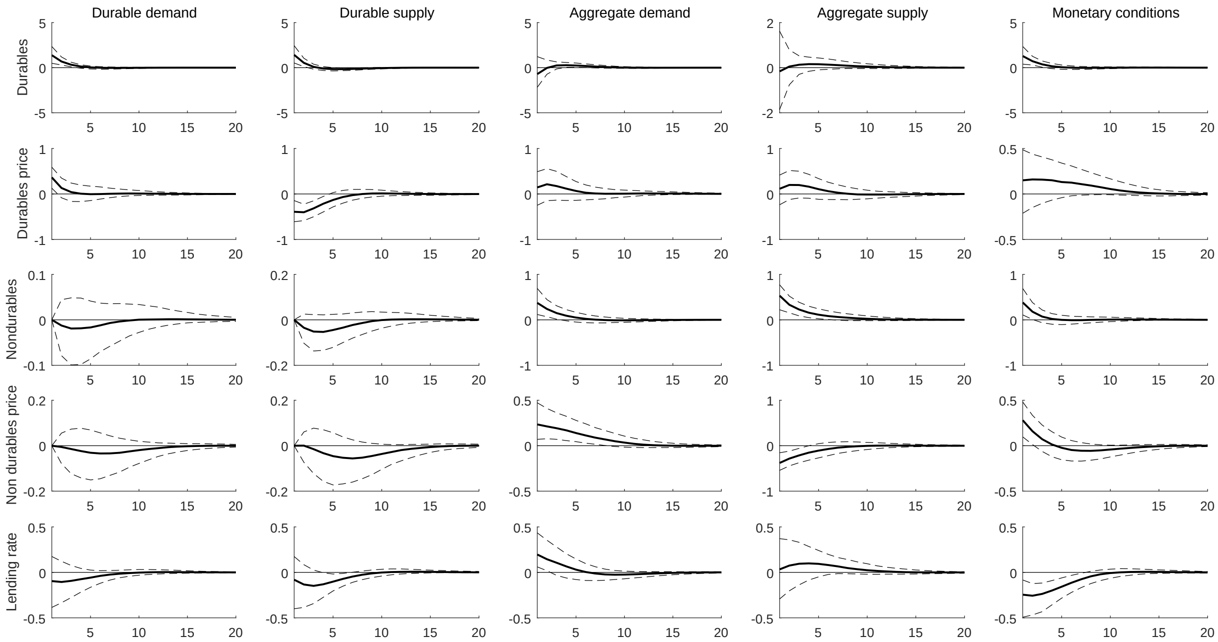
Note: Impulse response functions computed using the long-run, homoskedastic value of $\boldsymbol{\Sigma}_t$.

Figure G.2: United States impulse response functions



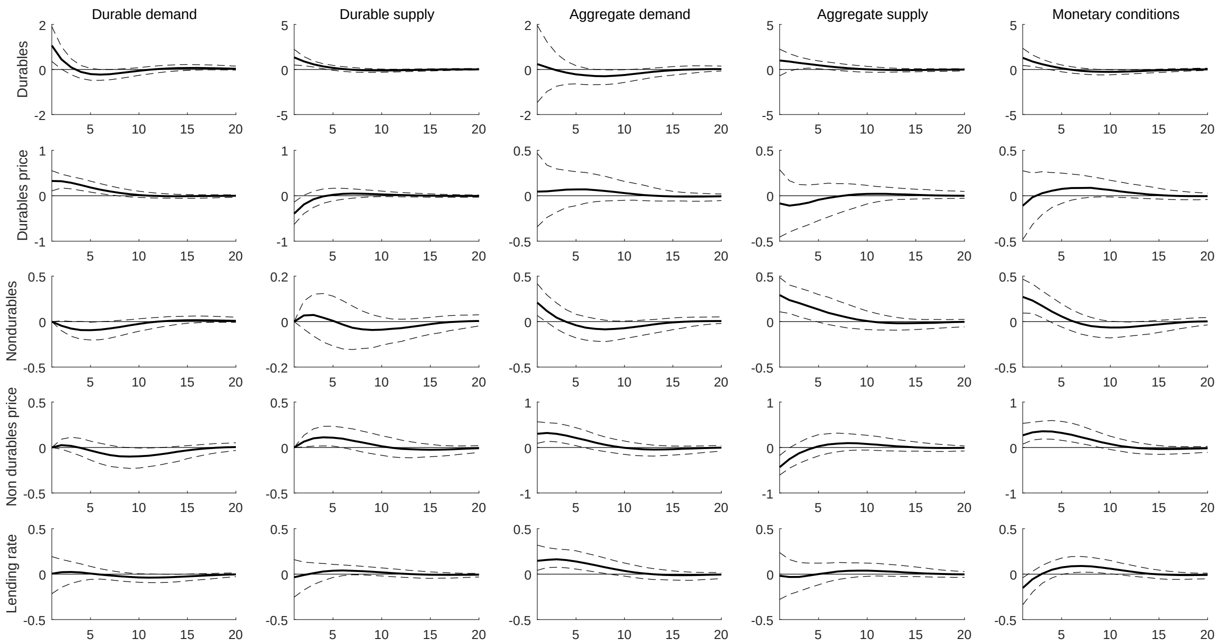
Note: Impulse response functions computed using the long-run, homoskedastic value of $\boldsymbol{\Sigma}_t$.

Figure G.3: Germany impulse response functions



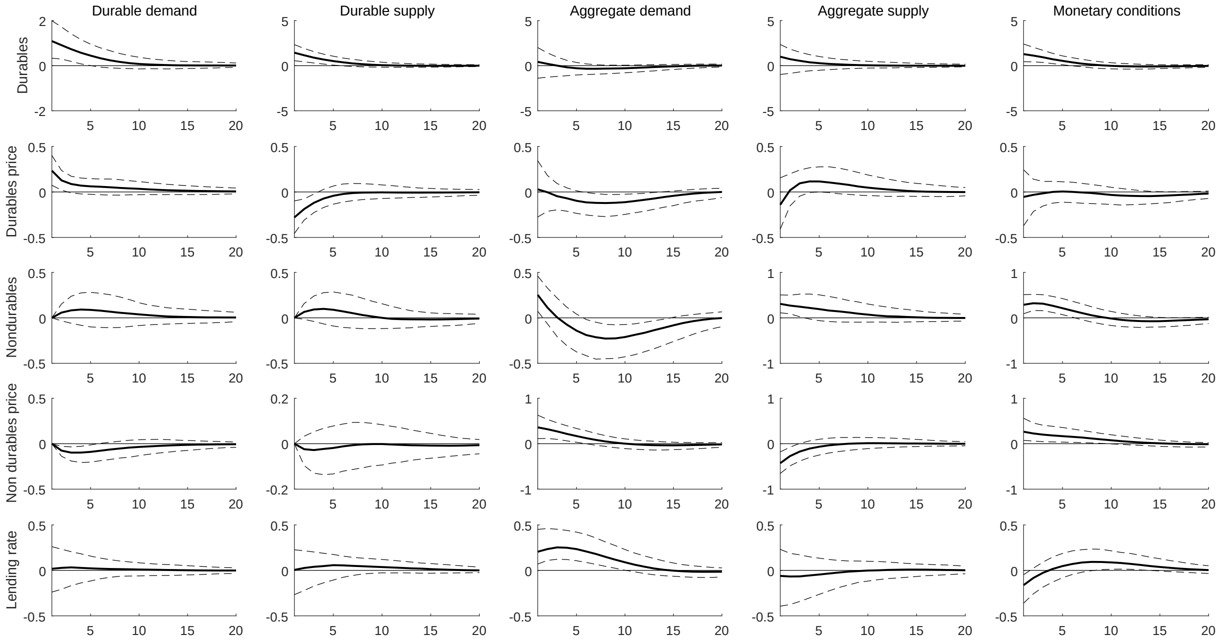
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$.

Figure G.4: France impulse response functions



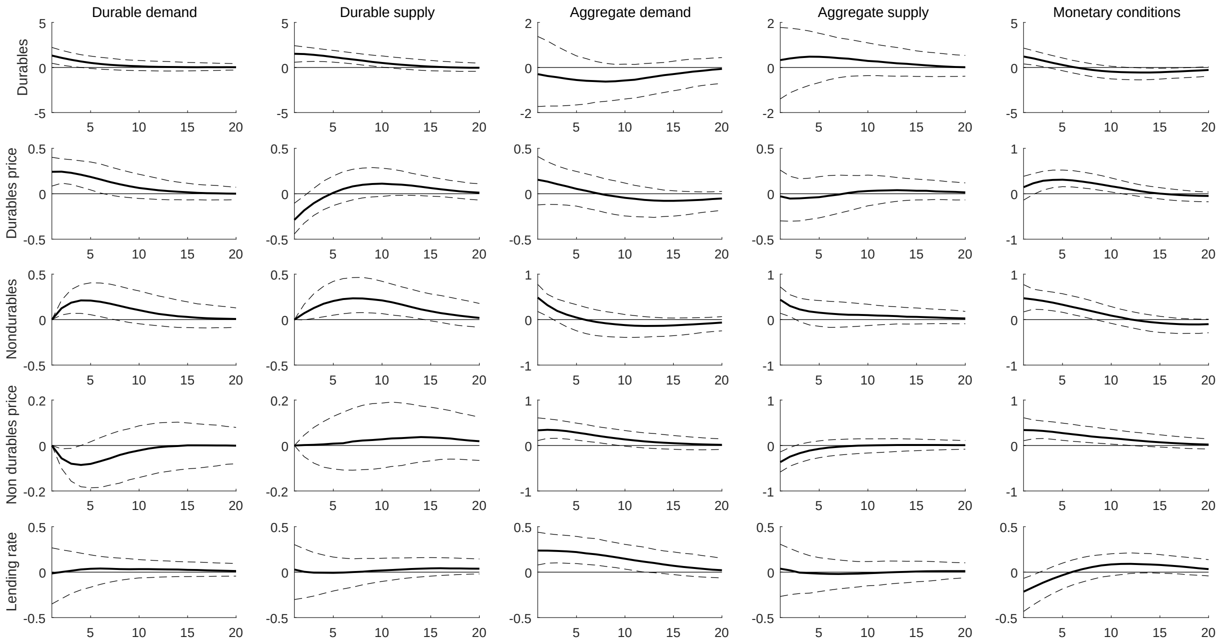
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$.

Figure G.5: Italy impulse response functions



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

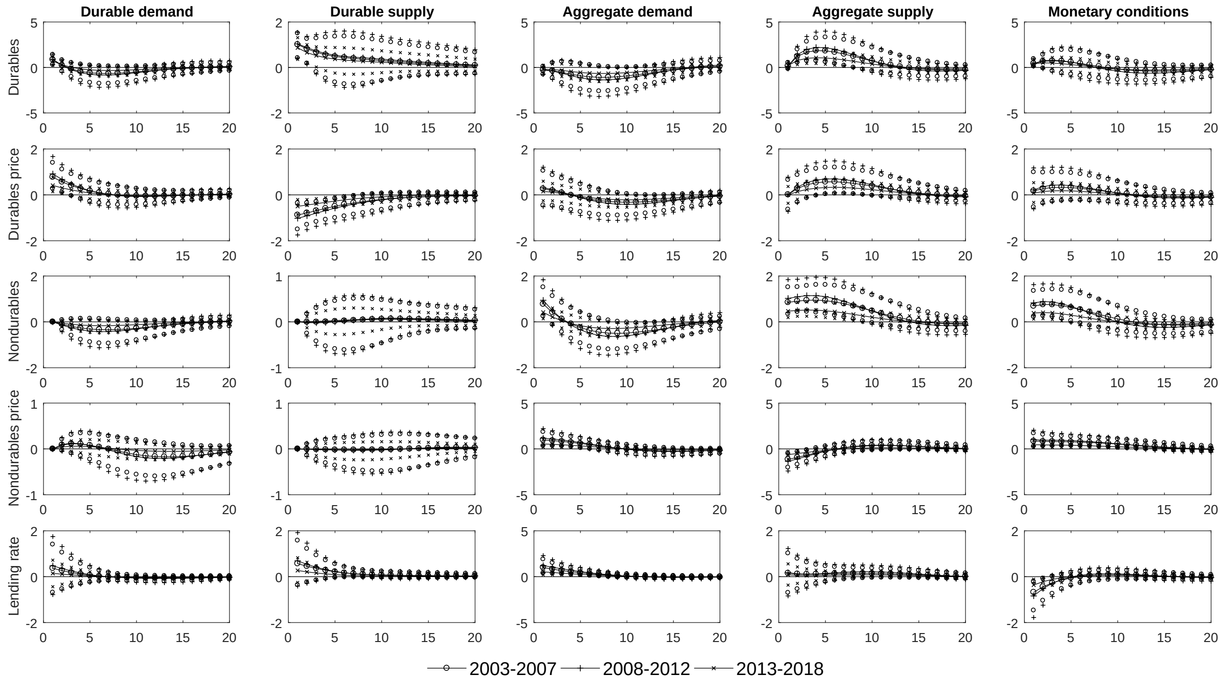
Figure G.6: Spain impulse response functions



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

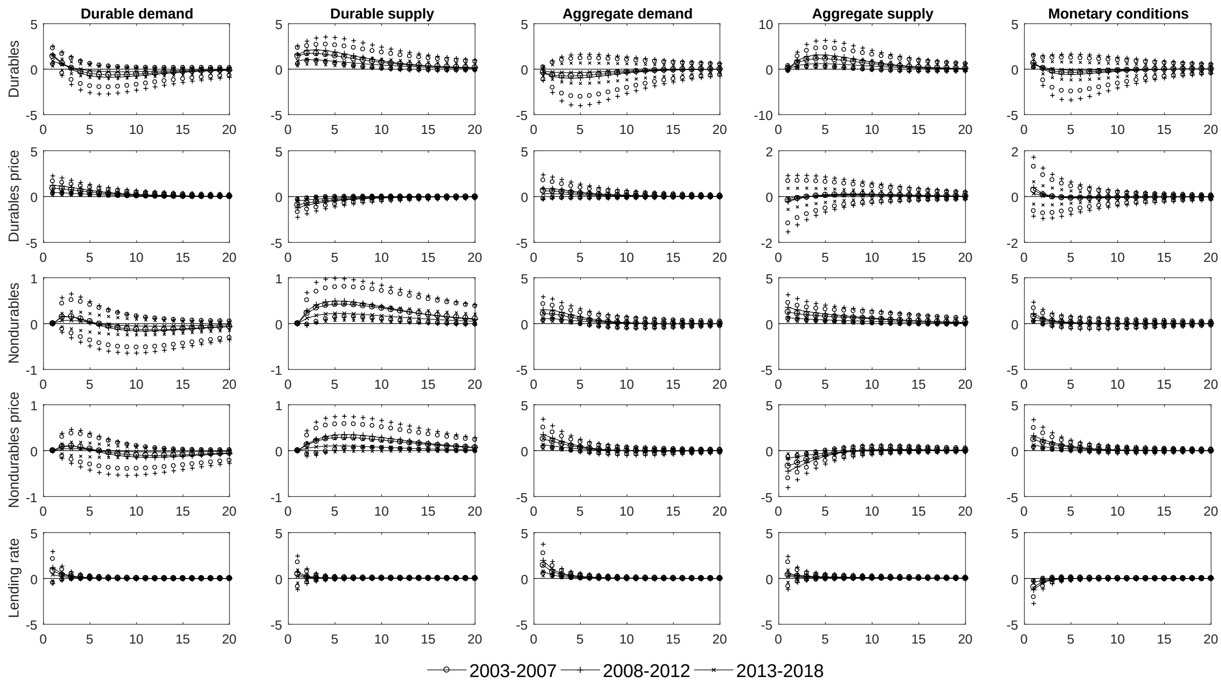
G.2 Impulse response functions computed with time-varying Σ_t, averaged over pre-crisis, crisis and post-crisis periods.

Figure G.7: Euro area impulse response functions



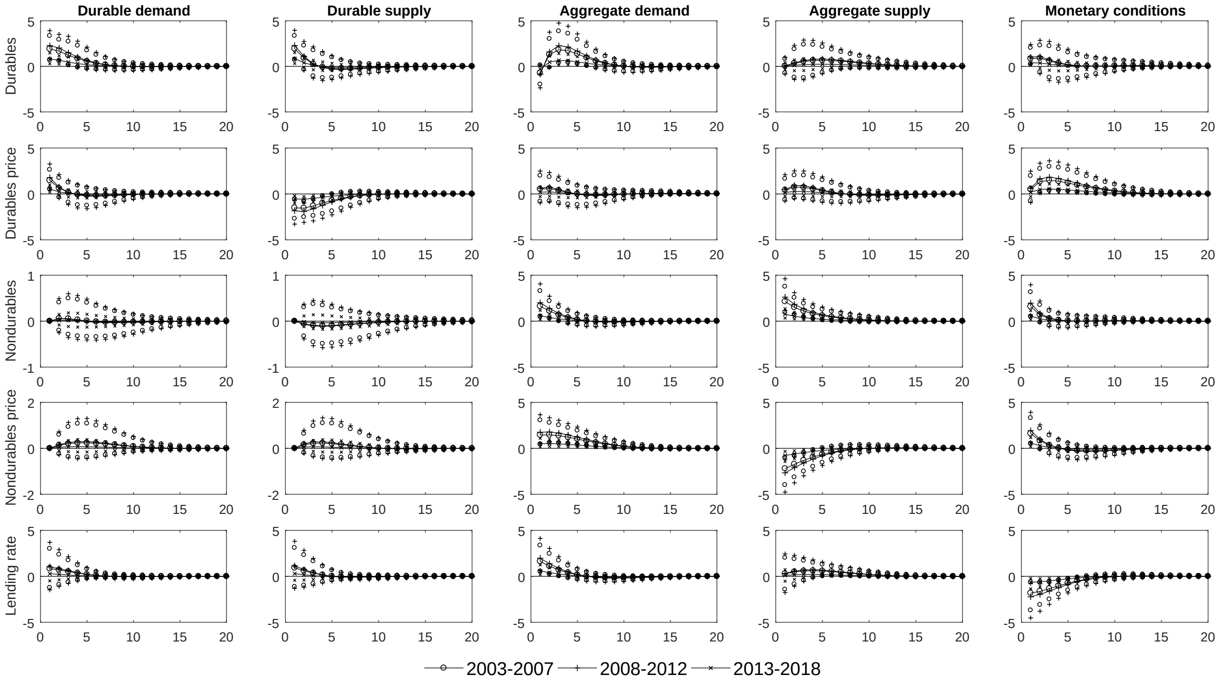
Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis) and 2013Q1-2018Q3 (post-crisis recovery).

Figure G.8: United States impulse response functions



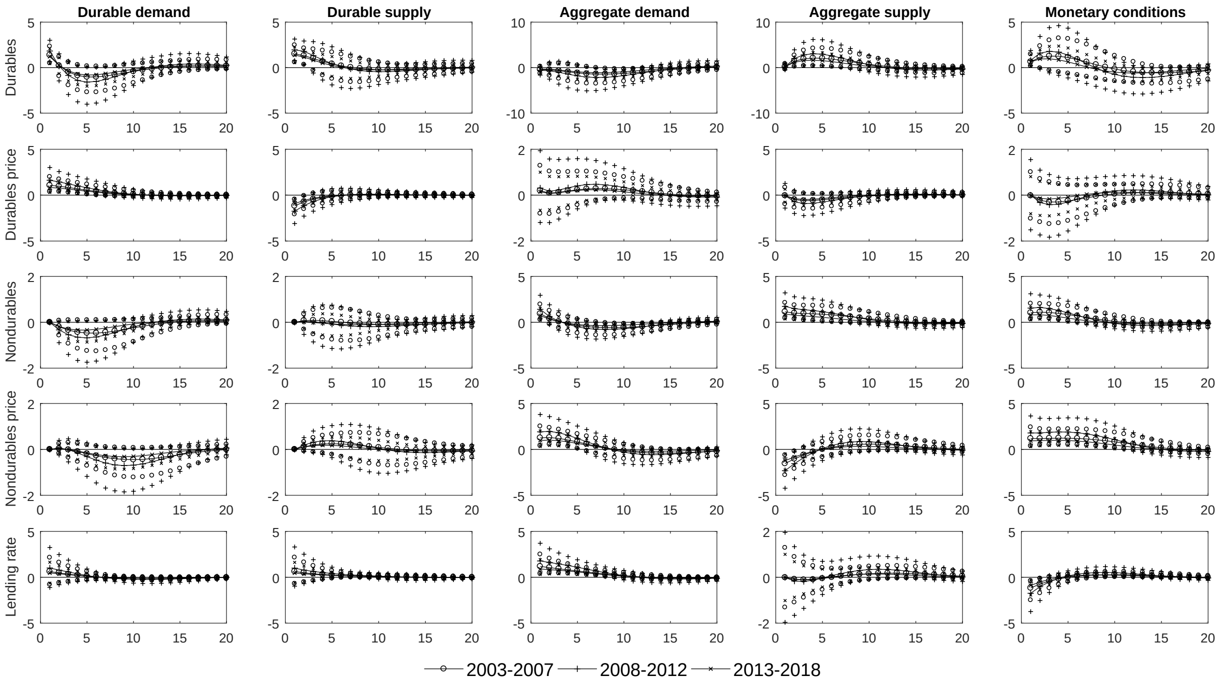
Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis) and 2013Q1-2018Q3 (post-crisis recovery).

Figure G.9: Germany impulse response functions



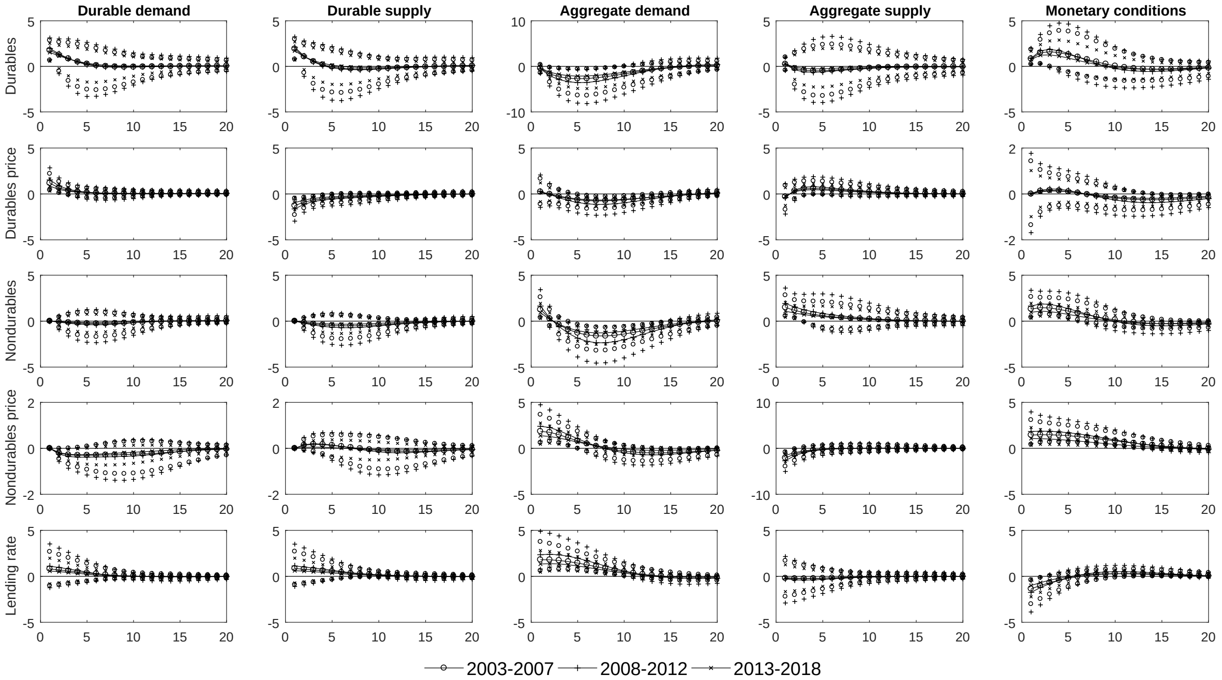
Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis) and 2013Q1-2018Q3 (post-crisis recovery).

Figure G.10: France impulse response functions



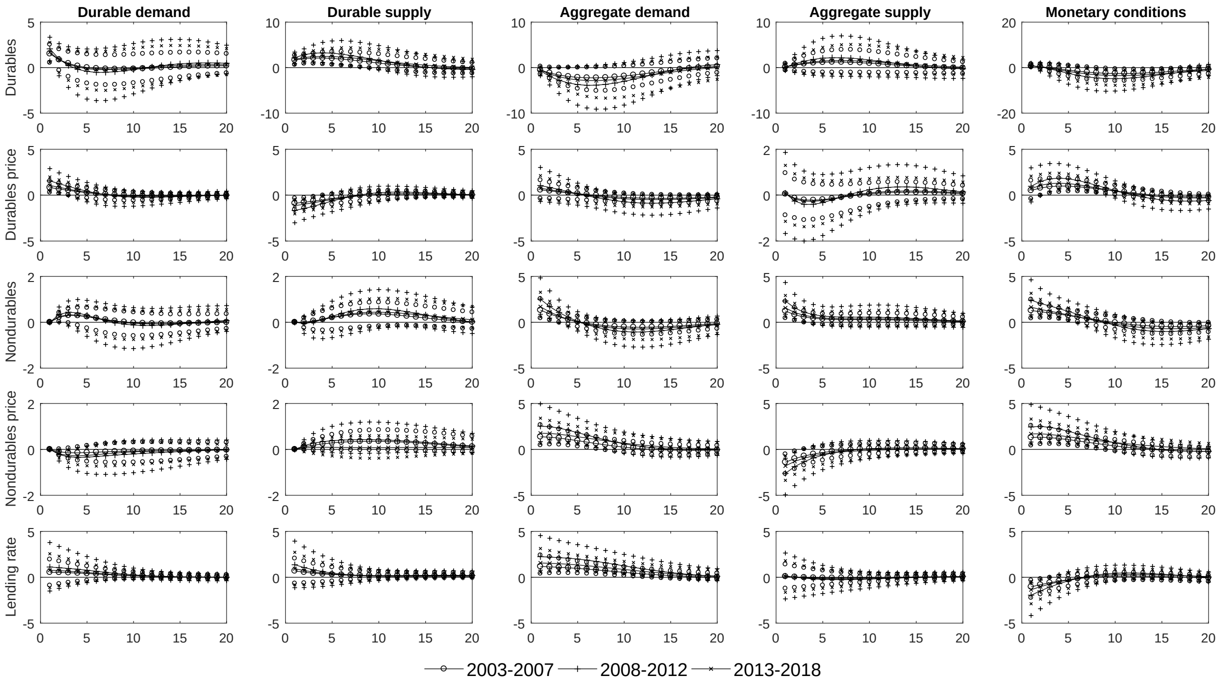
Note: Average of the time-contingent impulse response functions for three different periods: 2003Q1-2007Q4 (pre-crisis), 2008Q1-2012Q4 (crisis) and 2013Q1-2018Q3 (post-crisis recovery).

Figure G.11: 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).

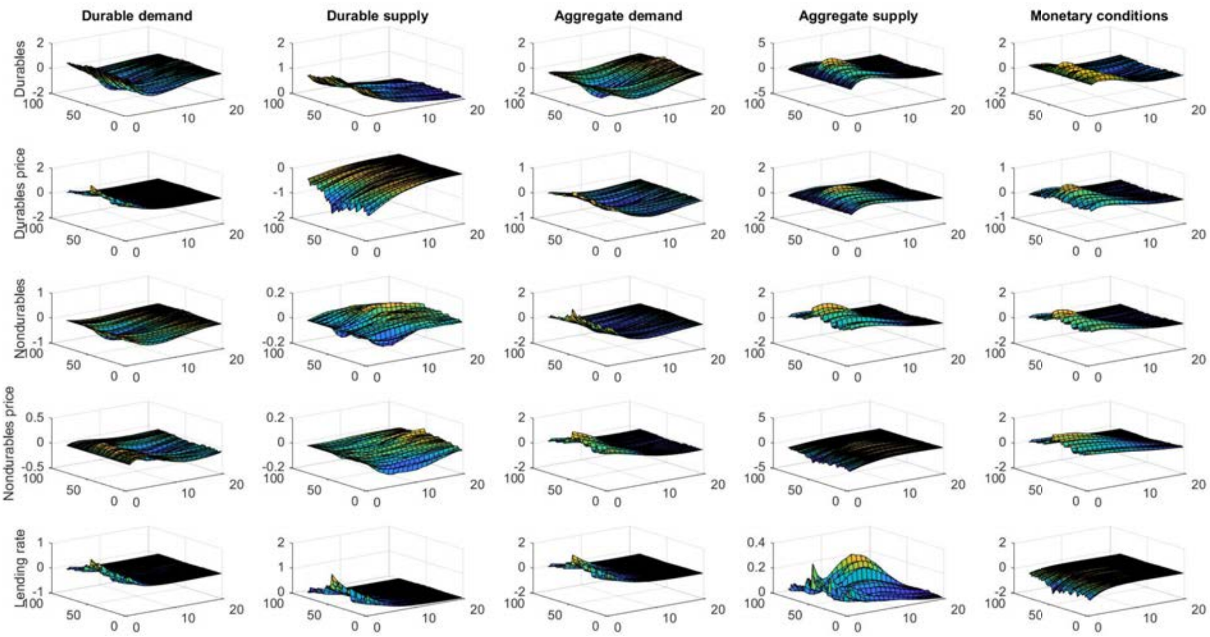
Figure G.12: Spain impulse response functions



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).

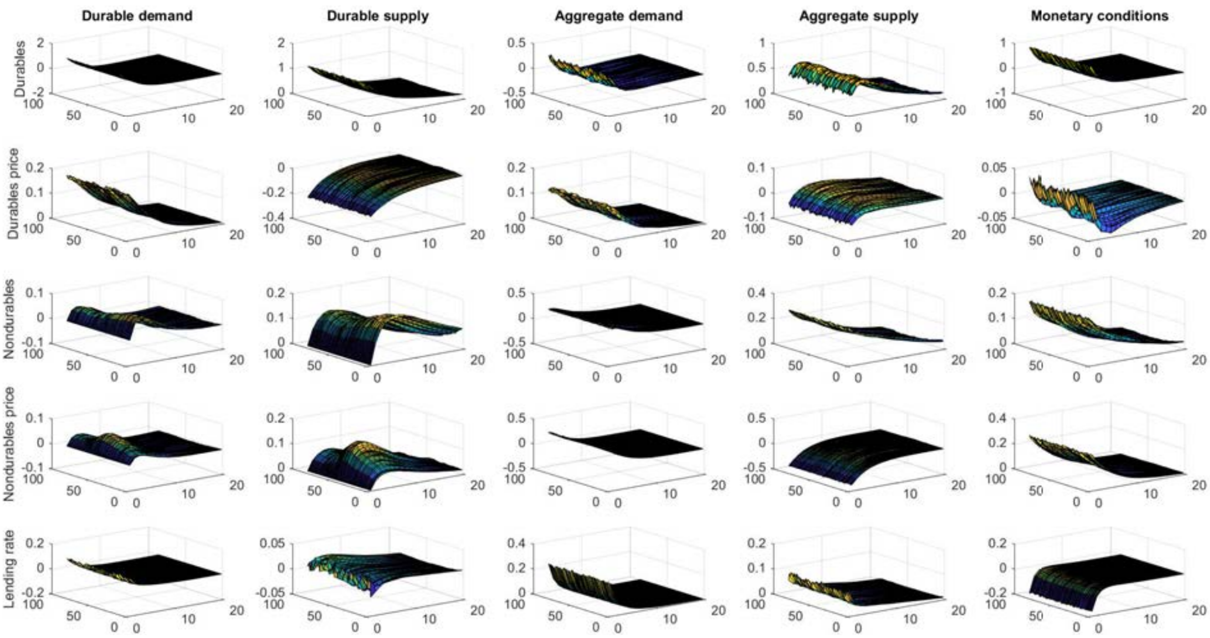
G.3 Impulse response functions over time

Figure G.13: Euro area impulse response functions



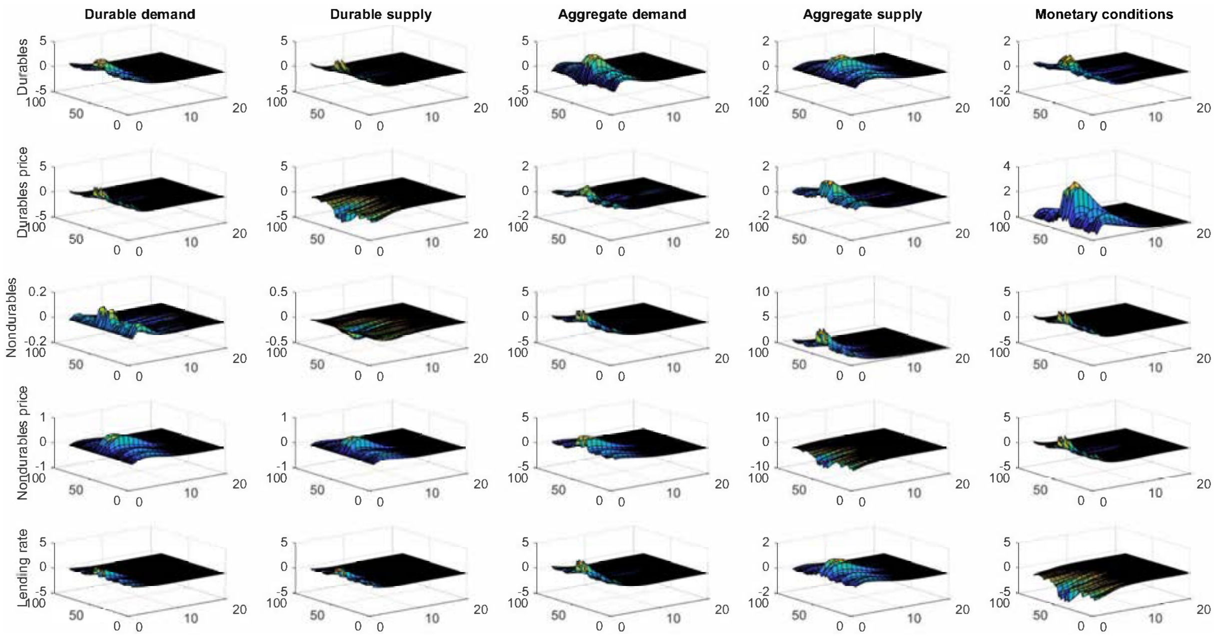
Note: Impulse response functions for each quarter in the sample.

Figure G.14: United States impulse response functions



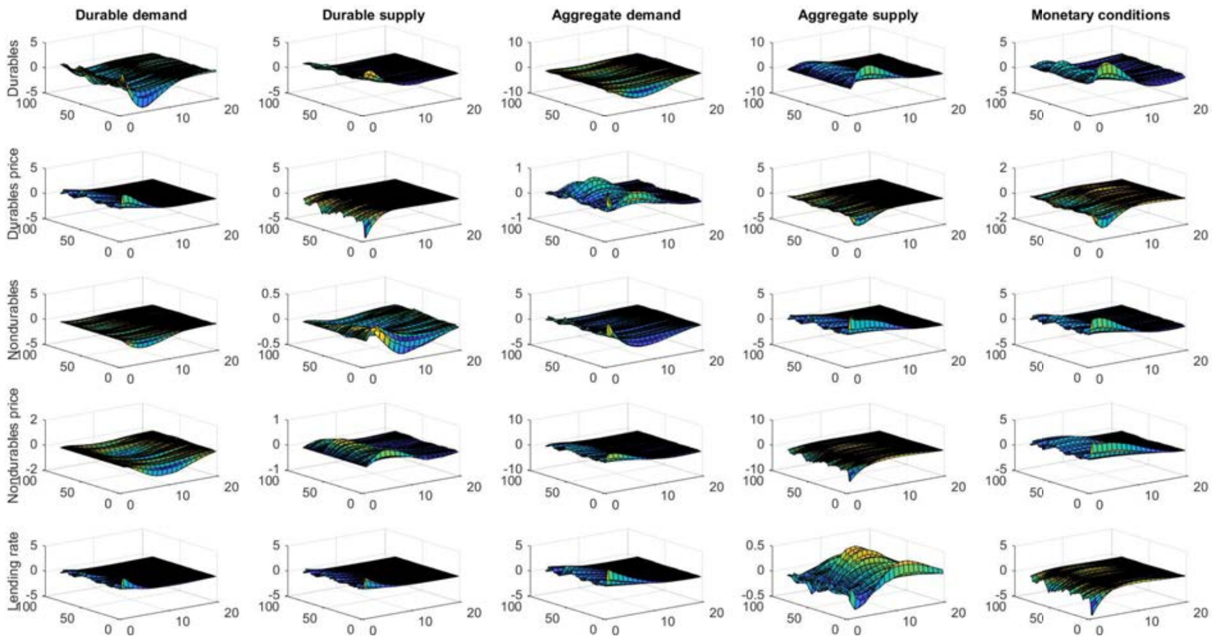
Note: Impulse response functions for each quarter in the sample.

Figure G.15: Germany impulse response functions



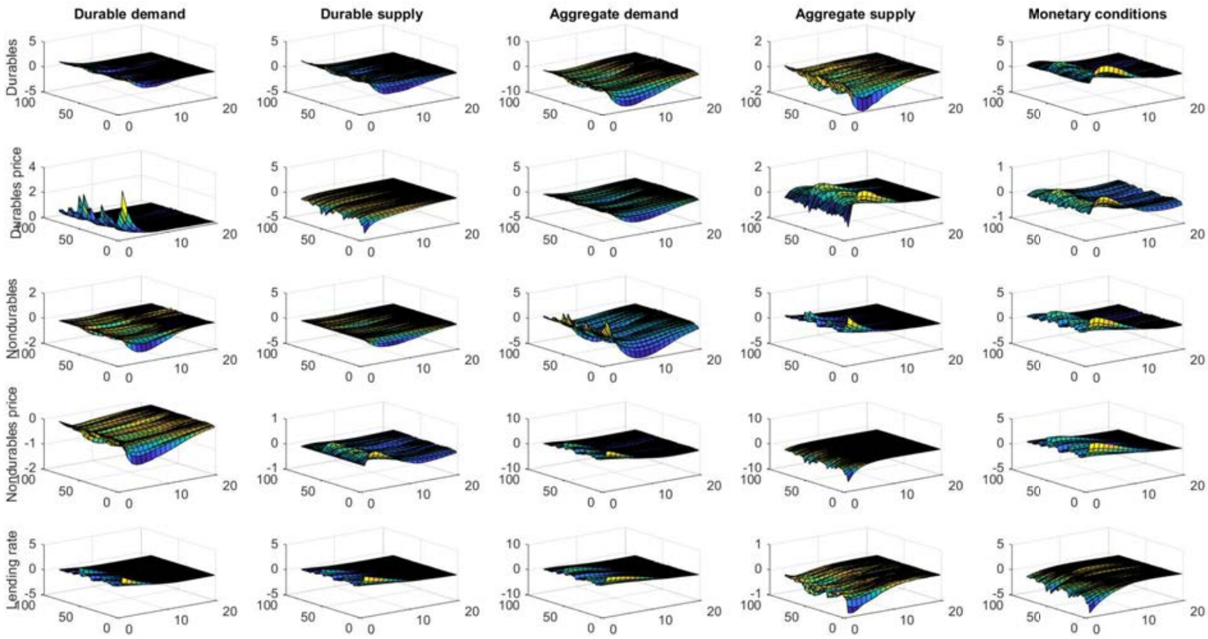
Note: Impulse response functions for each quarter in the sample.

Figure G.16: France impulse response functions



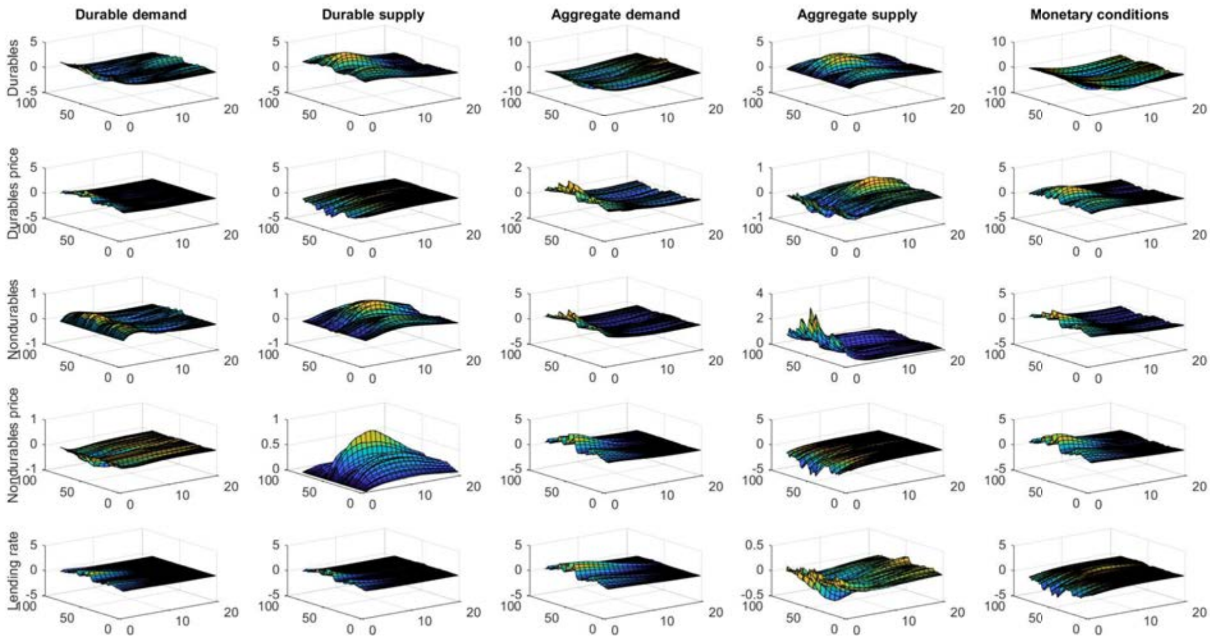
Note: Impulse response functions for each quarter in the sample.

Figure G.17: Italy impulse response functions



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

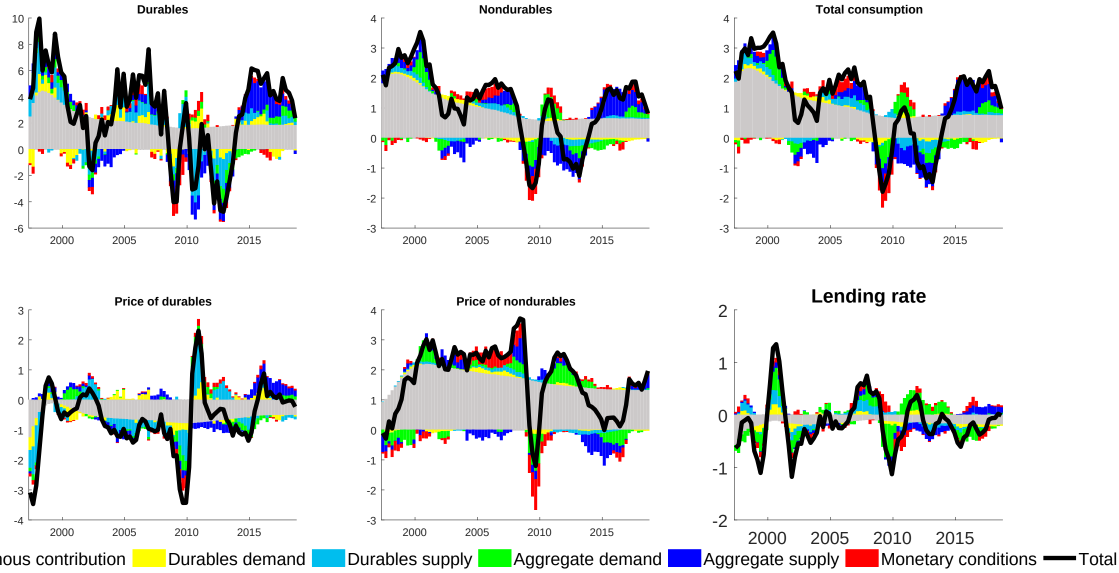
Figure G.18: Spain impulse response functions



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

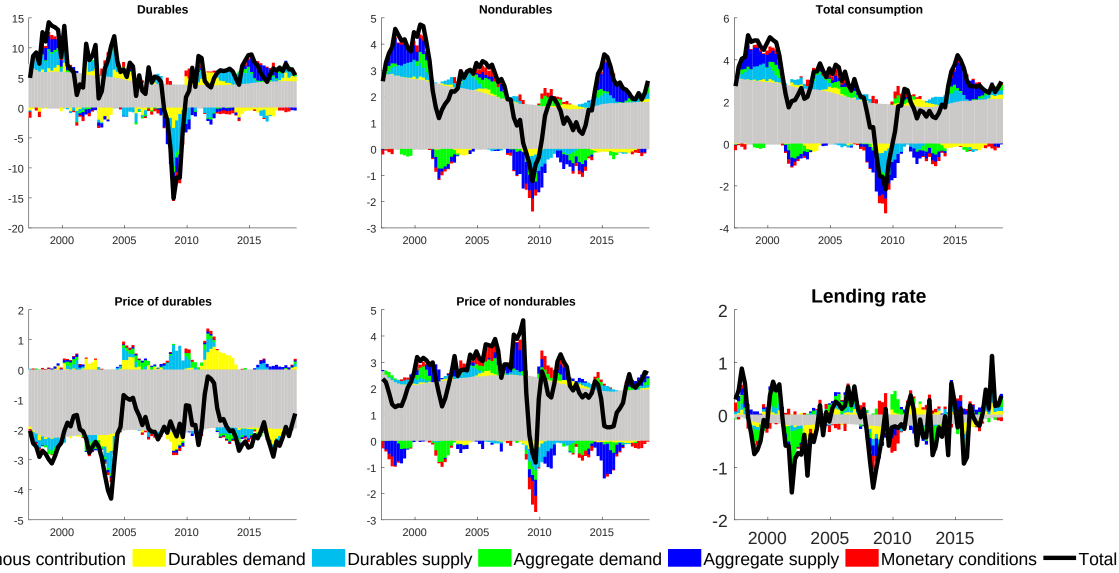
G.4 Historical decomposition

Figure G.19: Euro area historical decomposition



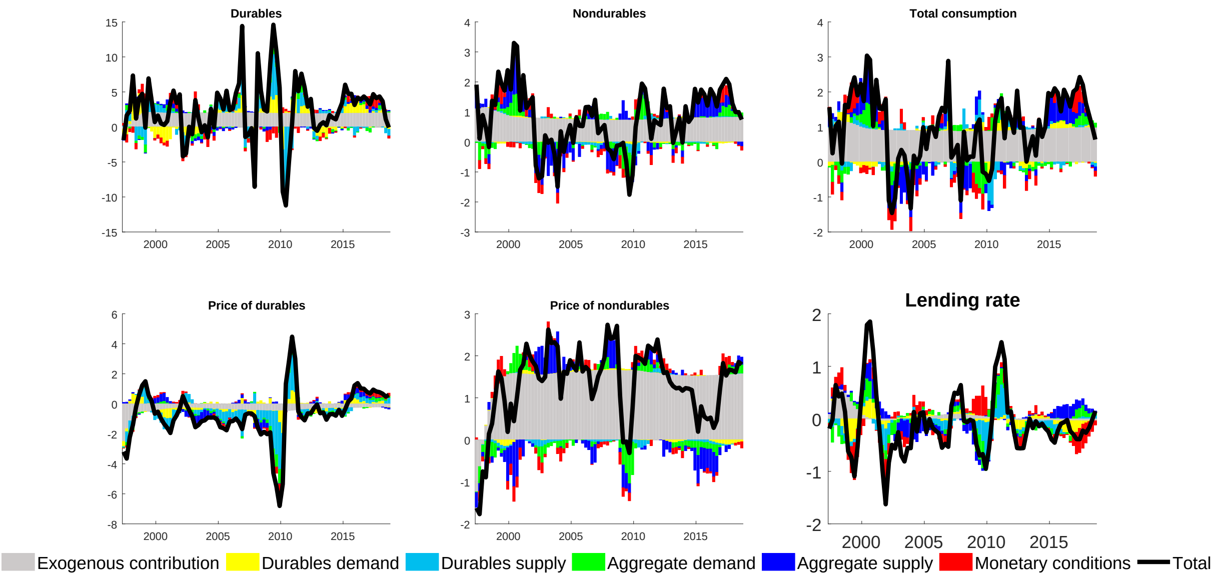
Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

Figure G.20: United States historical decomposition



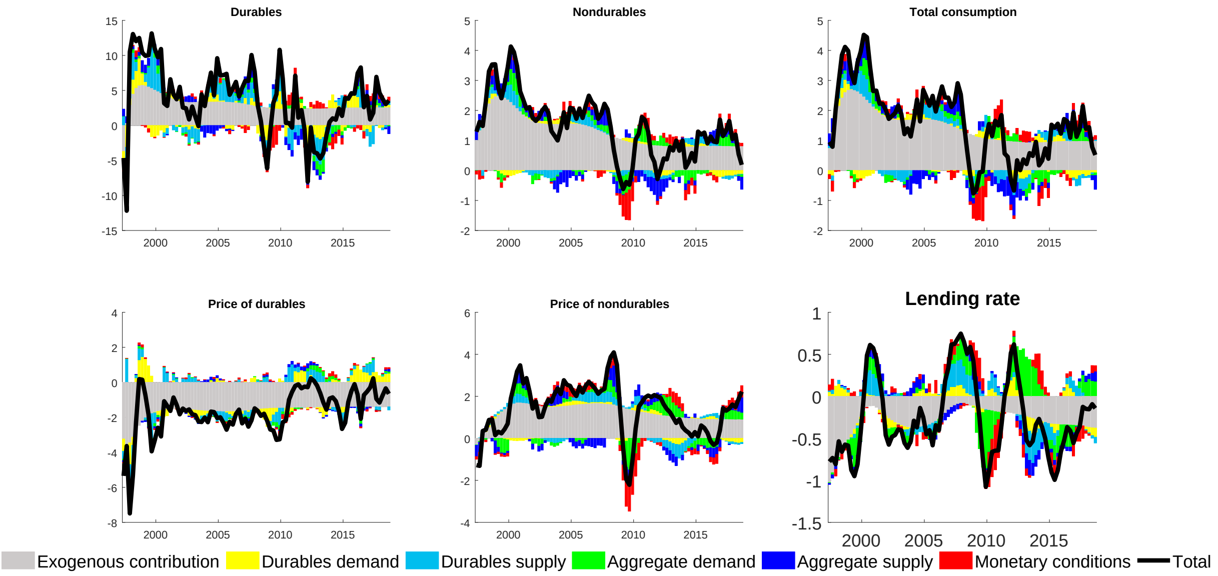
Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

Figure G.21: Germany historical decomposition



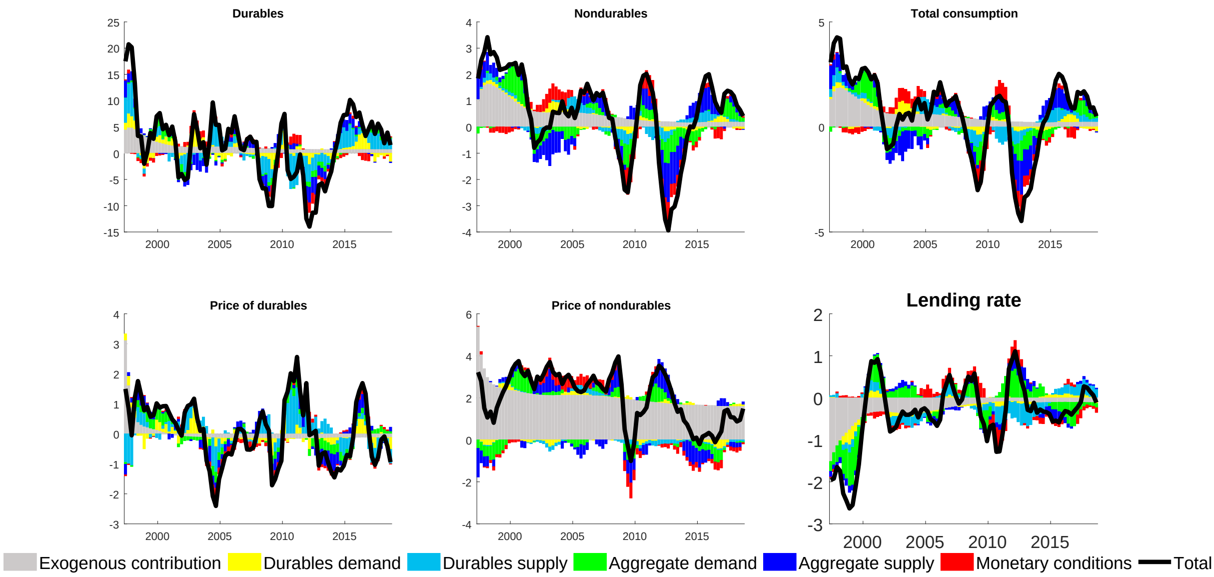
Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

Figure G.22: France historical decomposition



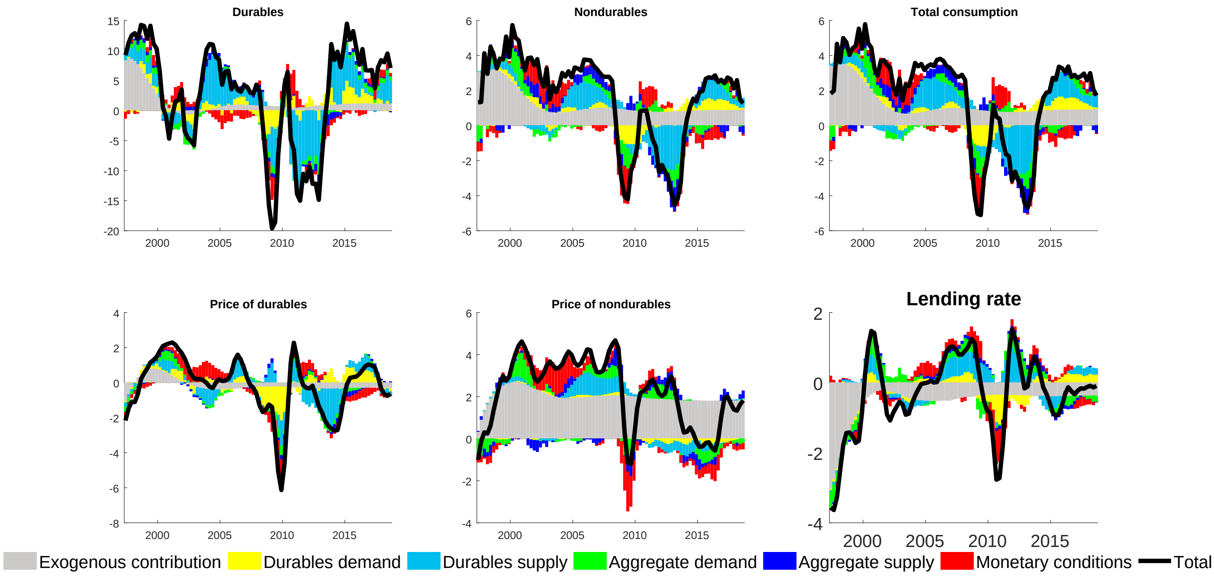
Note: Historical decomposition for year-on-year growth rate of the five endogenous variables and our total consumption aggregate.

Figure G.23: Italy historical decomposition



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

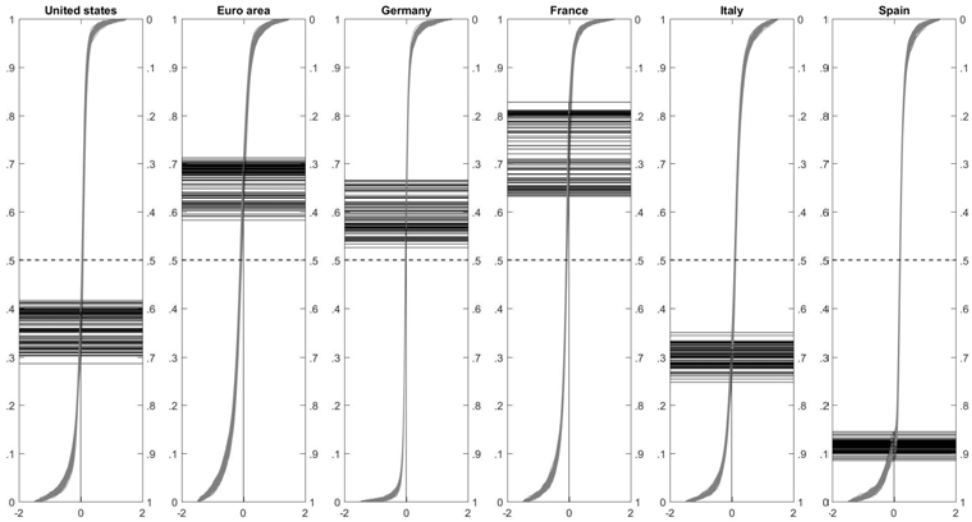
Figure G.24: Spain historical decomposition



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

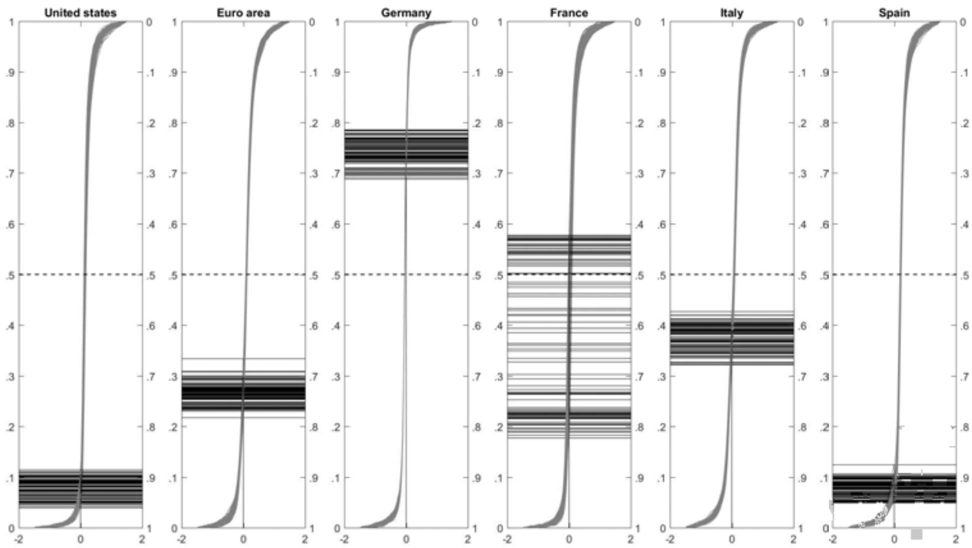
G.5 Spillovers: distributions of maxima over time

Figure G.25: 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 4.2. Each grey line represents the cumulative distribution for a given quarter, generated by 1500 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 indicates how much of the density function cumulates before (after) zero, on the left (right) scale.

Figure G.26: 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 4.2. Each grey line represents the cumulative distribution for a given quarter, generated by 1500 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 indicates how much of the density function cumulates before (after) zero, on the left (right) scale.

G.6 Forecast Error Variance Decomposition

Table G.1: Forecast Error Variance Decomposition and share of total variance explained by the model

	Horizon\Shock	Shares of explained variance (sum equals 100) ε_{DD}	ε_{DS}	ε_{DD+DS}	ε_{AD}	ε_{AS}	ε_{M}	Total variance 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

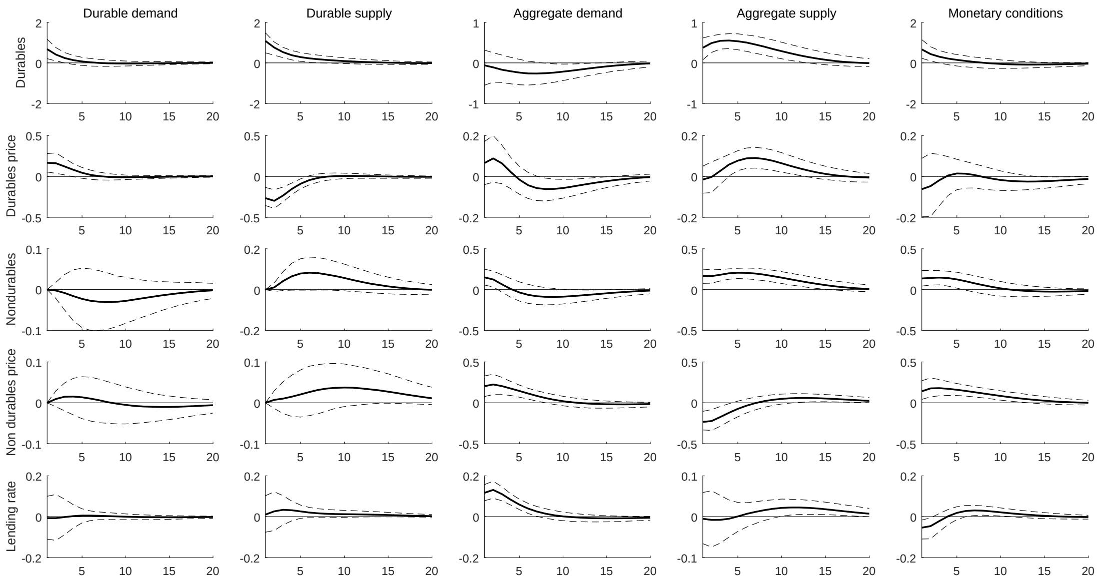
Note: Average percentage of the explained variance of the error made in forecasting total consumption, at horizons of 1, 4, 8 and 20 quarters, due to a specific shock. Last column is the total share of forecast error variance explained.

H 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 E.1, and a TVP-SVAR(1) as in the baseline, but replacing the nondurable consumption variable with real GDP excluding durable consumption expenditures.

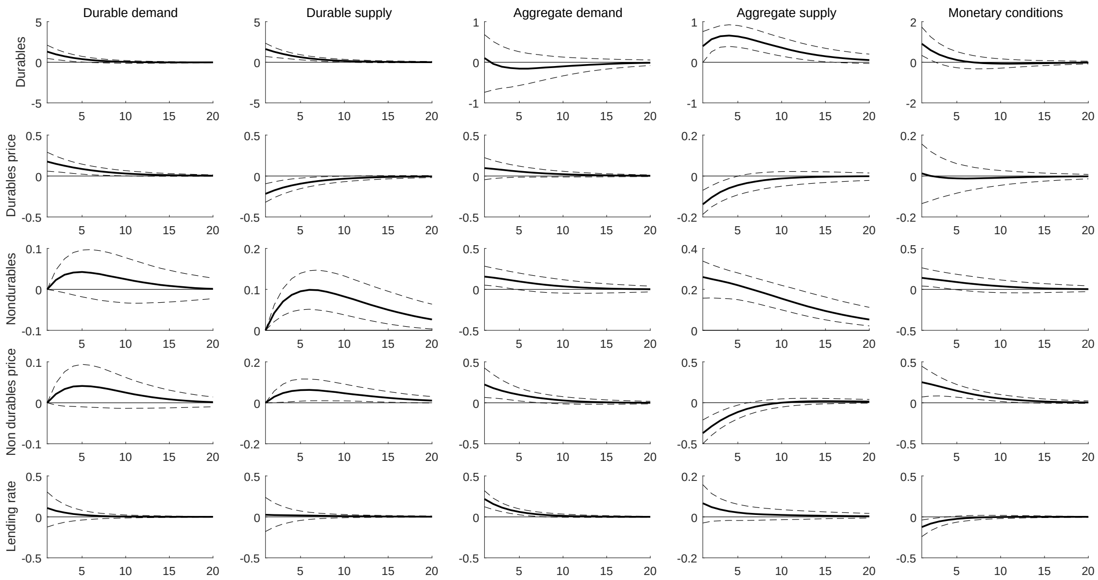
H.1 BVAR(p): Specification in y-o-y changes, constant parameters

Figure H.1: Euro area impulse response functions



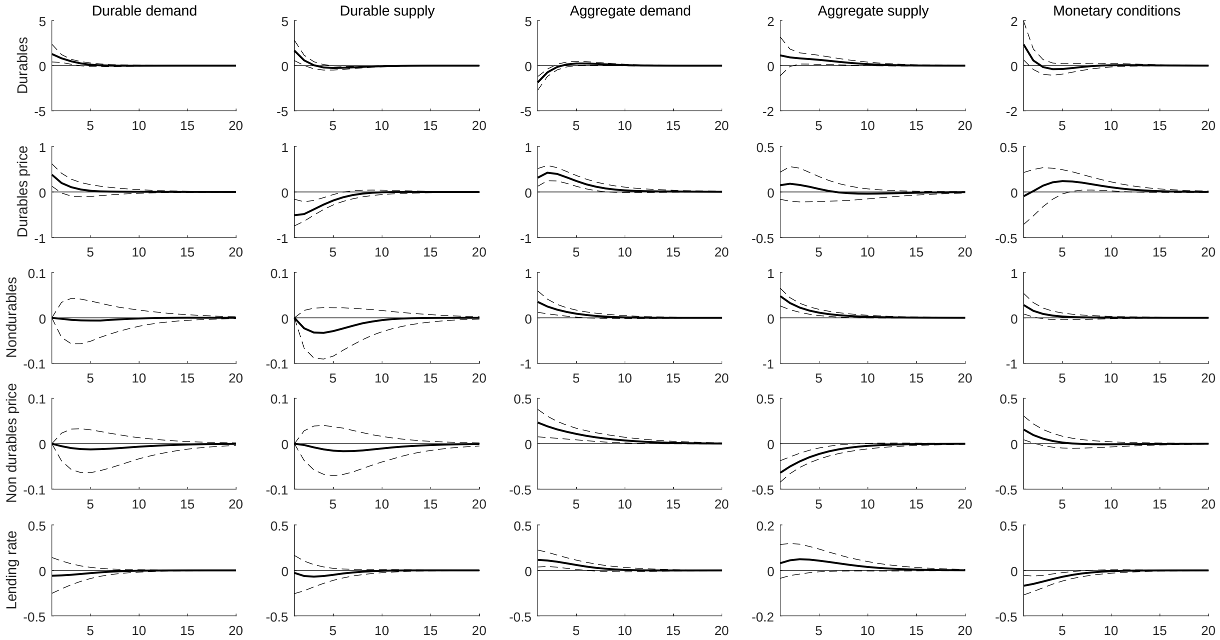
Note: Impulse response functions from a BVAR(2), with 68% credibility bands.

Figure H.2: United States impulse response functions



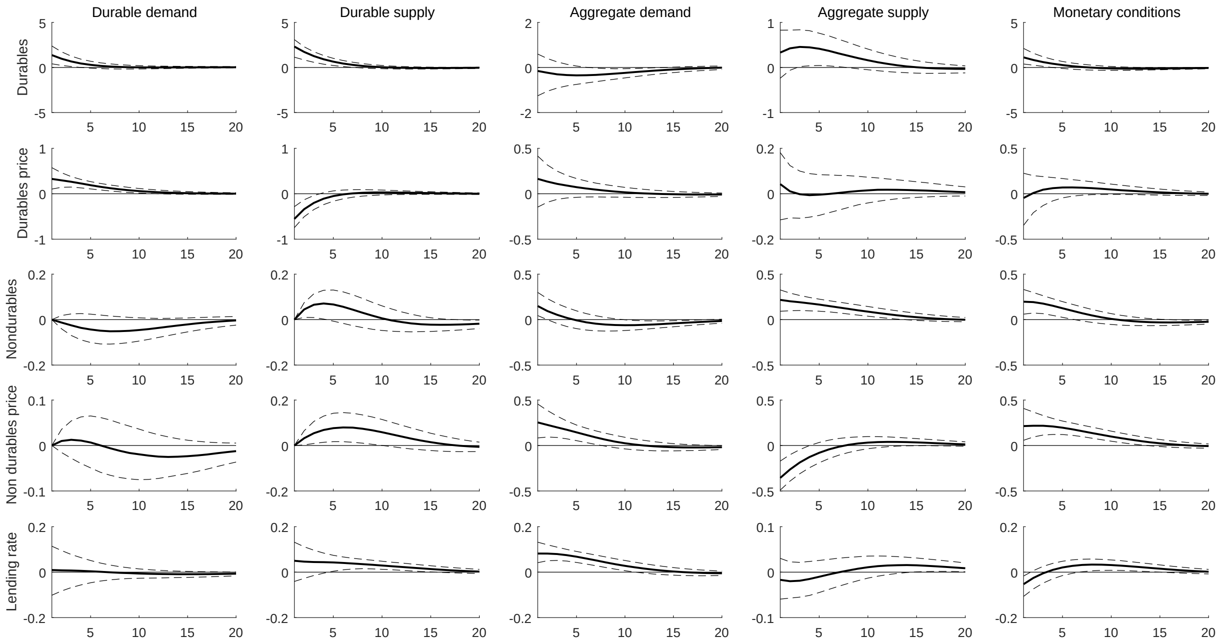
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure H.3: Germany impulse response functions



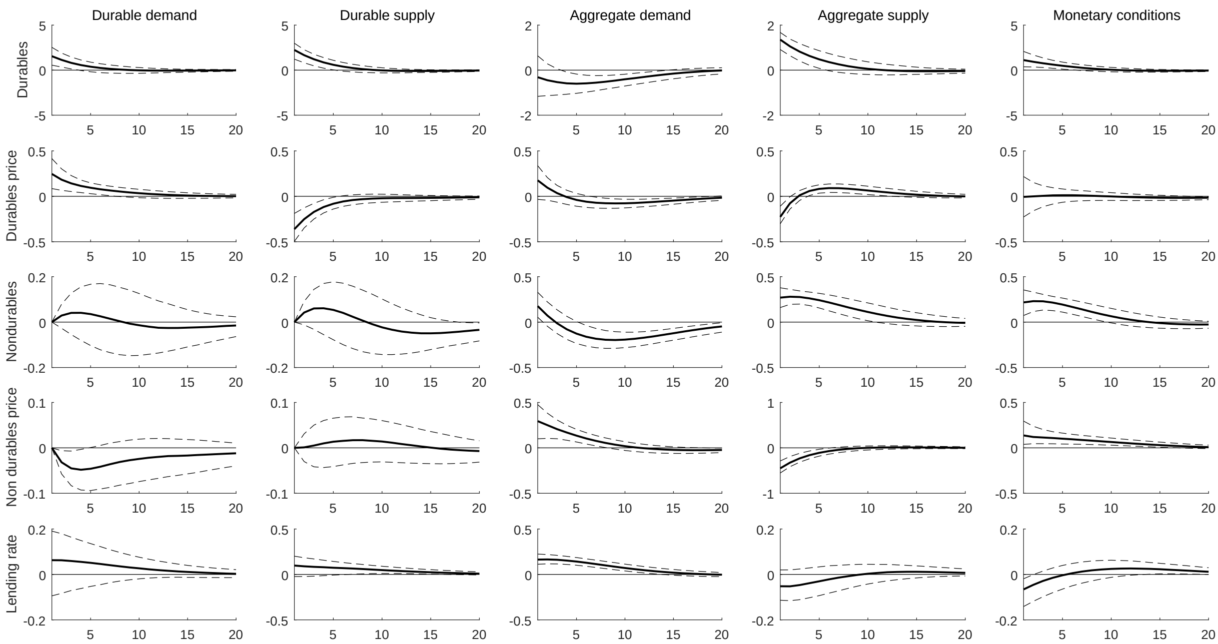
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure H.4: France impulse response functions



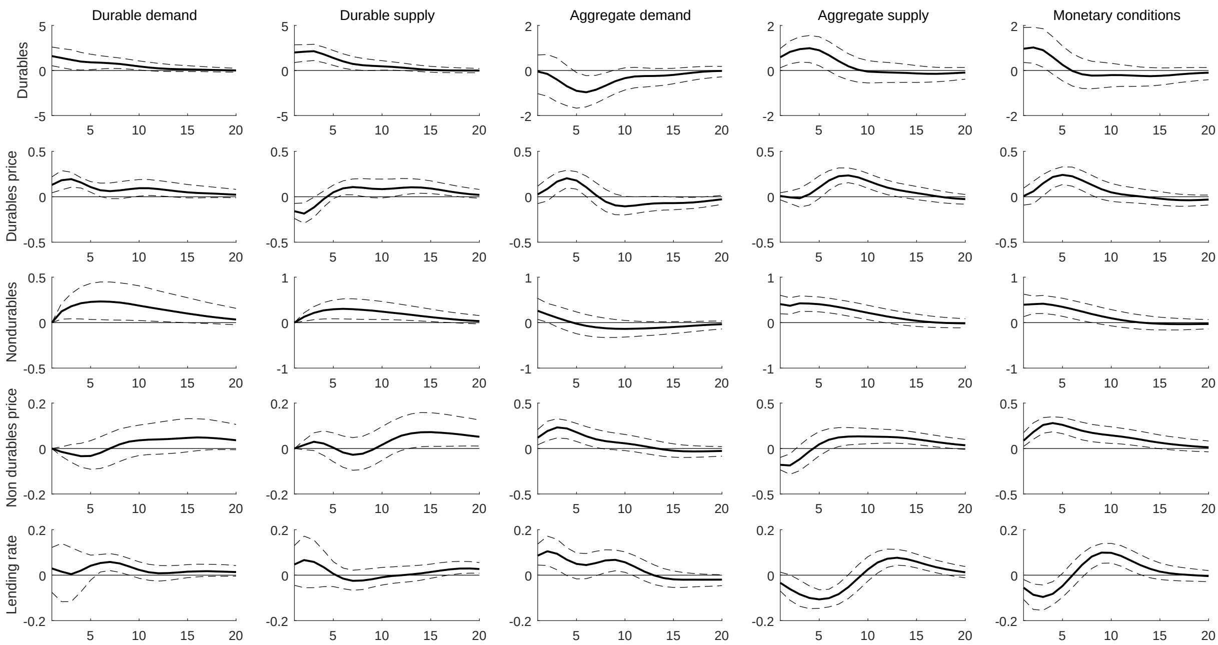
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure H.5: Italy impulse response functions



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

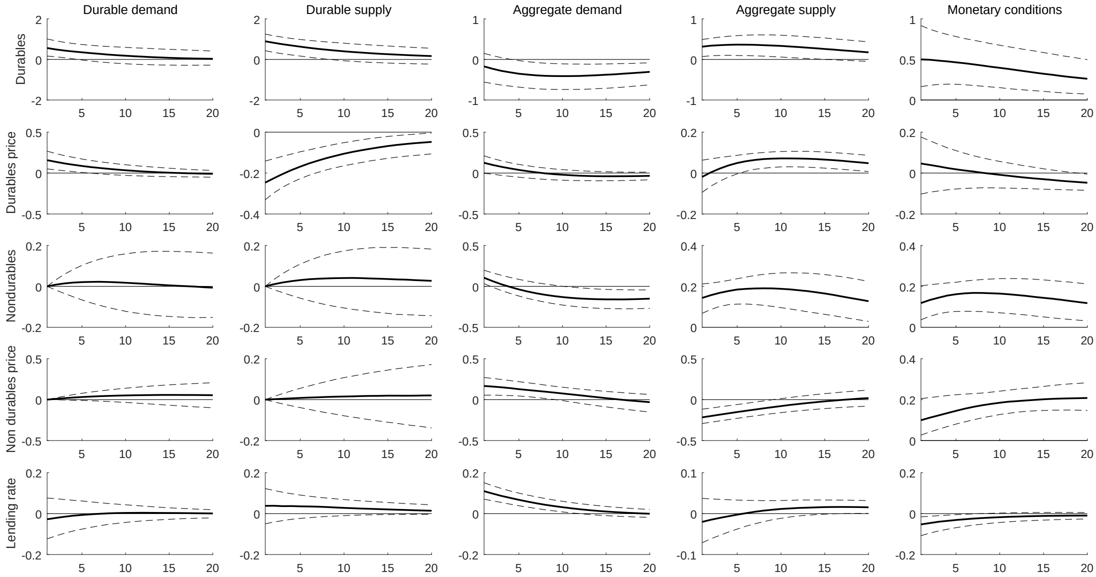
Figure H.6: Spain impulse response functions



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

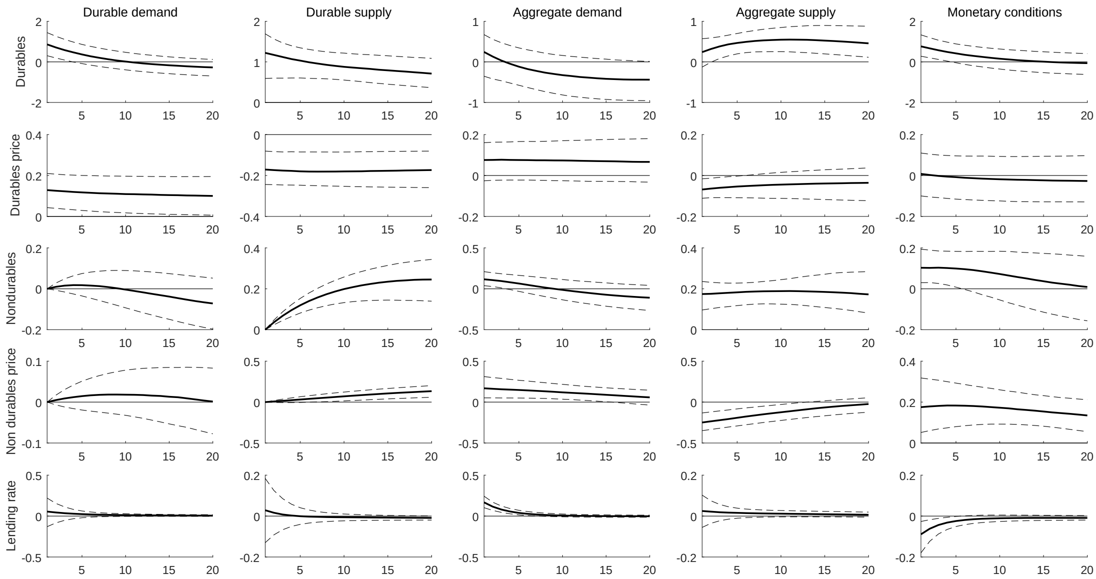
H.2 BVAR(p): Specification in levels, constant parameters

Figure H.7: Euro area impulse response functions



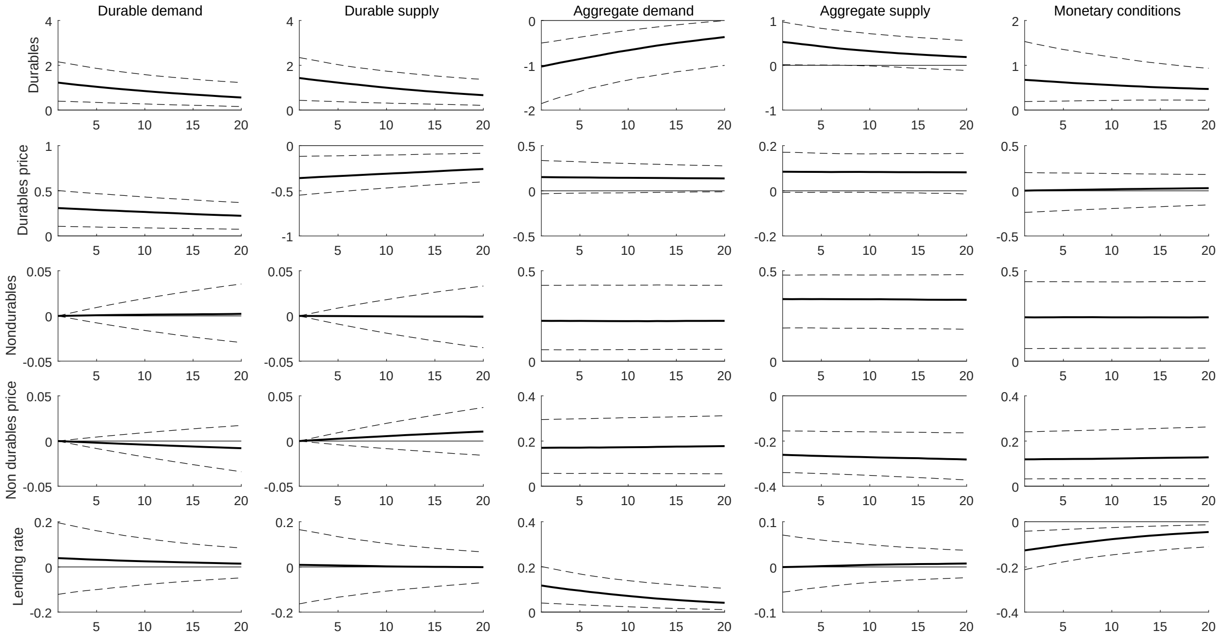
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure H.8: United States impulse response functions



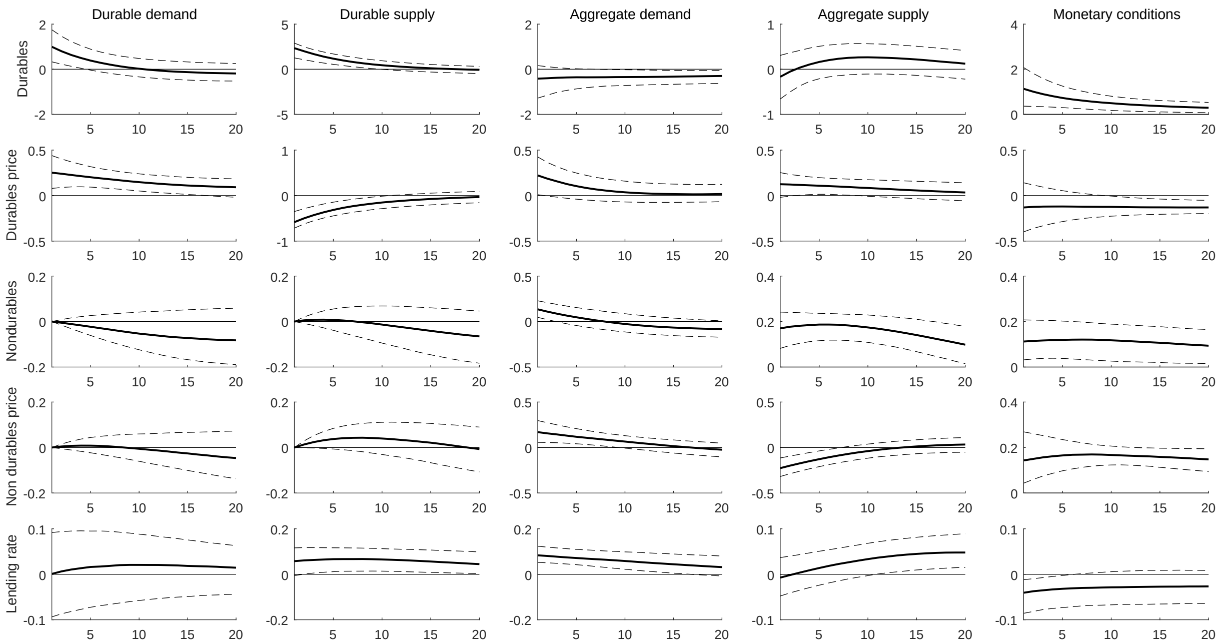
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure H.9: Germany impulse response functions



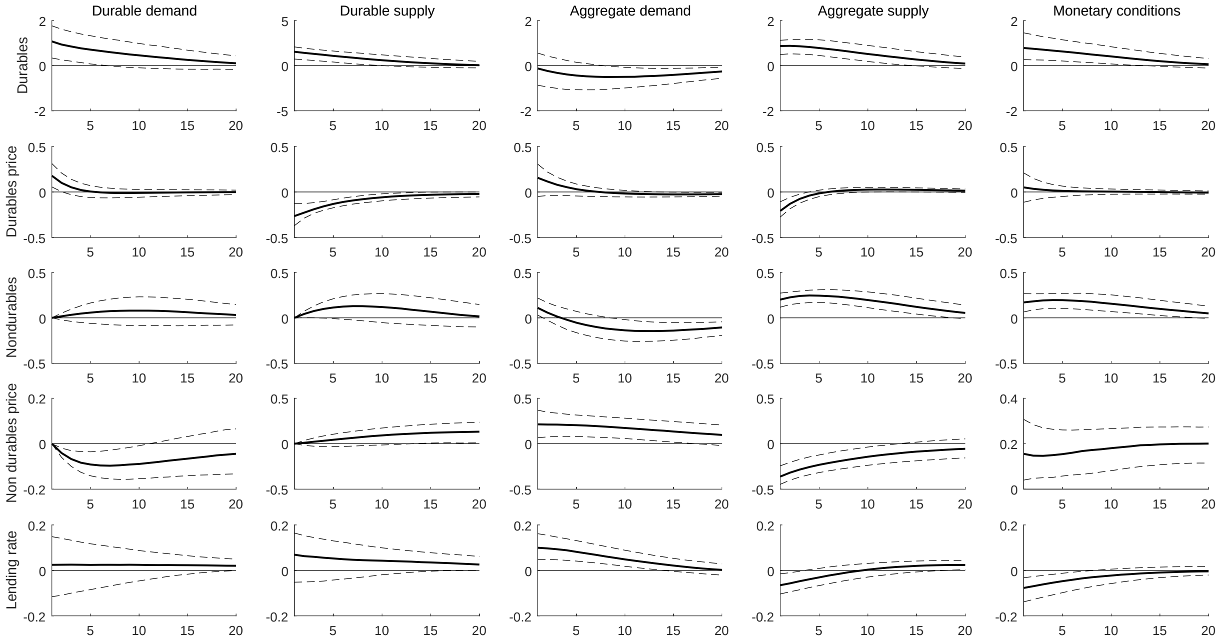
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure H.10: France impulse response functions



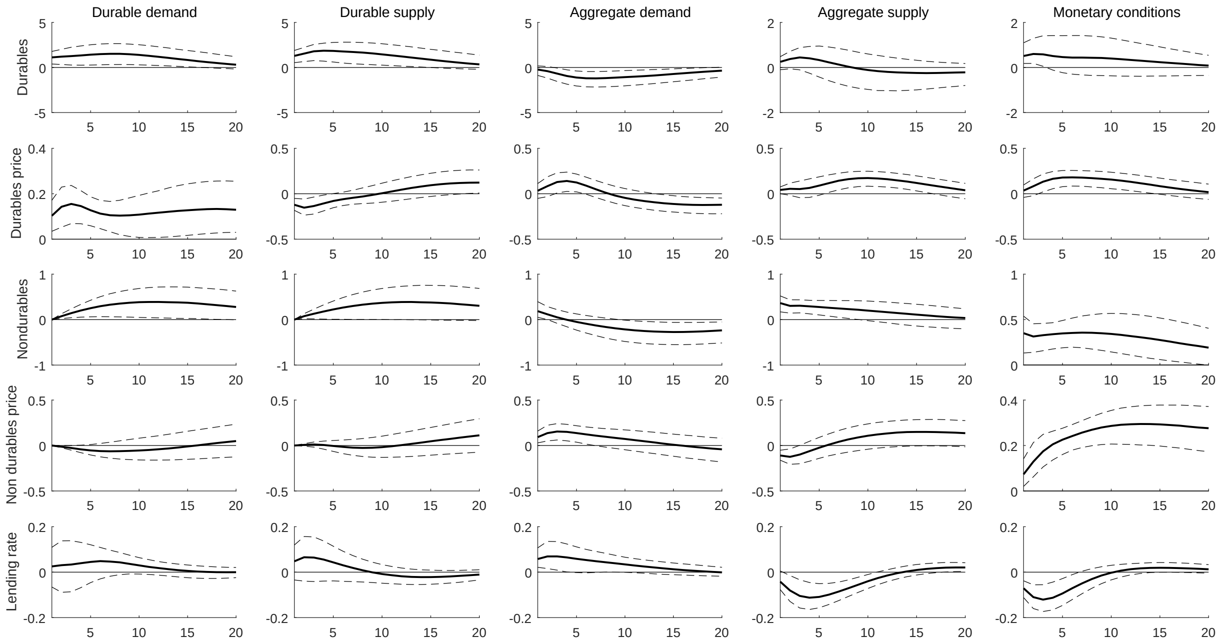
Note: Impulse response functions from a BVAR(1), with 68% credibility bands.

Figure H.11: Italy impulse response functions



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

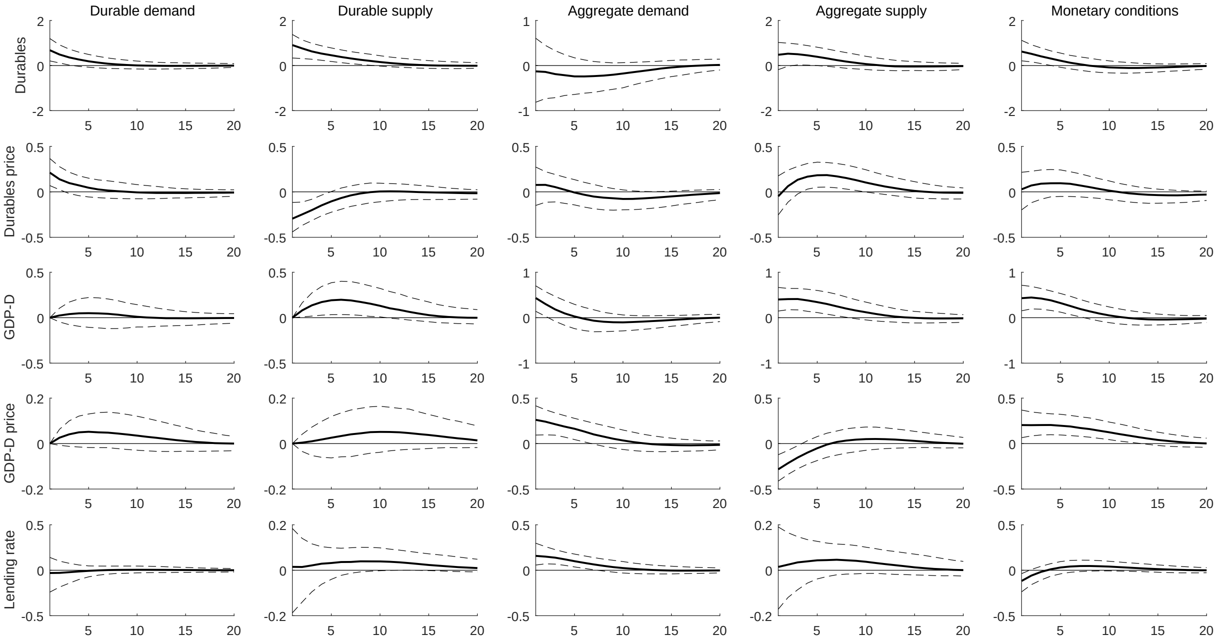
Figure H.12: Spain impulse response functions



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

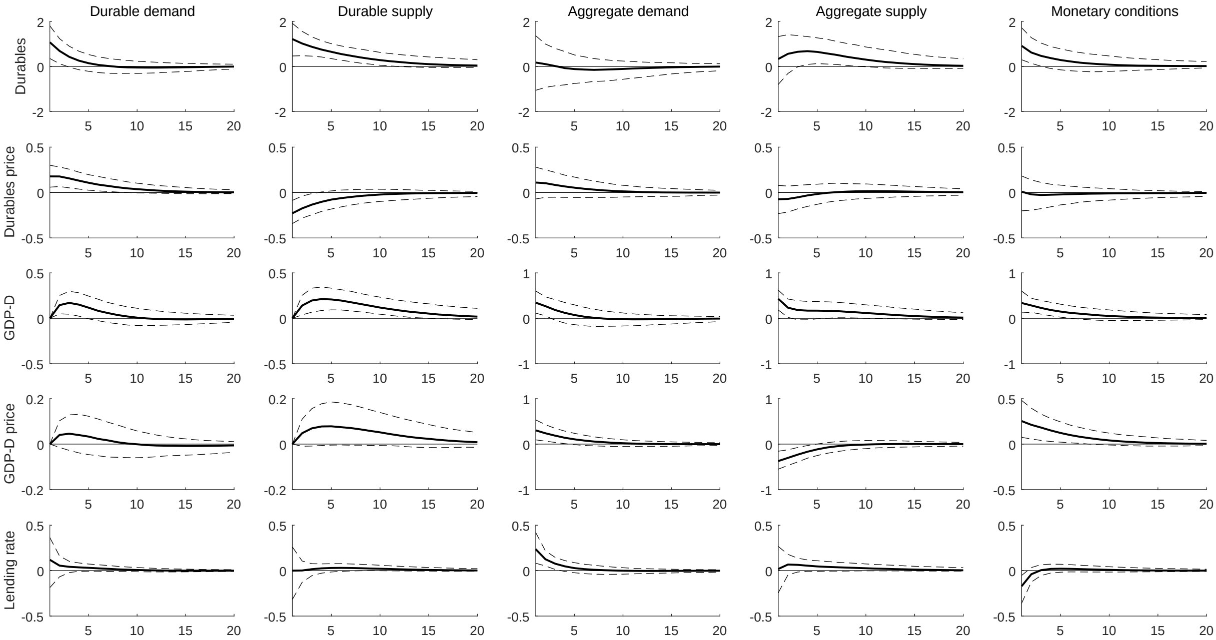
H.3 TVP-SVAR(1): Using GDP ex-durables, instead of nondurables

Figure H.13: Euro area impulse response functions



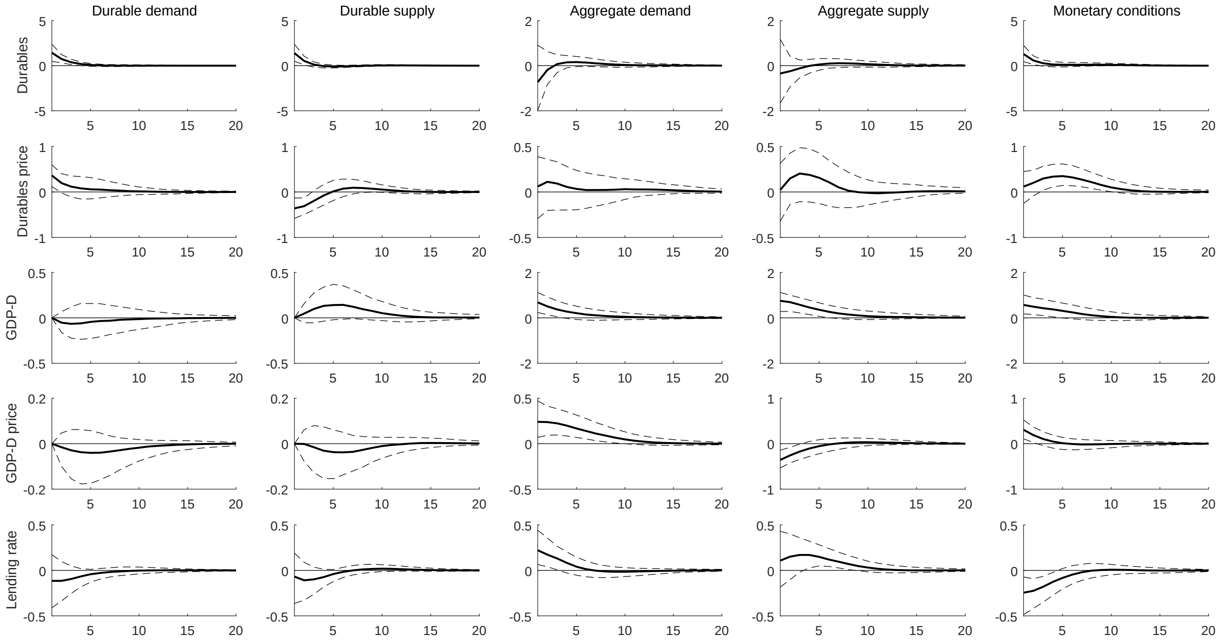
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure H.14: United States impulse response functions



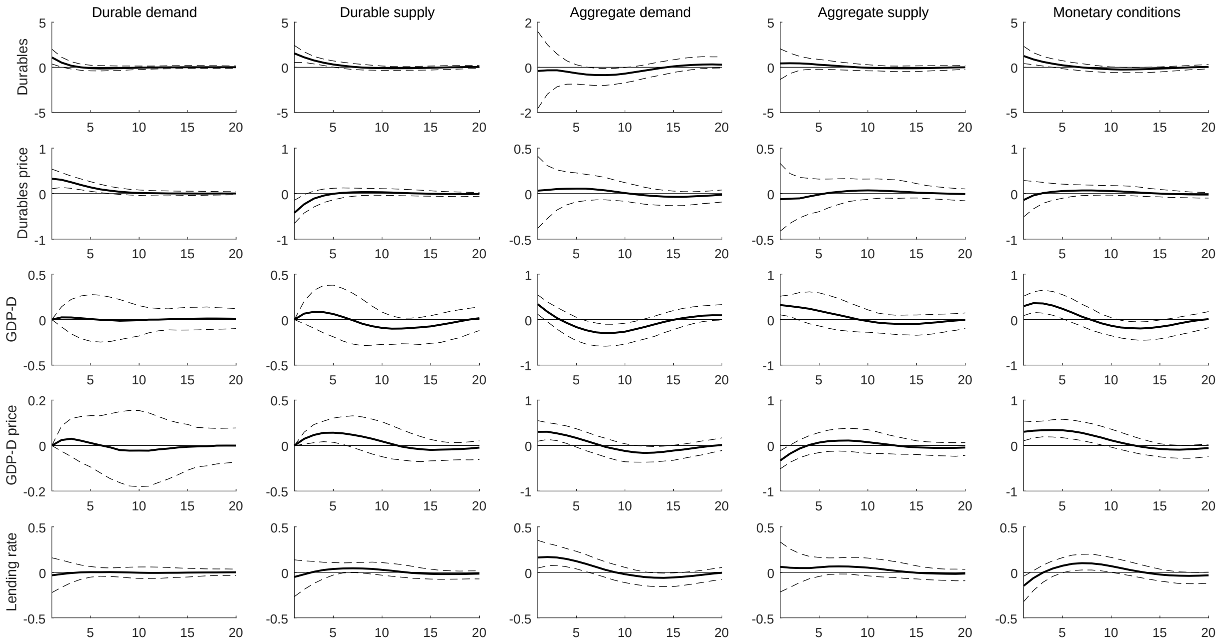
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure H.15: Germany impulse response functions



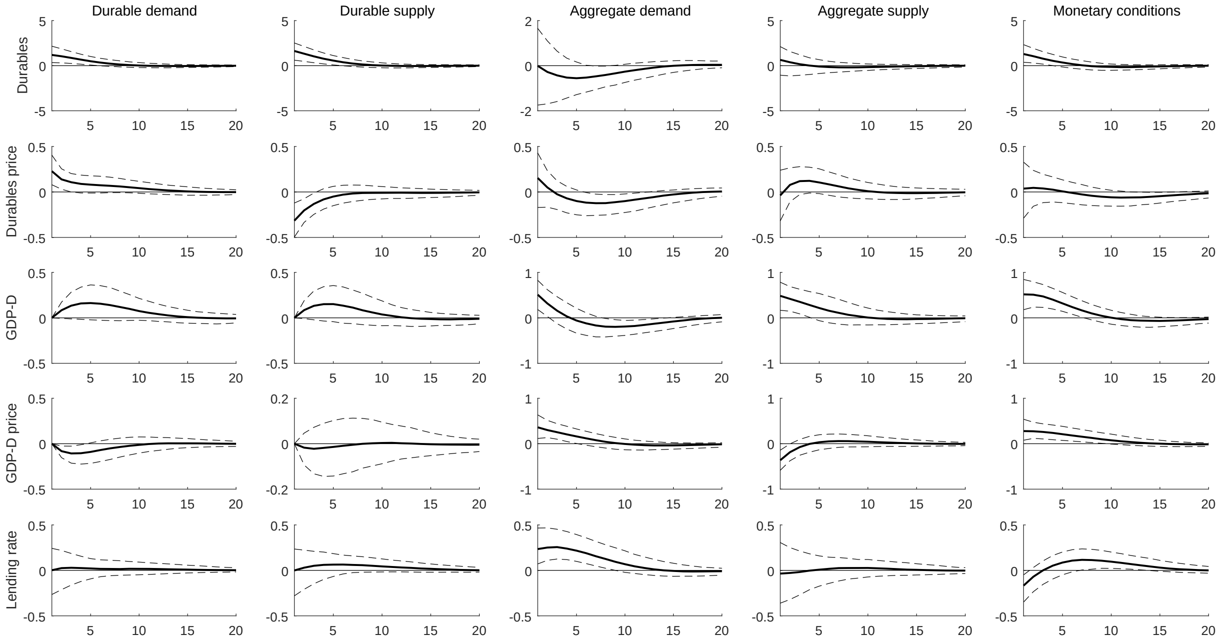
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure H.16: France impulse response functions



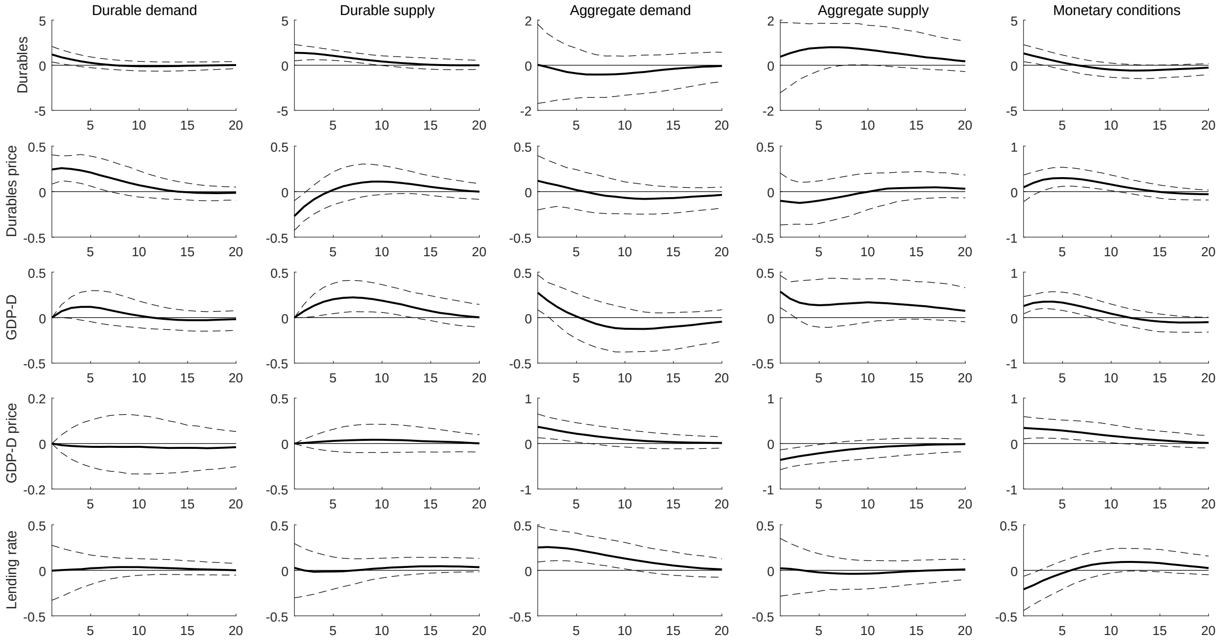
Note: Impulse response functions computed using the long-run, homoskedastic value of $\mathbf{\Sigma}_t$, with 68% credibility bands.

Figure H.17: Italy impulse response functions



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

Figure H.18: Spain impulse response functions



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

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André Casalis
European Central Bank, Frankfurt am Main, Germany; University of York; email: andre.casalis@ecb.europa.eu

Georgi Krustev (corresponding author)
European Central Bank, Frankfurt am Main, Germany; email: georgi.krustev@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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