How Does Monetary Policy Affect Income and Wealth Inequality?
Evidence from the Euro Area

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Abstract
We estimate how the recent nonstandard monetary policy measures affect income and wealth of individual households. We first identify the effects of the Asset Purchases Programme (APP) of the European Central Bank using a VAR estimated on aggregate data from the four largest euro area countries. The VAR includes key variables which affect household income and wealth: unemployment rate, wages, and house and stock prices. We then use a reduced-form simulation on data from the Household Finance and Consumption Survey to estimate how the APP affects individual households. We find that nonstandard monetary policy has only modest effects on wealth inequality. In contrast, monetary policy compresses the income distribution as disproportionately many households with lower incomes become employed.

Keywords Monetary Policy, Household Heterogeneity, Inequality, Income, Wealth, Quantitative Easing, Great Recession

JEL codes D14, D31, E44, E52, E58

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1 Introduction

Empirical evidence based on various data sources has recently documented the dynamics of income and wealth distributions in various countries. This evidence sparked an intense debate about the causes of economic inequality: Is it caused by skill-biased technological progress? Globalization? Progressivity of the tax system?

This paper quantifies the effects of monetary policy on income and wealth of individual households. We focus on the effects of the recent nonstandard monetary policy measures undertaken by the European Central Bank (ECB)—specifically on its Asset Purchases Programme[1] (APP). We combine aggregate and household-level data and proceed with estimation in two steps.

First, we identify the effects of nonstandard monetary policy using a Bayesian VAR estimated on aggregate data from the four largest euro area countries (France, Germany, Italy and Spain). This setting allows us to combine euro area and country-specific variables. Such mix is important so that we can account both for the common, euro-area-wide monetary policy and heterogeneity in the transmission mechanism across countries. The euro area variables thus include most notably euro area interest rates. The country-specific variables include those affecting household income and wealth: unemployment rate, wages and house prices. The impulse responses are identified using a mix of zero and sign restrictions, similar to Baumeister and Benati (2013).

In the second step we use a reduced-form simulation on micro data from the Household Finance and Consumption Survey (HFCS) to estimate how the APP affects individual households. The effects on wealth are estimated assuming that house and stock prices changed as identified in the VAR and that household portfolios were not rebalanced. The effects on income are estimated using a reduced-form simulation in which some households become employed depending on their demographic characteristics—these households then receive a substantial increase in (labor) income, as they start receiving wages rather than unemployment benefits. The simulation ensures that the reduction of the unemployment rate in the aggregate matches that estimated in the VAR impulse responses.

We find that nonstandard monetary policy has only modest effects on wealth inequality. It increases the prices of stocks, which are disproportionately held by richer households. However, our estimates also highlight the importance of accounting for housing wealth, which makes up around 80% of total assets and which is quite evenly distributed across households. Once housing wealth is included in the calculations, the effects of monetary policy on various measures of wealth inequality are very small.[2]

In contrast to wealth, monetary policy compresses noticeably the income distribution. The quantitatively decisive factor is that many unemployed households become employed

[1] The ECB's Asset Purchase Programme was started in January 2015 as a way to implement "quantitative easing", in order to address the risks of a too prolonged period of low inflation. The APP includes various purchase programmes under which private sector securities and public sector securities (including sovereign bonds) are purchased. For an early assessment of the APP see Andrade et al. (2016).

For most countries, the reference year of the HFCS wave 2 is 2014, which matches quite well the start of APP.

[2] In our baseline calculation we find that the APP actually *reduces* the Gini coefficient on net wealth, but the effect is negligible.

and consequently their income rises substantially.[3] We find that the APP reduces the unemployment rate among households in the bottom income quintile by 2 percentage points, which boosts their mean income by more than 3 percent. The effects on other parts of the income distribution are much more modest. The Gini coefficient on gross income decreases from 43.1 to 42.8 percent.

Literature on Monetary Policy and Household Heterogeneity

Our work is related to several strands of research on monetary policy and household heterogeneity. First, several recent papers identified the effects of *nonstandard* monetary policy using VARs: see Baumeister and Benati (2013), Altavilla et al. (2016) and others. For identification we follow the studies which impose a combination of zero and sign restrictions. The main identifying assumption is that an expansionary asset purchase shock reduces the term spread (defined as long-term minus short-term interest rate) and has a positive impact on the real economy. Alternatively to VARs, the effects of nonstandard monetary policy on the term spread can be estimated via event studies. Existing estimates of the effects of monetary policy on long-run interest rates, asset prices and real economy are summarized in Tables 1–3.

Coibion et al. (2017) use quarterly data from the US Consumer Expenditure Survey (CEX) in a VAR with narrative shocks to estimate the effects of (standard) monetary policy on the Gini coefficients for consumption and income (but not on wealth).[4] They find that contractionary monetary policy increases inequality in labor earnings, total income and consumption. Mumtaz and Theophilopoulou (2017) provide similar evidence for the UK. Hafemann et al. (2017) estimates the effects of monetary policy on income inequality in 6 countries (US, Canada, South Korea, Sweden, the Czech Republic and Hungary) to investigate how the degree of redistribution affects the transmission.

A separate strand of work building on the seminal paper of Doepke and Schneider (2006) estimates the distribution of net nominal positions across individual US households and their exposures to inflation shocks (see also Doepke et al. (2015)). Adam and Zhu (2016) provide analogous evidence for the euro area. Using hypothetical scenarios,[5] Adam and Tzamourani (2016) quantify the effects of prices of various assets (stocks, bonds, house prices) on wealth of euro area households.

Finally, Brinca et al. (2016) document using VARs cross-country a strong correlation between wealth inequality and the magnitude of fiscal multipliers. They then develop a life-cycle, overlapping-generations economy with uninsurable labor market risk and find that the fiscal multiplier is highly sensitive to the fraction of households facing binding credit constraints and also to the average wealth level in the economy.

[3] We also account for the second channel whereby all wages are increased by the aggregate factor estimated in the VAR impulse responses.

[4] Aladangady (2014) and Aladangady (2017) estimate the effects of monetary policy on house prices and eventually household consumption in the US using a two-step procedure combining a structural VAR with regional data and micro data from the CEX.

[5] An example of such scenario is: "What happens to household net wealth if bond, equity and house prices unexpectedly increase by 10%?"

So far however, there is little quantitative work on effects of nonstandard monetary policy on inequality, which would combine aggregate and household-level evidence and compare the effects on wealth and income (also accounting for the employment effects of monetary policy). That's where our paper comes in.

The remainder of the paper is organized as follows. Section 2 describes how we estimate the APP 'micro' impulse responses using a two-step method first based on a multi-country BVAR model and a simulation on household-level income and wealth data. Section 3 summarizes and interprets the empirical results. Section 4 concludes.

2 Estimation

To estimate the effects of monetary policy on wealth and income of individual households we follow a two-step procedure: First, we estimate a Bayesian VAR with aggregate data and identify the effects of monetary policy shocks at the aggregate level. Second, we undertake a reduced-form simulation using micro data to distribute the aggregate effects across individual households. This section describes both steps in detail.

2.1 The BVAR Model and the Identification of Monetary Policy

We identify the effects of nonstandard monetary policy using a large vector autoregression (VAR) with country-specific variables for four large countries, euro area variables and US variables. Such setup is useful because it allows us to estimate heterogeneities at the country level in responses to a common euro-area monetary policy.

To capture the dynamic interrelationships among the variables, we adopt the following setting. The VAR model for an N-dimensional vector of time-series y_t can be described as:

$$
\begin{aligned}
y_t &= C + B_1 y_{t-1} + ... + B_p y_{t-p} + \epsilon_t, \\
\epsilon_t &\sim \mathcal{N}(0, \Sigma),
\end{aligned}
$$

where $B_1, \ldots, B_p$ are $N \times N$ matrices of coefficients on the p lags of the variables, C is an N-dimensional vector of constants and Σ is the covariance distribution of the VAR errors. The model is specified in terms of the annualized (log-)levels of the variables and, in our specification, we have $N = 25$ and $p = 5$.

The large dimension of this model implies that we may face a "curse of dimensionality" due to the large number of parameters to be estimated, relative to the available sample. More precisely, the estimation of the model via classical techniques would very likely result in overfitting the data and large estimation uncertainty. De Mol et al. (2008) and Banbura et al. (2010) showed that imposing priors which push the parameter values of the model toward those of naïve representations (as, for example, the random walk model) reduces estimation uncertainty without introducing substantial bias in the estimates, thanks to the tendency for most macroeconomic and financial variables to comove. In fact, in presence of comovement, the information in the data strongly "conjures" against the prior and it allows the parameters to still reflect sample information even if very tight prior beliefs are enforced.

Therefore, we estimate the model with Bayesian techniques, with conjugate prior distributions belonging to the Normal/Inverse-Wishart family. The prior for the covariance matrix of the residuals Σ is Inverse-Wishart, while the prior for the autoregressive coefficients is (conditional on Σ) normal. As it is rather standard in the BVAR literature, we follow Litterman (1979) and parameterize the prior distribution to shrink the parameters toward those of the naïve and parsimonious random walk with drift model, $X_{i,t} = \delta_i + X_{i,t-1} + e_{i,t}$. Moreover, in order to address the tendency of VARs to overfit the data via their deterministic component (see Sims, 1996, 2000; Giannone et al., 2016, for an extensive discussion of this pathology of VARs), we also impose two priors on the sum of the VAR coefficients. The full specification and the estimation method used for the VAR model follows Giannone et al. (2015), to which the reader is referred for more details.[6] The setting of the prior distributions depends on the hyperparameters which describe their informativeness for the model coefficients. For these parameters, we follow the theoretically grounded approach proposed by Giannone et al. (2015) which suggests to treat them as random, in the spirit of hierarchical modelling, and conduct posterior inference also on them. As hyper-priors (i.e., prior distributions for the hyperparameters), we use proper but almost flat distributions.

In order to provide an estimate of the effects of the ECB asset purchases, we identify an exogenous asset purchase shock similarly to Baumeister and Benati (2013) for the US quantitative easing shock and, then, we offset the response of the euro area policy interest rate via a series of standard monetary policy shocks. This scenario captures the fact that standard monetary did not react, over the course of the recent crises, to offset the effects of the asset purchases.

To identify the effects of an ECB asset purchase shock, we resort to a mix of zero and sign restrictions, employing the algorithm described in Arias et al. (2014). The main identifying assumption is that an expansionary asset purchase shock decreases the term-spread (defined as long-term minus short-term interest rate) and has a positive impact on the real economy of the four countries under analysis. The decrease in the term-spread on impact is entirely accounted for by the drop in the long-term interest rates, given that standard monetary policy (captured by the short-term interest rates) is assumed not to react on impact to the asset purchases. For what concerns the specific restrictions on the response of the macroeconomic environment, we impose a positive sign on the responses of GDP. The responses of all other variables, i.e., the GDP deflator, the unemployment rate, wages and house prices in the four countries, the US variables and stock prices, are left unrestricted. Notice that all the identifying assumptions are only imposed on impact, i.e., for the same quarter in which the shock materializes. For what concerns the standard monetary policy shock, we identify it via standard zero restrictions. In particular, we assume that a change in the short-term interest rate can only affect, on impact, the long-term interest rate and the stock prices.[7]

[6] Appendix 2 at the end of the paper presents some of the details of our estimation method.

[7] In Appendix 1, we also summarize the identifying restrictions for the two shocks.

2.2 The Reduced-Form Simulation on Household-Level Wealth and Income Data

This section describes how we distribute the aggregate effects estimated in the BVAR across individual households depending on their characteristics: structure of their wealth portfolios, employment status and demographics.

We make use of the second wave of the Eurosystem Household Finance and Consumption Survey (HFCS). The HFCS is a unique ex ante comparable household-level dataset on the distribution of household wealth in many European countries. It contains rich information on the structure of household balance sheets and their variation across individual households. The dataset also collects information about socio-demographic variables, assets, liabilities, income and indicators of consumption.

We focus on the four largest euro area countries, in which the HFCS (net) sample ranges roughly between 4,500 households (Germany) and 12,000 households (France).[8] For Spain the reference year is 2011, for the other three countries 2014. Wealthy households are over-sampled in most countries.

2.2.1 Simulation of Household Wealth

The HFCS dataset contains detailed quantitative information about holdings of various asset classes by each household. To estimate the effect of monetary policy on household wealth we multiply the holding of each asset class (in EUR) by the factor of the corresponding asset price given by the VAR impulse response. The VAR includes two asset variables: house prices and stock prices. We multiply the holdings of housing wealth by house prices and the holdings of shares and voluntary pensions by stock prices.[9]

This calculation assumes that households do not adjust their portfolios in response to monetary policy. This seems a reasonable first-order approximation for two reasons. First, below we consider responses to relatively *small* monetary policy shock over the short-run horizon of several quarters. Second, substantial evidence exists on the sluggishness in household portfolios. This holds not only for very illiquid assets (such as housing) but also for many financial assets. For example, a well-known paper by Ameriks and Zeldes (2004) documents that almost half of the households in their sample made no active changes to their portfolio of stock over the *nine-year* period they consider. Similar findings are reported in Bilias et al. (2010): The bulk of US households exhibits considerable inertia in their stock portfolios.[10]

[8] See Eurosystem Household Finance and Consumption Network (2016), in particular Table 1.1, for information on the second wave of the HFCS.

[9] We assume other classes of net wealth, most importantly deposits and liabilities remain unaffected by monetary policy. For the time period we focus on—since 2014—this seems reasonable as the short-run interest rate was at the zero lower bound.

[10] Although Bilias et al. (2010) also finds that households with brokerage accounts exhibit a high incidence and frequency of trading, even these households hold a small share of their financial assets in those accounts.

2.2.2 Simulation of Household Income

The impulse responses estimated in the VAR model imply that nonstandard monetary policy reduces unemployment rate. Household-level data on employment and income make it possible to simulate how this reduction increases income of individuals who find jobs.

The simulation proceeds in two steps. First, we distribute the aggregate decline in unemployment across individuals, using a probit regression which takes into account their characteristics. This implies some people become newly employed. Second, these newly employed individuals receive a (substantially) higher income, as they switch from unemployment benefits to wage (estimated by the Heckman model).[11] The simulation is run at the individual level (not at the household level) and broadly follows the setup of Ampudia et al. (2016).

Step 1: Probit Simulation for the Employment Status
For each country c, we first estimate a probit model regressing individual's i employment status Y on demographic characteristics:

$$\Pr(Y_i = 1 | X_i = x_i) = \Phi(x_i' \beta_c), \tag{1}$$

where X denotes demographics: gender, education, age, marital status and the number of children; $\Phi(\cdot)$ denotes the normal cdf. For each individual we denote the fitted values, the estimated probability of being employed: $\hat{Y}_{c,i}$.

We then draw a uniformly distributed random shock ξ_i. If ξ_i is sufficiently below $\hat{Y}_{c,i}$ and the person is unemployed, she becomes employed. The threshold for moving into employment is implied by the VAR impulse response giving the reduction of aggregate unemployment rate.[12] We repeat the simulation many times and report the average results across repetitions.[13]

Step 2: Heckman Imputation of Labor Income
In the second step we estimate the wage of newly employed people with a two-step Heckman selection model. Our exclusion restrictions are the marital status and the presence of children. These factors may affect the work status but not the wage of the employed. The remaining regressors in the model are gender, education and age.

3 Empirical Results

This section describes our estimates, first focussing on the effects of monetary policy on aggregate variables identified using the VAR model, then considering the effects on wealth and income of individual households.

[11] Finally, income of all households is also increased by the amount given in impulse responses for wages.

[12] We sort unemployed individuals by their value of $(\xi_i - \hat{Y}_{c,i})$ and those with the lowest rank become employed until the reduction in the unemployment rate matches the value given by the impulse response. We use survey weights in this calculation.

[13] In results reported below we use 200 repetitions.

The VAR model includes country-specific variables (for France, Germany, Italy and Spain): real GDP, the GDP deflator, the unemployment rate, nominal wages and house prices. We also include the short- and long-term nominal interest rates and stock prices for the euro area and, finally, GDP and short-term nominal interest rates for the US. The VAR thus consists of 25 variables in total. The sample covers 1999Q1–2016Q4; the model is estimated at the quarterly frequency.[14]

3.1 Aggregate Effects of Asset Purchases

Figure 1 reports the impulse responses of selected variables to the asset purchase shock. In the top left panel, the figure shows the response of the long-term interest rate, which coincides with the term spread—given that the short-term interest rate is assumed not to change on impact.

We normalize the size of the shock to a 30-basis points drop. This size is in line with existing studies Altavilla et al. (2015) and Andrade et al. (2016); see Table 1. The term-spread shock has a relatively short-lived impact on the term-spread, whose median response is close to zero already after three quarters. The peak response of stock prices is quite large—4 %—but also quite short-lived: it last for roughly 4 quarters.

House prices increase in all countries, although with a relevant degree of heterogeneity. For example, in Spain the increase is close to two percent, while in Germany is about a third of that size. The reactions in the labor markets also show a marked heterogeneity across countries. The unemployment rates drop in all countries but, again, the response in Spain is about three times as large as in Germany, with Italy and France in between these two extremes. The response of wages, instead, also varies in sign, with a slight decrease in Spain and increases in other countries.

It is plausible that these differences in impulse responses arise due to different institutional settings. For example, house prices responsiveness to monetary policy may be higher in countries with a higher share of adjustable-rate mortgages, such as Spain. John Muellbauer and co-authors have provided substantial cross-country evidence that higher down-payments (e.g., in Germany) reduce the correlation between consumption and house prices (see, e.g., Aron et al. (2011), Muellbauer et al. (2016) and Muellbauer (2016)). Similarly, Bäckman and Khorunzhina (2017) report that an increasing share of interest-only mortgages in Denmark led to a strong correlation between house prices and consumption.[15]

3.2 Effects of Asset Purchases on Individual Households

We report the estimates of the effects on income and wealth of individual households using a series of figures with 'micro' impulse responses implied by micro-simulation of section 2.2. The impulse responses are summarized by various groups of households, e.g., quintiles of income. Because the VAR impulse responses and the regressions on

[14] See Appendix 1 for more details on our macroeconomic database.

[15] Table 3 gives a quantitative summary of the existing evidence on the effects on nonstandard monetary policy on asset prices and the real economy.

micro data are estimated as country-specific, these micro impulse responses also vary by country.

3.2.1 Effects on Household Income

Figure 2 shows the impulse responses of the unemployment rate by (country-level) income quintile. We find two main results. First, the stimulative effects on employment are strongly skewed toward low-income households. The key reason for this is that the number of unemployed is heavily skewed toward the bottom income quintile, a fact which holds across all four countries—see Figure 3. Consequently, it is not surprising that those who become employed predominantly come from the lower income quintiles.

This would arise mechanically if the probability of finding a job were independent of individual's characteristics. In our simulation, the probability comes from the probit model (1) and depends on individual's demographic characteristics, so that, e.g., people with a lower education level are less likely to be employed. In fact, this feature typically dampens a bit the stimulating effects on the lower income quintiles (compared to a counterfactual uniform probability model). However, only to a rather small degree—as documented in Figure 6 (which compares our baseline results with a simulation with a uniform employment probability model).

The second result of Figure 2 are the differences in micro impulse response across countries, both regarding the level of the response and the dispersion of responses across income quintiles. As we already saw in the left bottom panel of Figure 1 with VAR impulse responses, the overall reduction in unemployment is much larger in Spain than in the other three countries.

The extent of dispersion of micro impulse responses across income quintiles is affected by the distribution of the unemployed; see Figure 3.[16] For example, a substantial mass of unemployed people in Spain has income in higher quintiles, so that the differences in micro impulse response in Spain are smaller (Figure 2). In contrast, the number of the unemployed in Germany and Italy is more strongly skewed toward the lowest income quintile, which causes unemployment in the lowest income quintile to drop more (relative to other quintiles) in these two countries.

Figure 4 shows the micro responses of mean income by income quintile. These responses are primarily driven by the transitions into employment and by differences in replacement rates (as estimated by the Heckman model). The replacement rates are in general more generous in Germany and France than in Spain and, in particular, Italy.[17] As a result, the magnitude and dispersion of income responses in Italy and Spain is larger; see the right-hand panels in Figure 4. For example, the large positive response in mean income of the lowest quintile in Italy arises thanks to both a substantial decline in unemployment rate (see the bottom right panel of Figure 2) and a substantial increase in (labor) income of the newly employed individuals.[18]

[16] The dispersion is also affected—though less importantly—by the fact that the probit models (1) (and employment probabilities) are country-specific.

[17] See, e.g., data from the OECD: `http://www.oecd.org/els/benefitsandwagesstatistics.htm`.

[18] The results are shown for gross (pre-tax) income. The increase in after-tax income would be somewhat lower, however, not by much, as most newly employed people are not subject to large taxes.

3.2.2 Effects on Household Wealth

Figure 5 shows the micro responses of median net wealth by wealth quintile.[19] These responses arise from a combination of the response of house prices (top right panel of Figure 1), stock prices and holdings of wealth across the distribution (and countries). Broadly, the responses of wealth in quintiles 2–5 increase by around 1.5% in France, Spain and Italy, and are rather flat in Germany. There is little evidence that the median wealth among the top wealth quintile households would increase more strongly, though this does happen above percentile 90 (where the holdings of stocks are prevalent (though only within 4 quarters after the APP shock). An important takeaway from this exercise is the key role of including house prices in the analysis as housing wealth as most households own large holdings of housing wealth (in contrast to stocks and bonds, which are very disproportionately in the top tail of the distribution).[20]

These household-level responses have implications for common measures of income and wealth inequality, such as the Gini coefficient. Overall, the effect on income inequality is much stronger than the effect on wealth inequality: The Gini coefficient on income falls from 43.1 to 42.8, while the Gini on net wealth ticks down from 68.09 to 68.07.[21]

4 Conclusions

We quantify how the recent ECB nonstandard monetary policy measures (which are similar to the US quantitative easing) affect income and wealth of individual households. Using a combination of a four-country VAR with aggregate data and a simulation on household-level data from the Household Finance and Consumption Survey, we find that nonstandard monetary policy has only modest effects on wealth inequality. In contrast, monetary policy compresses the income distribution as disproportionately many households with lower incomes become employed.

We do not quantify the effects monetary policy on consumption inequality. Currently, substantial evidence exists that the marginal propensity to consume is higher at lower income levels. As a result, qualitatively, our results suggest that monetary policy easing reduces consumption inequality both because it disproportionately boosts incomes in the lower part of the distribution and because this impulse has a stronger effect on consumption via a larger MPC.

[19]The growth rate for the lowest quintile is not shown because its level is close to EUR 0.

[20]This finding is in line with Adam and Tzamourani (2016); see, e.g., their Figure 4.

[21]The results are similar for other inequality measures, such as the top shares.

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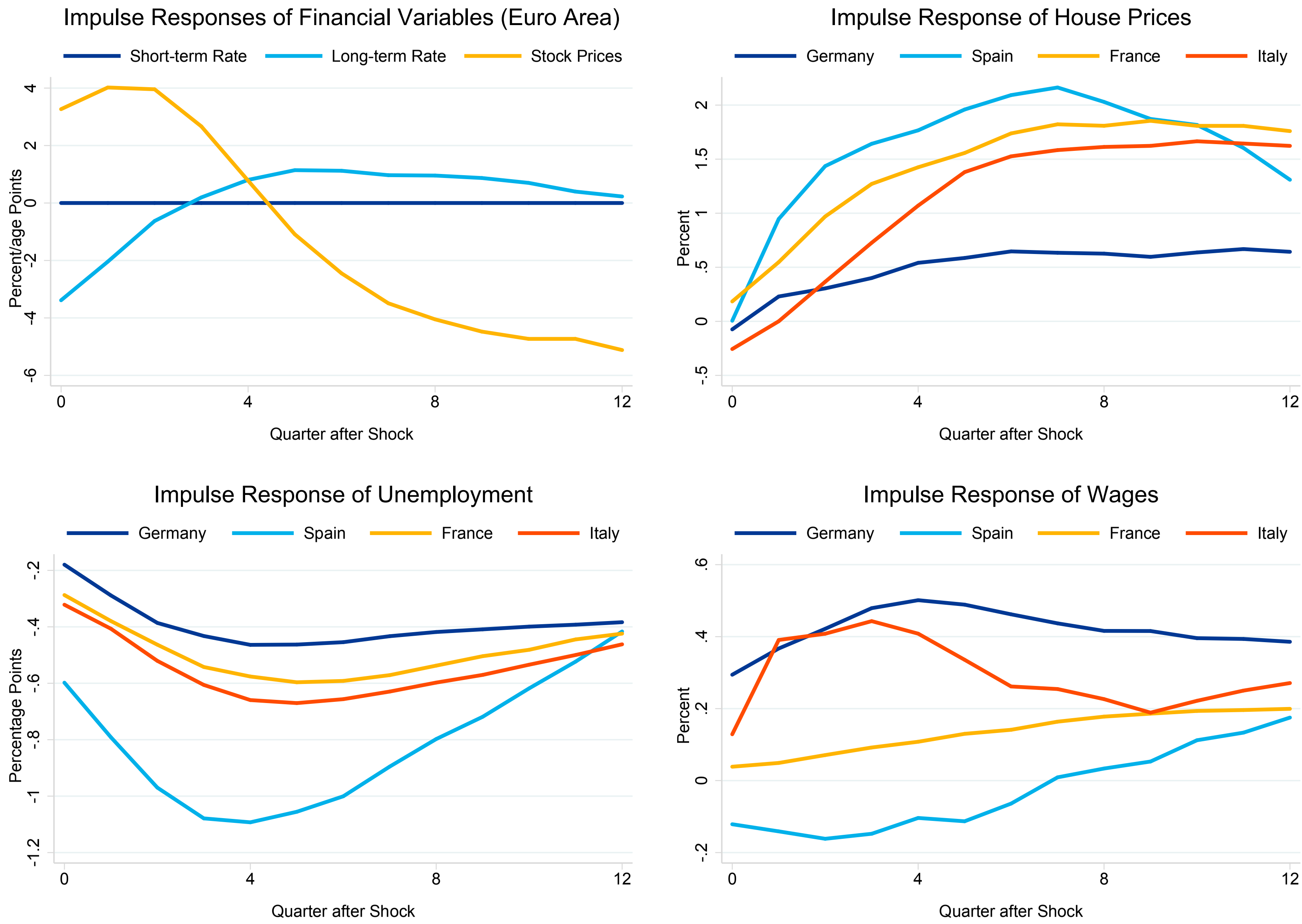
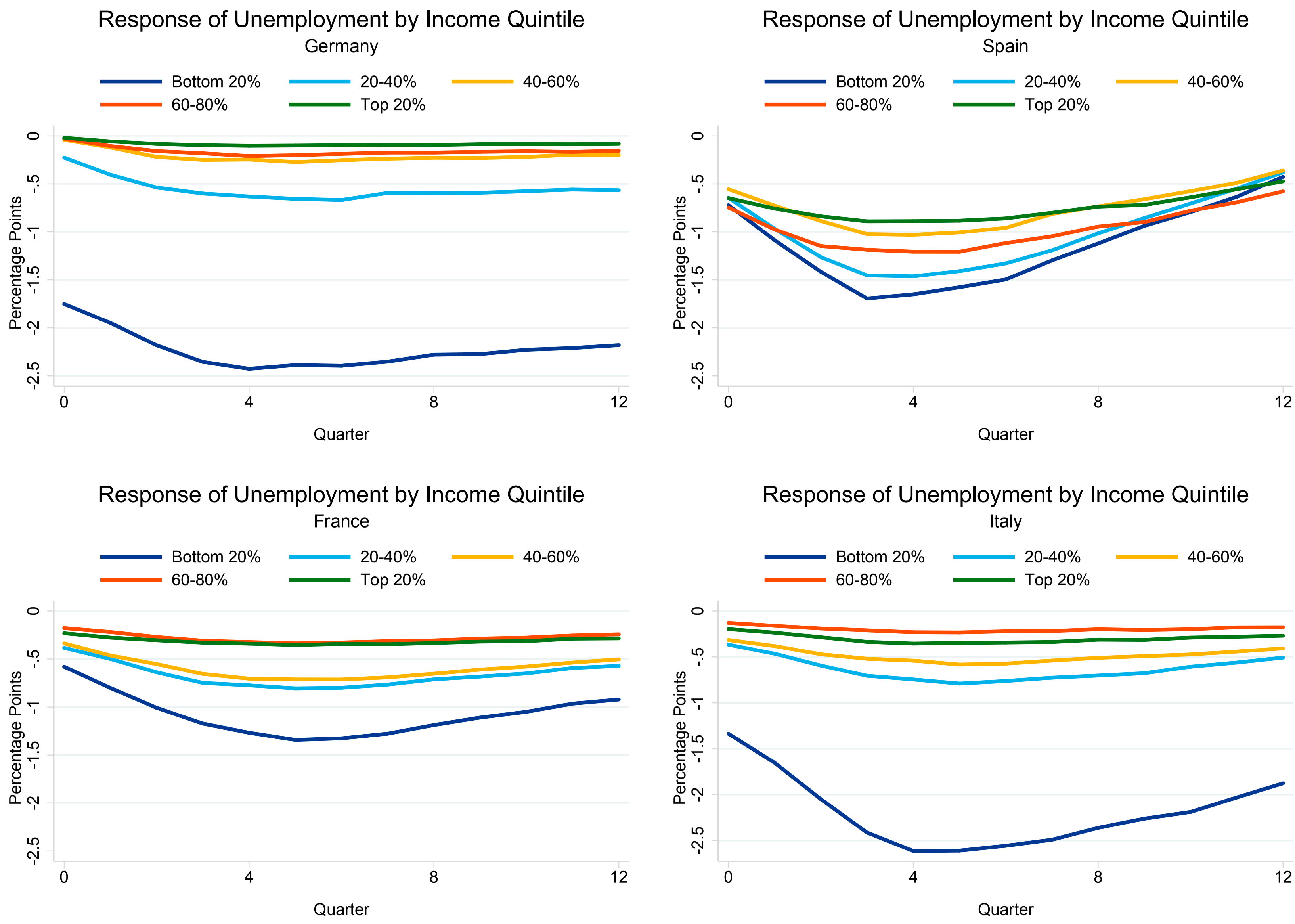
Figure 1 Asset Purchase Scenario: VAR Impulse Responses



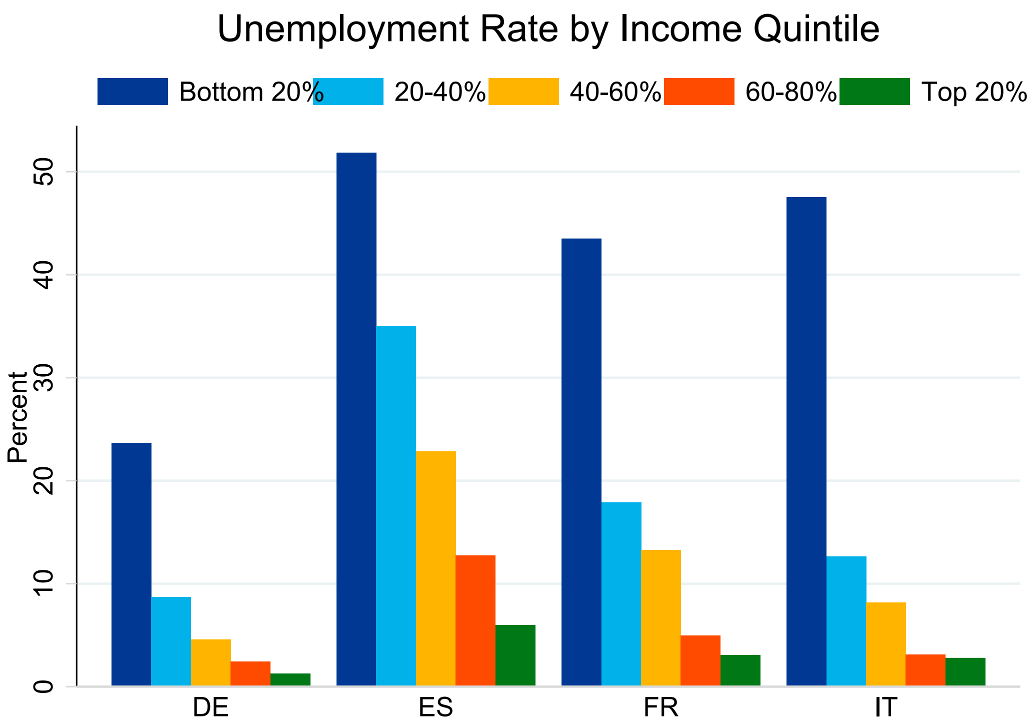
Note: The charts plots median responses to the asset purchase scenario. House prices: percentage deviation from baseline levels; wages: percentage deviation from baseline levels; unemployment rate: deviation from baseline level; stock price: percentage deviation from baseline levels.

Figure 2 Impulse Responses of Unemployment Rate by Country and Income Quintile



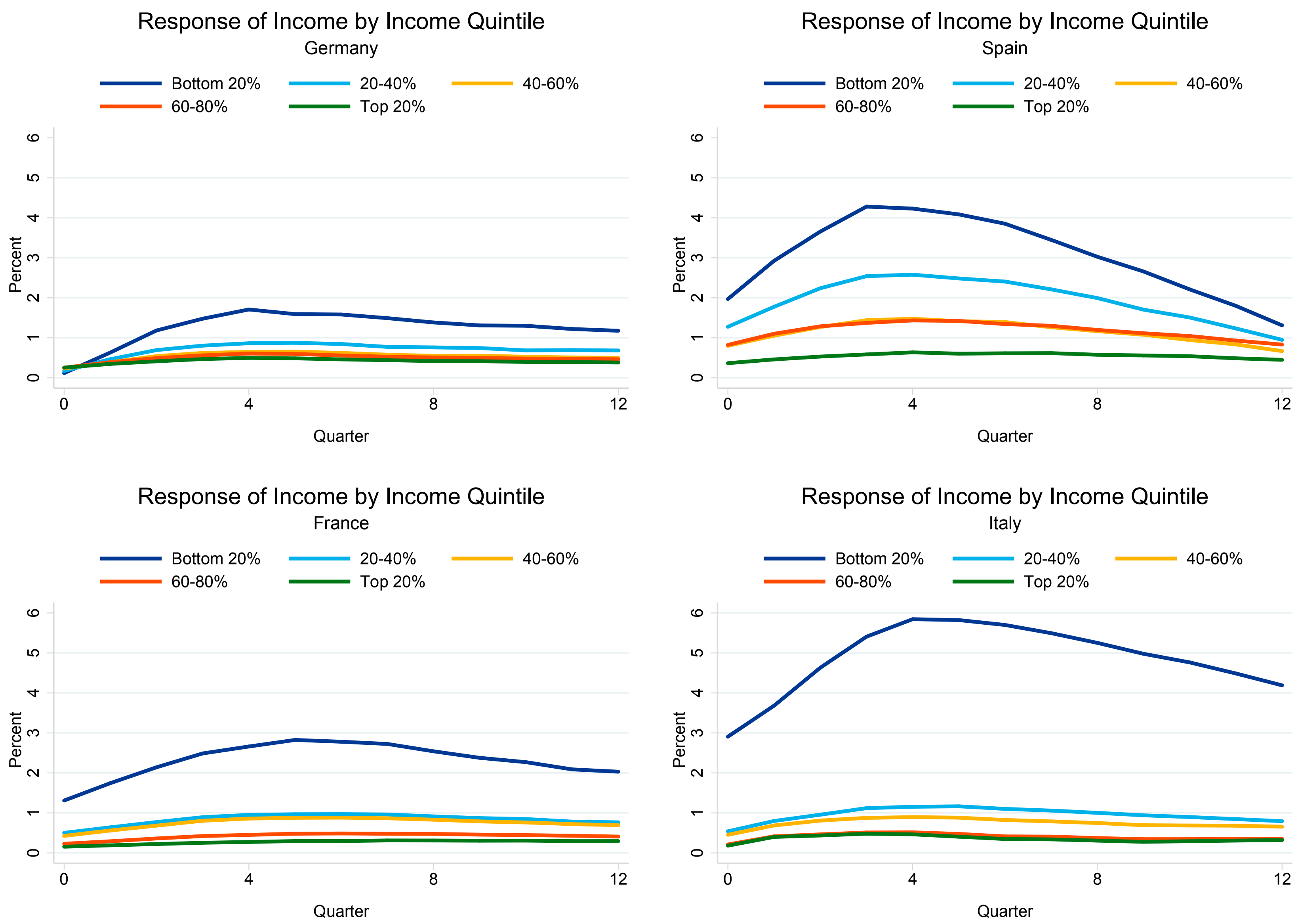
Source: Eurosystem Household Finance and Consumption Survey
Note: The charts show impulse responses of unemployment by income quintile.

Figure 3 Unemployment Rate by Country and Income Quintile



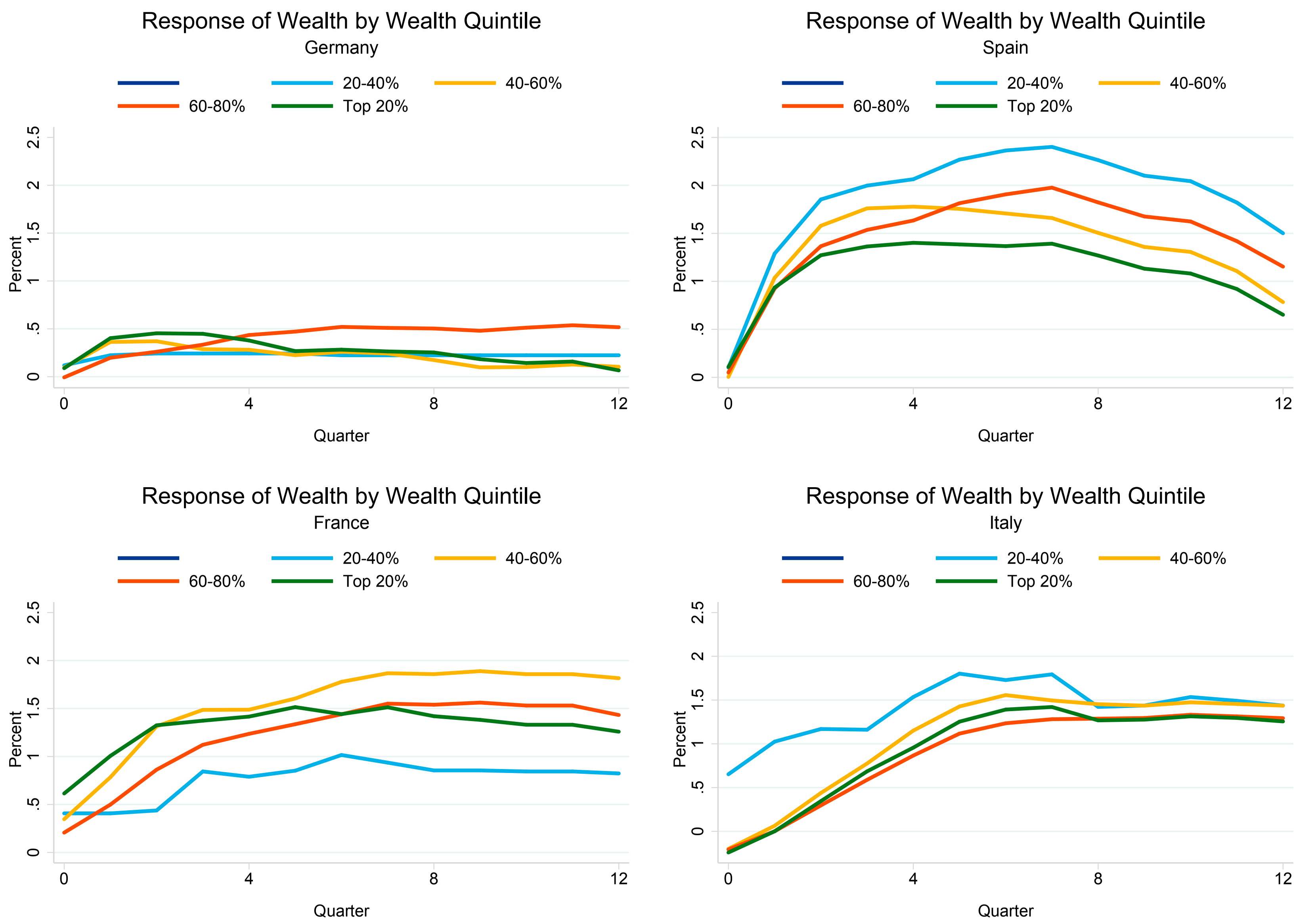
Source: Eurosystem Household Finance and Consumption Survey
Note: The chart shows ...

Figure 4 Impulse Responses of Mean Income by Country and Income Quintile



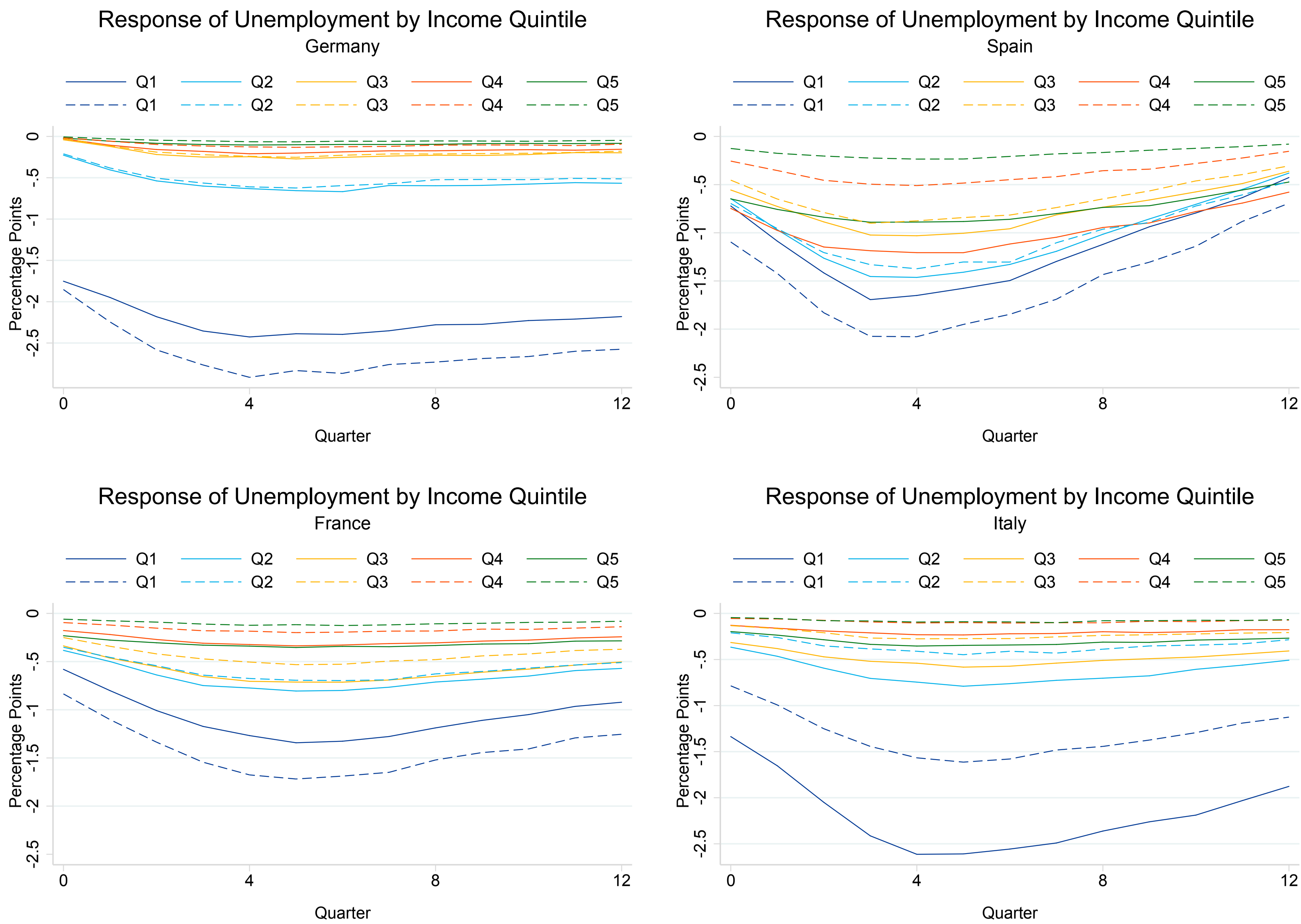
Source: Eurosystem Household Finance and Consumption Survey
Note: The charts show impulse responses of mean income by income quintile.

Figure 5 Impulse Responses of Median Net Wealth by Country and Net Wealth Quintile



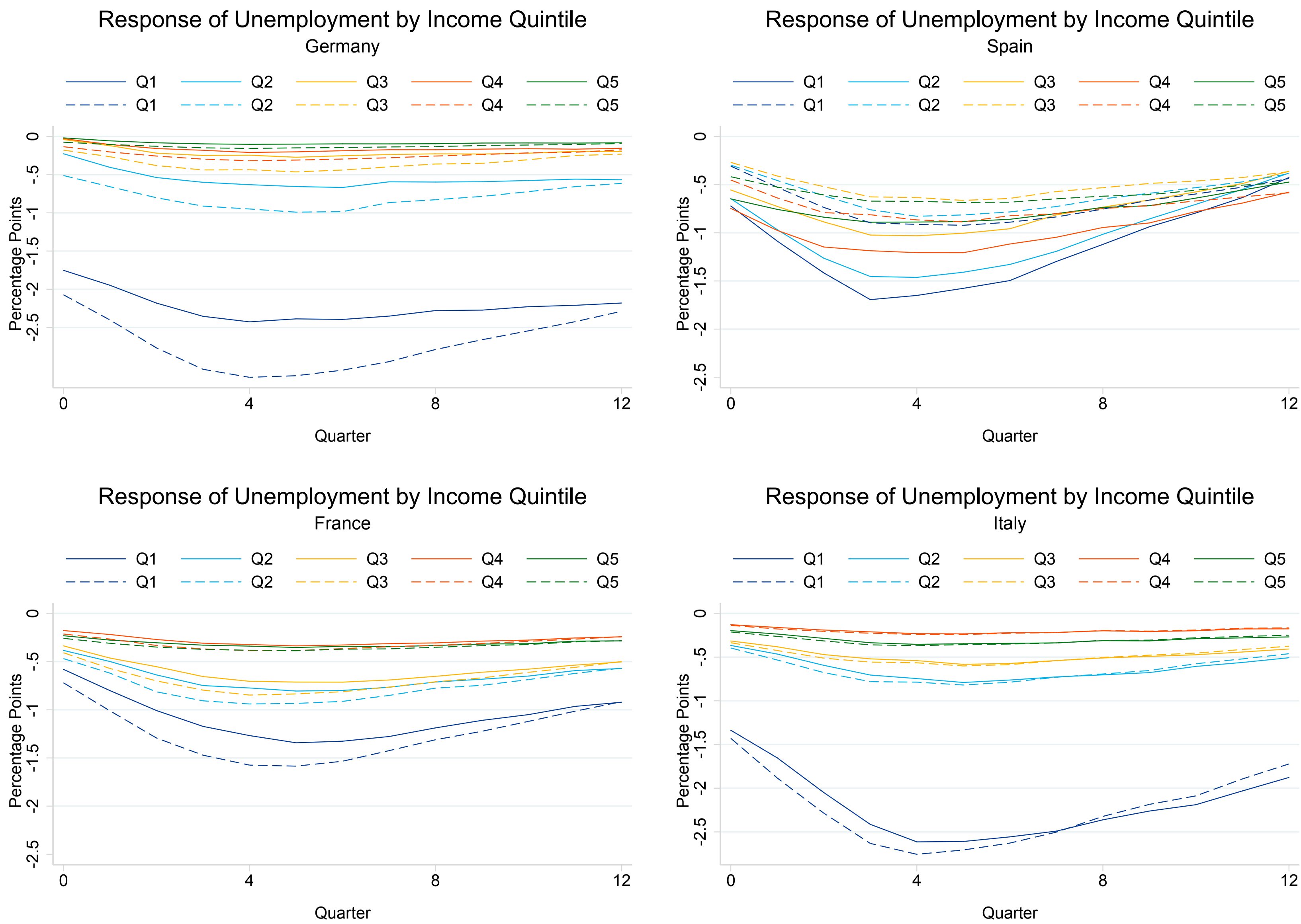
Source: Eurosystem Household Finance and Consumption Survey
Note: The charts show impulse responses of net wealth. The response for the bottom 20% not shown as the value of net wealth in the lowest quintile is close to EUR 0.

Figure 6 Impulse Responses of Unemployment—Baseline IRFs (Solid) vs IRFs Generated Under Uniform Probability of Getting Employed (Dashed)



Source: Eurosystem Household Finance and Consumption Survey
Note: The charts show impulse responses of unemployment by income quintile.

Figure 7 Impulse Responses of Unemployment—Baseline IRFs (Solid) vs IRFs Restricted to Be the Same Across Countries (Dashed)



Source: Eurosystem Household Finance and Consumption Survey
Note: The charts show impulse responses unemployment by income quintile.

Table 1 Empirical Estimates of the Effects of Nonstandard Monetary Policy Using Event Studies

Authors	Country	Type of Event	Typical Impact on 10-Year Rate (p.p.)	Notes
Altavilla et al. (2016)	DE, ES, FR, IT	OMT	0.2 to 1	
Altavilla et al. (2015)	EA, DE, ES, FR, IT	APP	0.3 to 0.5	
Andrade et al. (2016)	EA	APP	0.45	
Joyce and Tong (2012)	UK	APF1	1	
Christensen and Rudebusch (2012)	UK, US	APF1	0.43 to 0.89	
Lam (2011)	JP	CME+	0.24 to 0.27	
Fukunaga et al. (2015)	JP	QQE	0.33 to 0.47	
Gagnon et al. (2011)	US	LSAP1	0.55 to 1.05	
Krishnamurthy and Vissing-Jorgensen (2013)	US	LSAP1, LSAP2, MEP	0.07 to 1.07	
Bauer and Rudebusch (2014)	US	LSAP1	0.89	
Krishnamurthy and Vissing-Jorgensen (2011)	US	LSAP1, LSAP2	0.3 to 1.07	
Cahill et al. (2013)	US	LSAP1, LSAP2, MEP	0.089 to 0.131	for $100bn purchases

Notes: See also Andrade et al. (2016), Appendix B for other studies and details.

Table 2 Empirical Estimates of the Effects of Nonstandard and Standard Monetary Policy Using VARs

Authors	Country	Method	Type and Magnitude of Monetary Shock
Nonstandard Monetary Policy			
Altavilla et al. (2016)	DE, ES, FR, IT	VAR	Announcement: depending on the country −2.09% to 0% in 2-year rates over three years
Baumeister and Benati (2013)	US, UK	TVP VAR	Purchase: depending on the country 0.5% to 0.6% in 10-year spread
Kapetanios et al. (2012)	UK	TVP VAR	Purchase: −1% in 5- and 10-year spread
Weale and Wieladek (2016)	US, UK	Bayesian VAR	Announcement: 1% in nominal GDP
Gambacorta et al. (2014)	EA, non-EA countries	Panel VAR	Purchase: 3% in central bank balance sheet
Darracq-Paries and De Santis (2015)	EA countries	Panel VAR	Purchase: −20% and −4% in credit standards
Bernhard and Ebner (2017)	CH	OLS	Announcement: −0.25% in 10-year rates
Babecka Kucharcukova et al. (2016))	EA, EU countries	VAR	Purchase: 0.06% in Factor 2 (unconven MP) of Monetary Conditions Index
Haitsma et al. (2016)	EA, UK	OLS	Announcement: −0.06% in spread
Fratzscher et al. (2016)	various regions	Panel regression	Announcement: sum of SMP and OMT dummies Purchase: 660 billions euro for SLTROs 1019 billions euro for VLTROs
Bluwstein and Canova (2016)	EA, EU countries	Bayesian SVAR	Announcement: dummies Purchase: 10% (monthly) in quantity of UMP
Hachula et al. (2016)	EA, EA countries	SVAR	Purchase: −0.25% in 2-year rate
Mandler et al. (2016)	DE, ES, FR, IT	Bayesian VAR	0.25% in EONIA
Creel et al. (2016)	DE, ES, FR, IT	SVAR	Purchase: 0.16% of EA GDP in excess liquidity 0.32% of EA GDP in LTROs 0.04% of EA GDP in SHMPP
Swanson (2017)	US	OLS	Announcement: 1 s.d. in LSAP factor
Behrendt (2017)	EA	SVAR	Purchase: 0.5% to 2.5% in excess reserves
Boeckx et al. (2017)	EA, EA countries	SVAR	Purchase: 1% to 3% in total assets
Koijen et al. (2017)	EA, EA countries	IV and OLS	Announcement: depending on the country and on the maturity of the bond
Standard Monetary Policy			
Cloyne et al. (2015)	UK, US	VAR	−0.25% in policy rate
Aladangady (2014)	US	SVAR	−0.71% in Fed funds rate

Notes: See also Andrade et al. (2016), Appendix B for other studies and details.

Table 3 Empirical Estimates of the Effects of Nonstandard and Standard Monetary Policy Using VARs (Table 2 Continued)

Authors	Typical Estimates Asset Prices	Typical Estimates Real Economy
Nonstandard Monetary Policy		
Altavilla et al. (2016)	2-year rates: −2.34% to 0.08	Real GDP: 0.34%–2.01%, HICP: 0.28%–1.21%
	10-year rates: −1.15% to 0.23%	Retail Loans: 1.08%–3.58%
Baumeister and Benati (2013)		Inflation: trough of −1% to −4%
		GDP gr: trough −10% to −12%, UR: peak 10.6%
Kapetanios, Mumtaz		Real GDP: peak effect of 1.42%
Stevens, Theodoridis (2012)		CPI Inflation: peak effect of 1.21%
Weale and Wieladek (2016)		Real GDP: 0.25%–0.58%, CPI: 0.32%–0.62%
Gambacorta et al. (2014)		GDP: −0.25% to 0.25%, CPI: −0.12% to 0.10%
Darracq-Paries and De Santis (2015)		GDP: peak of 0.8%, GDP Defl: peak of 0.35%
Bernhard and Ebner (2017)	Long-term gov't bond yields: −0.06%	
	Long-term corp bond yields: −0.045%	
	Stock Market Index: −1%	
Babecka Kucharcukova et al. (2016)	Int rates non-EA cntries: −0.05% to 0.08%	IP: −0.2% to 0.2%, HICP: −0.1% to 0.06%
Haitsma et al. (2016)	EURO STOXX 50 and FTSE100: +0.5%	
Fratzscher et al. (2016)	10-year rates: −1.21% to 0.11%	
	Equity indices: −3.49% to 10.69%	
	Bank equity prices: −4.18% to 15.65%	
Bluwstein and Canova (2016)	Stock market index: −0.2% to 0.5%	IP: −0.1% to 0%, CPI: 0%–0.5%
Hachula et al. (2016)	Stock prices: 0%–7%, 2Y rate: −1.1%–0.15%	GDP: 0.1%–0.65%, CPI: 0%–0.45%
	3M rate: −0.02%–0.05%, 10Y rate: −0.11%–0%	UR: −0.21%–0.07% Cred vol NFC: 0.8%–4%
Mandler et al. (2016)	1Y rate: −0.08%–0.2%, 10Y: −0.1%–0.05%	Real GDP: −0.25%–0.05%, HICP: −0.3%–0%
Creel et al. (2016)	6M rate: −0.15%–0.1%, 5Y rate: −0.17%–0.07%	Loans to NFCs: −0.15% to 0.3%
	10Y rate: −0.08%–0.12%	Housing loans: −0.0025% to 0.045%
Swanson (2017)	6M rate: 0.0019%, 2Y: 0.002%, 5Y: −0.0292%	
	10Y: −0.0649%, 30Y: −0.0577%, S&P500: 0.12%	
	Aaa corp yields: 0.0451%, Baa corp: 0.0525%	
Behrendt (2017)		IP −0.0032%–0.0023%, HICP −0.0006%–0.0005%
Boeckx et al. (2017)	Equity prices: −0.2%–2.3%	GDP: −0.35%–0.6%, HICP: −0.1%–0.3%
	EA sovereign bond: −0.085% to −0.005%	Loans NFCs: −0.4%–0.6%, HHs: −0.33%–0.33%
Koijen et al. (2017)	Sovereign bond rates: −0.6% to −0.02%	
Standard Monetary Policy		
Cloyne et al. (2015)		Non-dur cons peak: 0.2%, Dur cons: 1%–1.3%
		Income 0.3%–0.4%, Mortg paymnts −0.7%–0.15%
Aladangady (2014)		House prices: peak of 3–4%

Notes: See also Andrade et al. (2016), for other studies and details.

A Macroeconomic Database

Macroeconomic database and identification assumptions

Table 1. Database

Variables	Transformation	Source	APP shock	MP shock
1 DE GDP	log-levels	TBA	+	0
2 DE GDP Deflator	log-levels	TBA		0
3 DE Unemployment rate	levels	TBA		0
4 DE House prices	log-levels	TBA		0
5 DE Compensation per employee	log-levels	TBA		0
6 FR GDP	log-levels	TBA	+	0
7 FR GDP Deflator	log-levels	TBA		0
8 FR Unemployment rate	levels	TBA		0
9 FR House prices	log-levels	TBA		0
10 FR Compensation per employee	log-levels	TBA		0
11 IT GDP	log-levels	TBA	+	0
12 IT GDP Deflator	log-levels	TBA		0
13 IT Unemployment rate	levels	TBA		0
14 IT House prices	log-levels	TBA		0
15 IT Compensation per employee	log-levels	TBA		0
16 ES GDP	log-levels	TBA	+	0
17 ES GDP Deflator	log-levels	TBA		0
18 ES Unemployment rate	levels	TBA		0
19 ES House prices	log-levels	TBA		0
20 ES Compensation per employee	log-levels	TBA		0
21 Euro Area Short-term interest rates	levels	TBA	0	−
22 Euro Area Long-term interest rates	log-levels	TBA	−	
23 Euro Area Stock prices	log-levels	TBA		
24 US GDP	log-levels	TBA		0
25 US Short-term interest rates	log-levels	TBA		0

Note: Notes to be added.

B Prior Setup

For the prior on the covariance matrix of the errors, we set the degrees of freedom of the Inverse-Wishart distribution equal to $N+2$, the minimum value that guarantees the existence of the prior mean, and we assume a diagonal scaling matrix Ψ. We treat Ψ as a hyperparameter.

The baseline prior on the model coefficients is a version of the so-called Minnesota prior (see Litterman (1979)). This prior is centered on the assumption that each variable follows an independent random walk process, possibly with drift. The prior first and second moments for the VAR coefficients are as follows:

$$\mathbf{E}\big[(B_s)_{ij}|\Sigma\big] = \begin{cases} 1 & \text{if } i=j \text{ and } s=1 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{cov}\big(\,(B_s)_{ij}\,,(B_r)_{hm}\,|\Sigma\big) \quad = \quad \begin{cases} \lambda^2 \frac{1}{s^2} \frac{\Sigma_{ih}}{\psi_j/(d-n-1)} & \text{if } m=j \text{ and } r=s \\ 0 & \text{otherwise} \end{cases} .$$

Notice that the variance of this prior is lower for the coefficients associated with more distant lags, and that coefficients associated with the same variable and lag in different equations are allowed to be correlated. Finally, the key hyperparameter is λ—which controls the scale of all variances and covariances, and effectively determines the overall tightness of this prior. The terms Σ_{ih}/Ψ_j account for the relative scale of the variables. The prior for the intercept C is non-informative.

The Minnesota prior is complemented with two priors on the sum of the VAR coefficients, introduced as refinements of the Minnesota prior to further "favor unit roots and cointegration, which fits the beliefs reflected in the practices of many applied macroeconomists" (see Sims and Zha, 1998, p. 958). These additional priors tend to reduce the importance of the deterministic component implied by VARs estimated conditioning on the initial observations (see Sims, 1992a and Giannone et al., 2016). The first of these two priors is known as no-cointegration (or, simply, sum-of-coefficients) prior. To understand what this prior entails, we rewrite the VAR equation in an error correction form:

$$y_t = C + (B_1 + \cdots + B_p - I_N)y_{(t-p)} + A_1\Delta y_{t-1} + \cdots + A_p\Delta y_{(t-p)} + \epsilon_t,$$

where $A_s = -B_{s+1} - \cdots - B_p$.

A VAR in first differences implies the restriction $\Pi = (B_1 + \cdots + B_p - I_N) = 0$. Doan, Litterman, and Sims (1984) introduced the no-cointegration prior which centered at 1 the sum of coefficients on own lags for each variable, and at 0 for the sum of coefficients on other variables' lags. This prior also introduces correlation among the coefficients on each variable in each equation. The tightness of this additional prior is controlled by the hyperparameter μ. As μ goes to infinity the prior becomes diffuse while, as it goes to 0, it implies the presence of a unit root in each equation.

The fact that, in the limit, the prior just discussed is not consistent with cointegration motivates the use of an additional prior on the sum of coefficients that was introduced by Sims (1993), and is known as dummy-initial-observation prior. This prior states that a no-change forecast for all variables is a good forecast at the beginning of the sample. The hyperparameter δ controls the tightness of this prior. As δ tends to 0, the prior becomes more dogmatic and all the variables of the VAR are forced to be at their unconditional mean, or the system is characterized by the presence of an unspecified number of unit roots without drift. As such, the dummy-initial observation prior is consistent with cointegration.

The setting of the prior distributions depends on the hyperparameters, λ, μ, δ and Ψ, which describe the informativeness of the prior distributions for the model coefficients. In setting these parameters, we follow the theoretically grounded approach proposed by Giannone et al. (2015), which suggest to treat the hyper-parameters as additional parameters, in the spirit of hierarchical modelling. As hyper-priors (i.e., prior distributions for the hyperparameters), we use proper but almost flat distributions.