How Does Monetary Policy Affect Income and Wealth Inequality? Evidence from Quantitative Easing in the Euro Area Online Appendix

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Online appendix: http://slacalek.com/research/lsMPinequality/lsMPinequality_appendix.pdf

Appendix A: Estimation

A.1 The BVAR Model and the Identification of the QE shock

We identify the effects of QE using a large multi-country vector autoregression (VAR).[1] Such setup allows us to estimate possibly heterogeneous country responses to a common euro area QE shock. In more detail, to capture the dynamic interrelationships among the variables, we adopt the following VAR setting:

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

where y_t is an N-dimensional vector of time-series, $B_1, \ldots, B_p$ 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 matrix of the errors. The model is specified in terms of the annualized (log-)levels of the variables and, in our specification, we have $N = 22$ and $p = 5$. In particular, for France, Germany, Italy and Spain, we consider real GDP, the GDP deflator, the unemployment rate, house prices, wages and financial income. We also include long-term interest rates and stock prices for the euro area. The variables are available at the quarterly frequency, for the sample 1999Q1 to 2019Q4.

Potentially, this model may be subject to the "curse of dimensionality" due to the large number of parameters to be estimated, relative to the available sample. In such circumstances, the estimation via classical techniques would very likely result in overfitting the data and large estimation uncertainty. De Mol et al. (2008) and Bańbura et al. (2010) showed that imposing informative priors which push the parameter values of the model toward those of naïve representations (such 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 co-move. In fact, in presence of comovement, the information in the data strongly "conjures" against the prior, so that the parameter estimates reflect sample information even if very tight prior beliefs are enforced.

For this reason, we adopt a Bayesian estimation technique. The prior for the covariance matrix of the residuals Σ is Inverse Wishart, while the prior for the autoregressive coefficients is normal (conditional on Σ). More in details, the prior distributions in our Bayesian VAR are specified as follows. For the prior on the covariance matrix of the errors Σ, we set the degrees of freedom of the Inverse Wishart distribution equal to $N + 2$ (where $N = 26$ is the number of variables in the model), the minimum value that guarantees the existence of the prior mean, and we assume a diagonal scaling matrix Ψ, which we parameterize by setting the diagonal values equal to the variance of the residual from an AR(1) model for each individual variable. The baseline prior on the model coefficients is a version of the Minnesota prior (see Litterman, 1979). This prior is centered on the assumption that each variable follows an independent random walk

[1] See online Appendix B for the details on the macroeconomic database.

process, possibly with drift. The prior first and second moments for the VAR coefficients are:

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

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

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 setting of the prior distributions depends on the hyperparameter λ, which describes the informativeness of the prior distributions for the model coefficients. In setting this parameter, we follow the theoretically grounded approach proposed by Giannone et al. (2015), who suggest to treat the hyperparameters as additional parameters, in the spirit of hierarchical modelling. As hyper-prior (i.e., prior distribution for the hyperparameter), we use a proper but almost flat distribution.[2]

To estimate the effects of quantitative easing, we identify a QE shock by means of an external instrument approach. Here we provide the intuition for this method, for an extensive and rigorous treatment, see Stock (2008); Stock and Watson (2012); Mertens and Ravn (2013); Ramey (2016); Miranda-Agrippino and Ricco (2019); Montiel Olea et al. (2021); Jentsch and Lunsford (2019).[3] Define the moving average representation of the VAR above as:

$$y_t = \sum_{k=0}^{\infty} D_k \epsilon_{t-k}.$$

The N-dimensional vector of structural shocks ε_t is linearly related to the vector of the VAR reduced form residuals via the N-dimensional square matrix Θ_0:

$$\epsilon_t = \Theta_0 \varepsilon_t.$$

Let us also assume, without loss of generality, that the QE shock is ordered first in the vector of structural shocks and it is defined as $\varepsilon_{1,t}$. Once the first column of Θ_0, denoted $\Theta_{0,1}$, is retrieved, the moving average VAR representation can be used to find the impulse response of each variable y_t to the shock $\varepsilon_{1,t}$. An external instrument z_t for the structural shock $\varepsilon_{1,t}$ is essentially a variable that is correlated with that structural

[2] A few papers lend support to this strategy to model cross-country macroeconomic data, showing that VAR models of the type we adopt in this paper provide accurate out-of-sample forecasts of macroeconomic and financial variables in the euro area (see, for example, Angelini et al., 2019; Capolongo and Pacella, 2019). A similar framework has been also used to estimate the effects of common euro area monetary policy shocks on various countries by Altavilla et al. (2016) (for both standard monetary policy and outright monetary transactions, OMT) and Mandler et al. (2016) (for standard monetary policy shocks). To appropriately capture the transmission channels of QE to different components of household wealth and income, we add more variables such as house prices to the existing frameworks.

[3] In this paper we use the toolbox developed by Miranda-Agrippino and Ricco (2019).

shock and uncorrelated with all the other $N-1$ structural VAR shocks:

$$\begin{aligned}\mathbf{E}(z_t \varepsilon_{1,t}) &= \zeta, \\ \mathbf{E}(z_t \varepsilon_{j,t}) &= 0, j = 2, \ldots, N.\end{aligned}$$

Then the covariance between z_t and the reduced form VAR shocks is:

$$\mathbf{E}(z_t \epsilon_t) = \zeta \Theta_{0,1},$$

which can be used to identify $\Theta_{0,1}$ up to a scaling constant.

Of course, the method relies on the existence of a suitable instrument to identify the QE shock. To address this potential challenge, we follow the insight of Gertler and Karadi (2015), who suggest that the high frequency changes recorded in specific financial variables during the policy announcements of central banks could be used as external instruments to identify monetary policy shocks. The idea is that such changes in financial variables are correlated to the monetary policy shocks and, at the same time, they are unlikely to reflect other sources of shocks given that the monetary policy announcements are the main drivers of the surprises in financial variables over narrow time windows around those announcements.

To derive a specific external instrument for the euro area QE shock, we use the changes in the OIS rates with maturity from one month to ten years recorded during the Eurosystem press conferences (available in the Monetary Policy Database of Altavilla et al., 2019) in which the ECB President announces and describes the monetary policy decisions taken by the Governing Council.[4] Gürkaynak et al. (2005) pointed out that the changes in financial variables during policy announcements are likely to reflect more than one type of monetary policy measure, especially after the collapse of Lehman Brothers paved the way for unconventional monetary policy measures. Hence, we take additional steps to disentangle the fluctuations in OIS rates due to QE from those due to other policy announcements. Specifically, we use as external instrument the so called QE factor of Swanson (2021) and Altavilla et al. (2019), an aggregate of the changes in the yield structure of the OIS rates during the ECB press conferences. The QE factor is identified by assuming (i) that it is orthogonal to the two policy factors capturing forward guidance and conventional monetary policy and (ii) that it explains only a negligible share of the volatility in the OIS rates during the press conferences preceding the Lehman crisis, when QE-type policies were not in place. Altavilla et al. (2019) show that the QE factor does not explain much of the volatility in the short-term segment of the OIS yield curve, while it is a relevant driver of the long-term segment, lending support to the idea that the factor correctly captures the fluctuations in OIS rates due to QE.

As mentioned above, the external instrument approach identifies the QE shock up to a scaling constant. To pin down the constant to a reasonable value, we set the size of the shock to imply a 30 basis points impact reduction in the euro area long-term interest

[4]The quantitative easing program of the ECB is defined as Asset Purchase Programme (APP). It started in January 2015 to address the risks of a long period of low inflation. The APP includes various purchase programmes under which private sector securities and public sector securities (including sovereign bonds) are bought. For an early assessment of the macroeconomic effects of the APP see Andrade et al. (2016).

rate, the lower boundary of the estimated effects of the first QE announcement on the euro area long-term bond yields (Altavilla et al., 2015).

Notice that we assess the uncertainty around our structural impulse responses by repeating the procedure discussed above for all the MCMC draws of the lag coefficients and the error covariance matrix of our BVAR. This procedure allows us to account for most sources of uncertainty, including the uncertainty on the prior hyperparameters, due to our adoption of the hierarchical VAR estimation method developed in Giannone et al. (2015). One source of uncertainty that our methodology does not cover is the potential uncertainty in the instrument itself. Jentsch and Lunsford (2019) develops a bootstrap procedure that encompasses that source of uncertainty.

A.2 The Local Linear Projection method

Our robustness exercises in section 3.2.4 adopt the local linear projection method to derive the response of various variables to the shocks we estimate in the VAR. Let us briefly describe our application of the method developed in Jordà (2005). Denote G_t an additional variable of interest. We transform these variables as for the VAR, i.e., we compute annualized log-levels unless the variable is already expressed in terms of rates. Denote as g_t the transformed variable.

We evaluate the impulse response ϑ^h of g_t to the shock $\varepsilon_{1,t}$ at the horizon h by regressing g_{t+h} on $\varepsilon_{1,t}$ and the lags of g_t. Specifically, we estimate the following OLS regression:

$$g_{t+h} = \alpha + \vartheta^h \varepsilon_{1,t} + \gamma(L) g_t + \eta_t.$$

Appendix B: Macroeconomic Data

Table 1 Macroeconomic Database

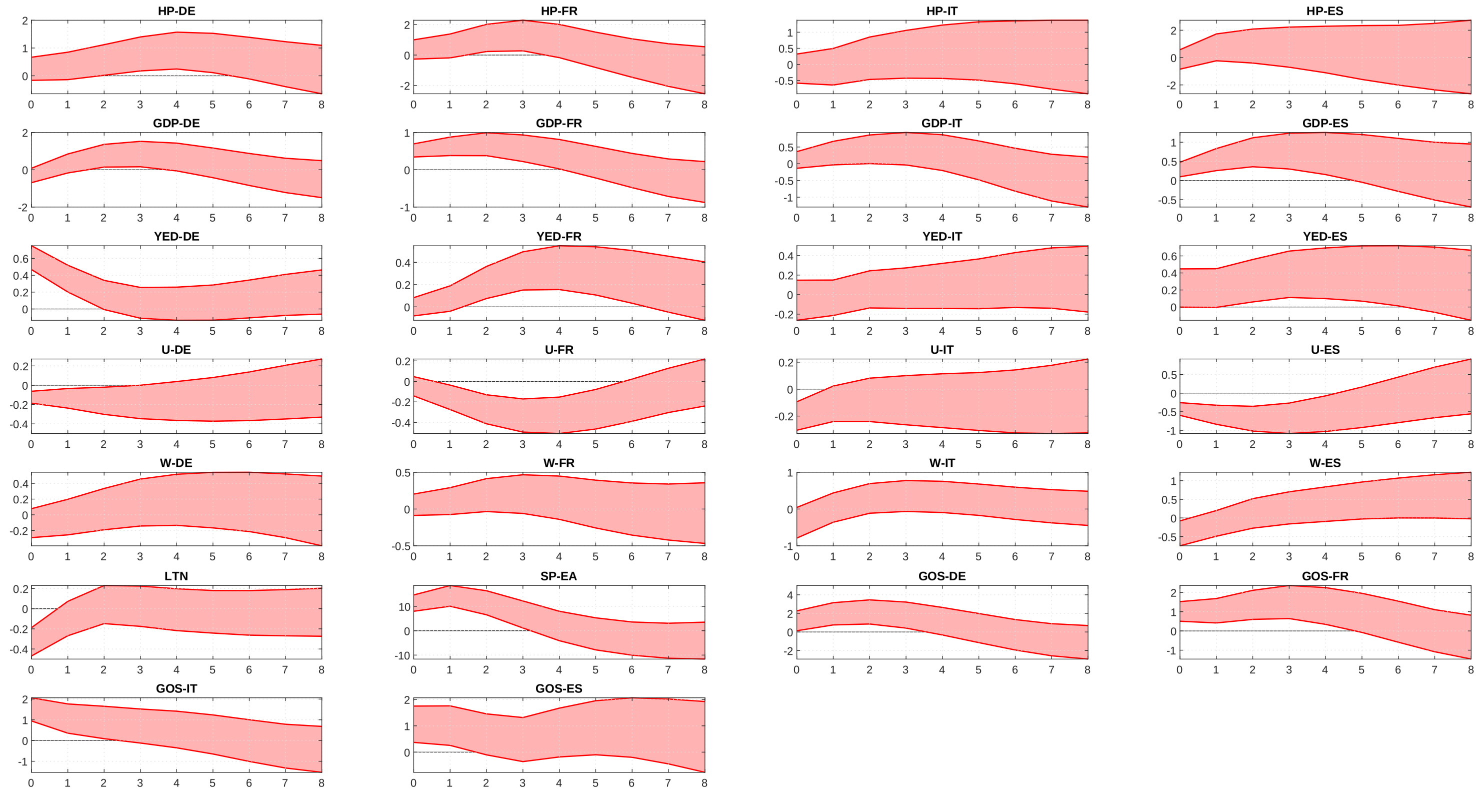
Variable	Transformation	Source
France, Germany, Italy, Spain		
GDP	log-levels	Eurostat
GDP deflator	log-levels	Eurostat
Unemployment rate	levels	Eurostat
House prices	log-levels	Eurostat
Compensation per employee	log-levels	Eurostat
Gross operating surplus	log-levels	Eurostat
Euro area		
Long-term interest rate	levels	AWM database (LTN)
Stock prices	log-levels	ECB SDW

Table 1 describes our aggregate time series.

In our robustness exercises, we exploit some additional data sources, available at quarterly frequency for the sample 1999Q1–2019Q4. The data on stock holdings of the four countries under analysis come from the Euro Area Sectoral Accounts. The data on regional house prices in Spain are available from the website of the Spanish government, Ministerio de Fomento. Specifically, we use the series "valor tasado medio de vivienda libre" (the aggregate house price, total national, and the house prices of the 17 regions for which the quarterly data are available, i.e., we exclude the autonomous cities Ceuta and Melilla): `http://www.fomento.gob.es/BE2/?nivel=2&orden=35000000`.

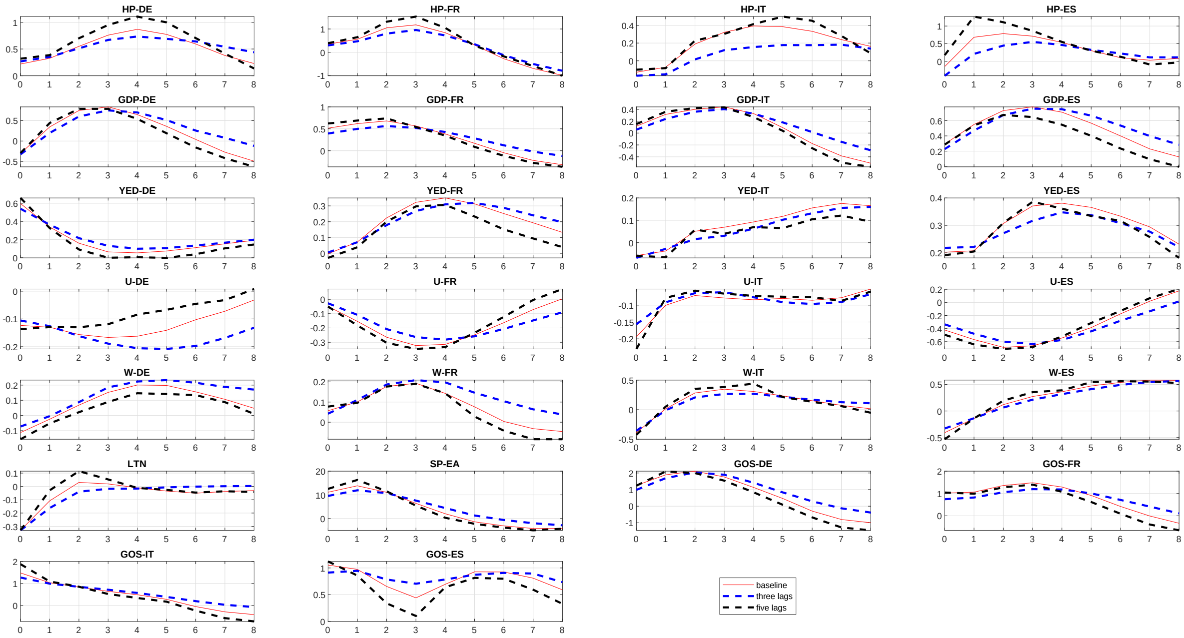
Appendix C: Additional Figures and Tables

Fig. C1 Impulse Responses to QE Shock



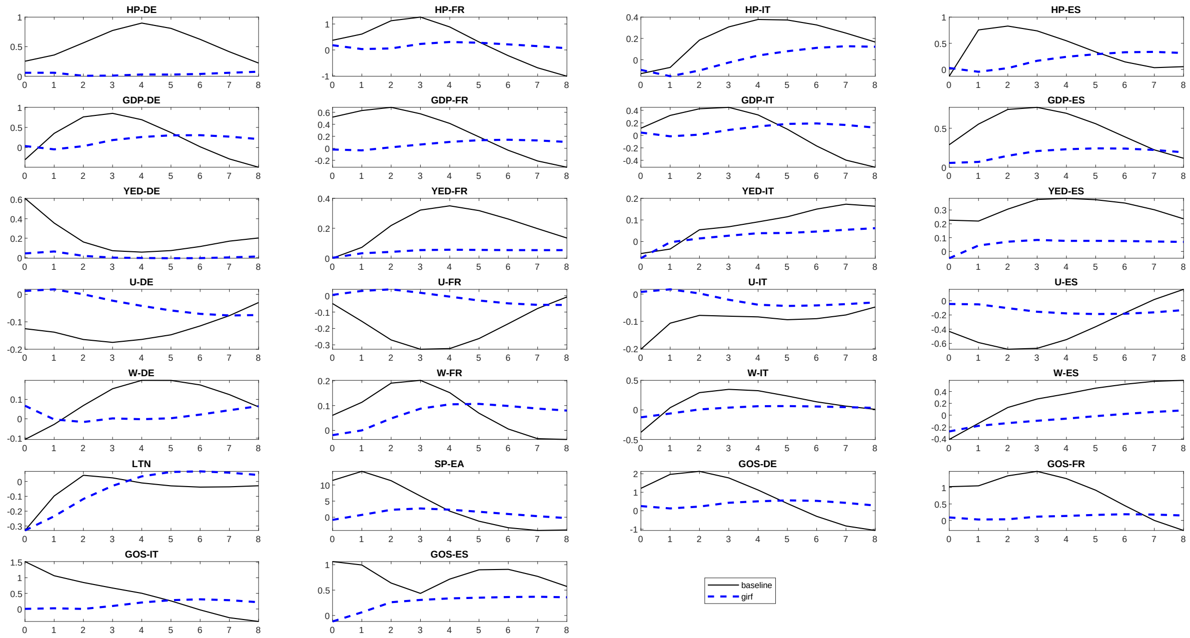
Note: The figure shows the impulse response of all the variables in the model to the QE shock (30 bp drop in the term spread). The red shaded area reflects the 16th–84th percentile range. HP: house prices; GDP: real gross domestic product; YED: GDP deflator; U: unemployment rate; W: compensation per employee, wage; LTN: nominal long-term interest rate; SP: stock prices; GOS: Gross Operating Surplus. EA: euro area; DE: Germany; FR: France; IT: Italy; ES: Spain.

Fig. C2 VAR Impulse Responses with different numbers of lags



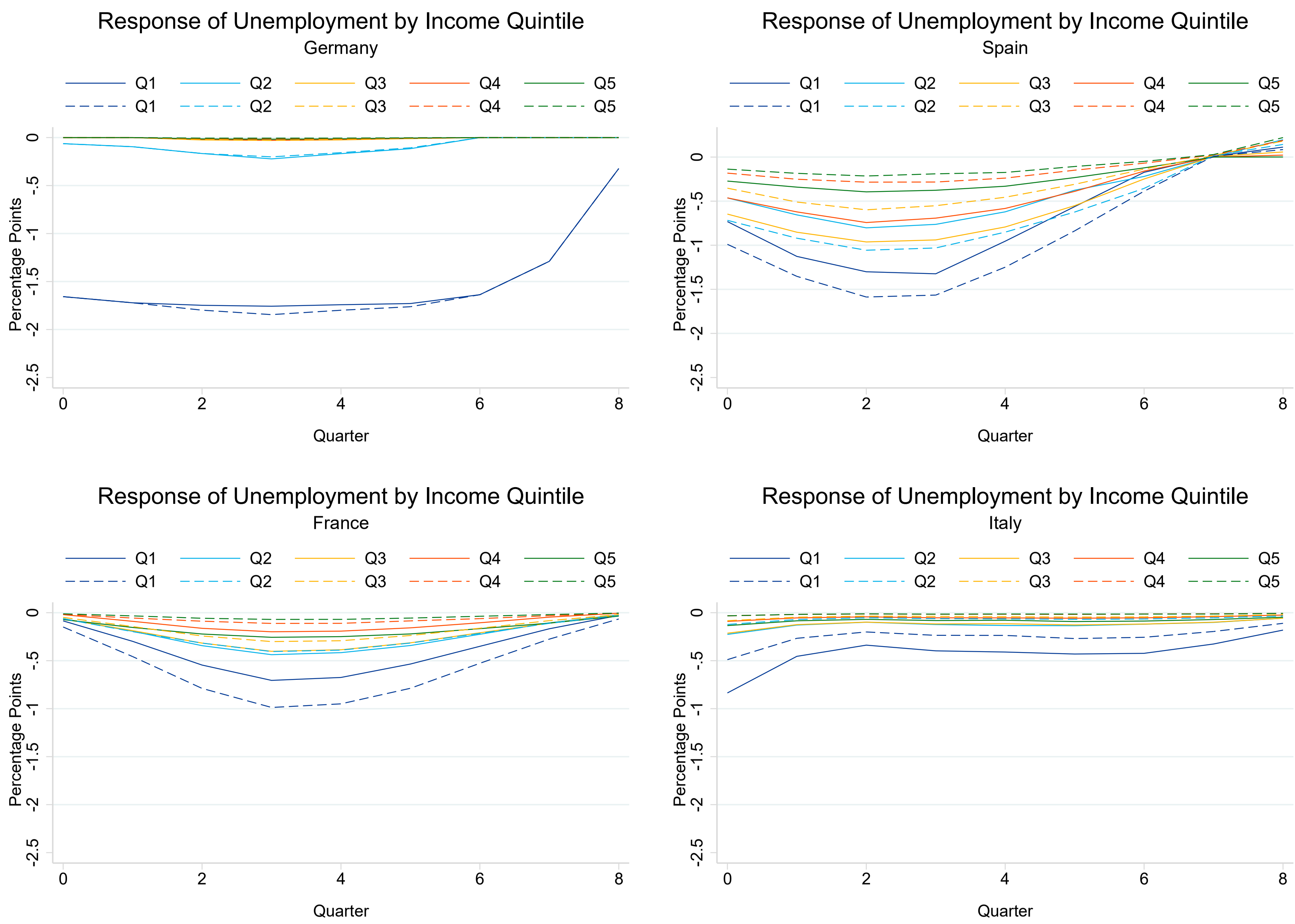
Note: VAR with four lags: solid red line; VAR with three lags: dashed blue line; VAR with five lags: dashed black line

Fig. C3 Median baseline impulse responses to QE shock and generalized impulse responses to a change in long-term interest rates



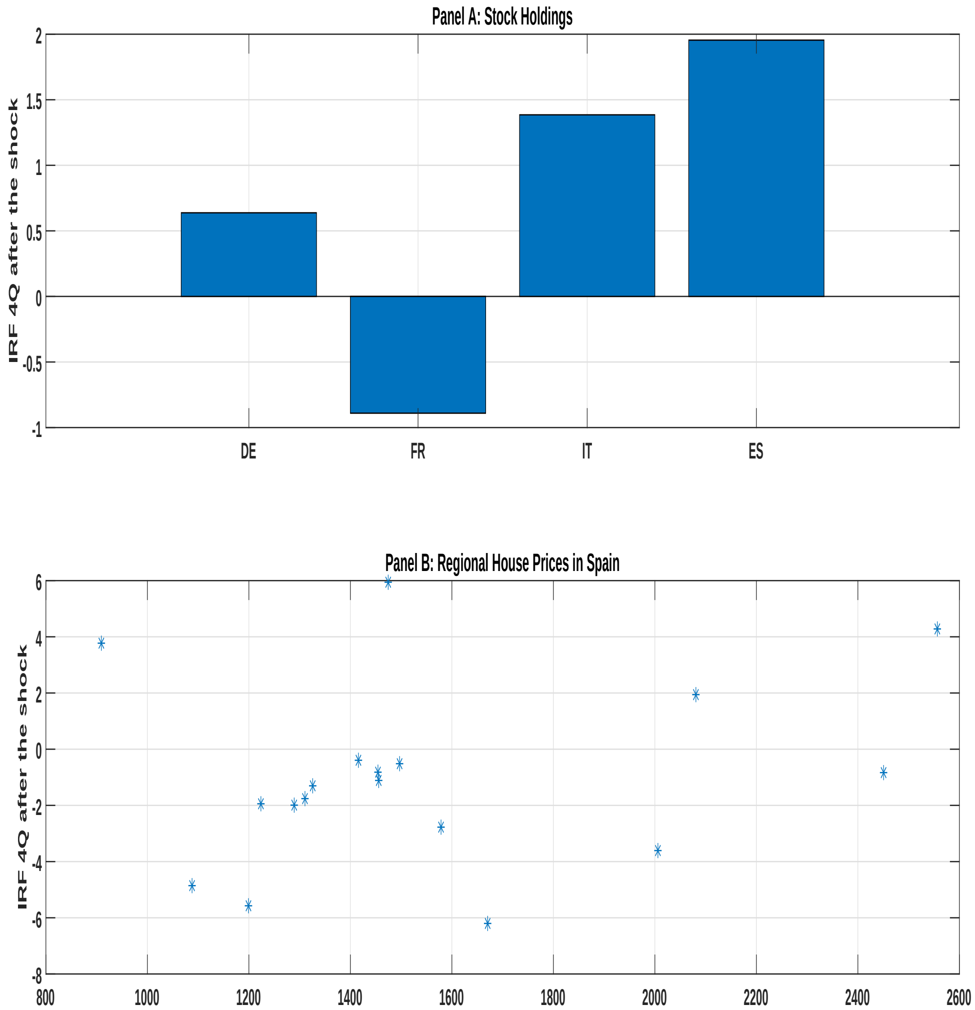
Note: Baseline QE IRF: solid black line; GIRF to long-term interest rate: dashed blue line.

Fig. C4 Impulse Responses of Unemployment—Baseline IRFs (Solid) vs IRFs Generated Under Uniform Probability of Getting Employed (Dashed)



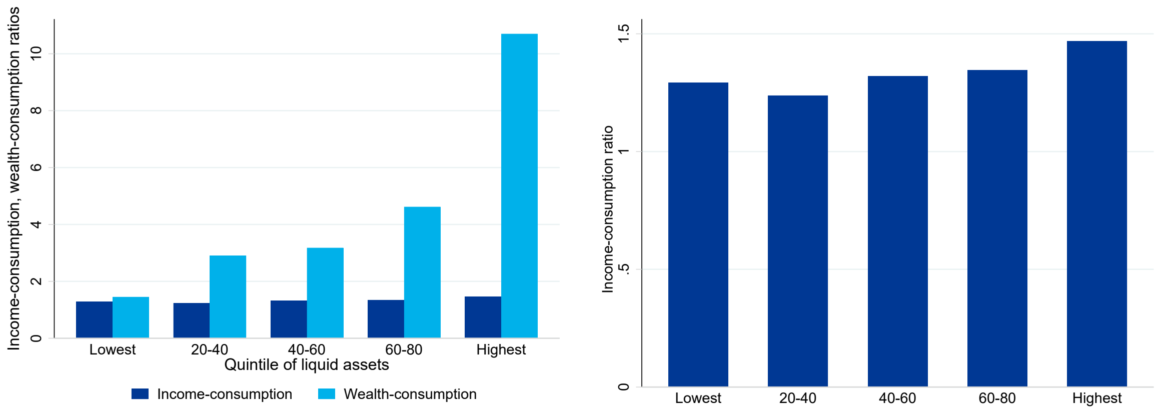
Source: Household Finance and Consumption Survey
Note: The charts show impulse responses of unemployment by income quintile.

Fig. C5 Robustness analysis



Note: The figure reports the median of the impulse responses (four quarters after the shock) of the additional variables used in the robustness checks. The responses are estimated by means of the local linear projection method of Jordà (2005) applied to the median QE shock estimated in the VAR. Units: percentage point deviation from pre-shock levels. Panel B shows a scatter plot of impulse responses of regional house prices across provinces in Spain across house prices per square meter (in EUR). DE: Germany; FR: France; IT: Italy; ES: Spain.

Fig. C6 Wealth–consumption and income–consumption ratios by liquid assets



Note: The figure shows mean ratios of net wealth and income to annual nondurables consumption by quintile of liquid assets. The right-hand panel reproduces the rescaled version of the income–consumption ratios shown also in the left-hand panel.
Source: German Household Budget Survey, "Einkommens- und Verbrauchsstichprobe" 2018.

Probit and Heckman estimates

Table 2 Probit Estimation Results—Germany

Variable	Coefficient	(Std. Err.)
gender	-0.047	(0.060)
college	0.962^{**}	(0.100)
highschool	0.539^{**}	(0.087)
age2	-0.052	(0.098)
age3	0.034	(0.088)
age456	-0.170ý	(0.091)
single	-0.348^{**}	(0.072)
children	0.104	(0.076)
Intercept	1.136^{**}	(0.111)
N	4868	
Log-likelihood	-1020.965	
$\chi^2_{(8)}$	172.886	

Significance levels : ý : 10% $*$: 5% $**$: 1%

Table 3 Probit Estimation Results—Spain

Variable	Coefficient	(Std. Err.)
gender	0.178^{**}	(0.035)
college	0.695^{**}	(0.040)
highschool	0.335^{**}	(0.048)
age2	0.264^{**}	(0.055)
age3	0.259^{**}	(0.053)
age456	0.415^{**}	(0.055)
single	-0.400^{**}	(0.045)
children	0.068	(0.045)
Intercept	0.211^{**}	(0.061)
N	6815	
Log-likelihood	-3320.85	
$\chi^2_{(8)}$	619.444	

Significance levels : ý : 10% $*$: 5% $**$: 1%

Table 4 Probit Estimation Results—France

Variable	Coefficient	(Std. Err.)
gender	0.006	(0.030)
college	0.809**	(0.041)
highschool	0.401**	(0.039)
age2	0.394**	(0.043)
age3	0.552**	(0.042)
age456	0.504**	(0.047)
single	-0.368**	(0.034)
children	0.110**	(0.035)
Intercept	0.509**	(0.053)

N	13408	
Log-likelihood	-4291.914	
$\chi^2_{(8)}$	1026.339	

Significance levels : ý : 10% $*$: 5% $**$: 1%

Table 5 Probit Estimation Results—Italy

Variable	Coefficient	(Std. Err.)
gender	0.106**	(0.035)
college	0.805**	(0.054)
highschool	0.501**	(0.038)
age2	0.591**	(0.049)
age3	0.857**	(0.050)
age456	0.931**	(0.056)
single	-0.395**	(0.046)
children	0.145**	(0.046)
Intercept	-0.002	(0.061)

N	7979	
Log-likelihood	-3552.257	
$\chi^2_{(8)}$	1210.823	

Significance levels : ý : 10% $*$: 5% $**$: 1%

Table 6 Heckman Estimation Results—Germany

Variable	Coefficient	(Std. Err.)
Equation 1 : log_laborincome		
gender	0.591**	(0.028)
college	1.021**	(0.125)
highschool	0.579**	(0.099)
age2	0.428**	(0.046)
age3	0.500**	(0.044)
age456	0.459**	(0.041)
Intercept	8.912**	(0.155)
Equation 2 : job		
gender	-0.031	(0.061)
college	1.016**	(0.102)
highschool	0.588**	(0.089)
age2	-0.030	(0.099)
age3	0.064	(0.089)
age456	-0.150	(0.092)
single	-0.348**	(0.072)
children	0.099	(0.077)
Intercept	1.038**	(0.115)
Equation 3 : /mills		
lambda	-0.778*	(0.377)
N	4650	
Log-likelihood	.	
$\chi^2_{(6)}$	760.647	

Significance levels : ý : 10% ∗ : 5% ∗∗ : 1%

Table 7 Heckman Estimation Results—Spain

Variable	Coefficient	(Std. Err.)
Equation 1 : log_laborincome		
gender	0.323**	(0.028)
college	0.604**	(0.052)
highschool	0.233**	(0.044)
age2	0.190**	(0.057)
age3	0.426**	(0.057)
age456	0.568**	(0.062)
Intercept	9.300**	(0.127)

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... table 7 continued

Variable	Coefficient	(Std. Err.)
Equation 2 : job		
gender	0.187^{**}	(0.036)
college	0.712^{**}	(0.041)
highschool	0.341^{**}	(0.049)
age2	0.360^{**}	(0.056)
age3	0.364^{**}	(0.055)
age456	0.518^{**}	(0.057)
single	-0.428^{**}	(0.046)
children	$0.086^{ý}$	(0.046)
Intercept	0.060	(0.063)
Equation 3 : /mills		
lambda	-0.859^{**}	(0.138)
N	6365	
Log-likelihood	.	
$\chi^2_{(6)}$	278.775	

Significance levels : ý : 10% $*$: 5% $**$: 1%

Table 8 Heckman Estimation Results—France

Variable	Coefficient	(Std. Err.)
Equation 1 : log_laborincome		
gender	0.414^{**}	(0.017)
college	0.593^{**}	(0.043)
highschool	0.094^{**}	(0.033)
age2	0.248^{**}	(0.035)
age3	0.361^{**}	(0.038)
age456	0.465^{**}	(0.037)
Intercept	9.454^{**}	(0.076)
Equation 2 : job		
gender	-0.001	(0.031)
college	0.866^{**}	(0.042)
highschool	0.442^{**}	(0.040)
age2	0.447^{**}	(0.044)
age3	0.613^{**}	(0.042)
age456	0.563^{**}	(0.048)
single	-0.380^{**}	(0.034)
children	0.142^{**}	(0.036)

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... table 8 continued

Variable	Coefficient	(Std. Err.)
Intercept	0.385**	(0.055)
Equation 3 : /mills		
lambda	-0.808**	(0.119)
N	12753	
Log-likelihood	.	
$\chi^2_{(6)}$	1124.399	

Significance levels : ý : 10% ∗ : 5% ∗∗ : 1%

Table 9 Heckman Estimation Results—Italy

Variable	Coefficient	(Std. Err.)
Equation 1 : log_laborincome		
gender	0.376**	(0.017)
college	0.580**	(0.036)
highschool	0.265**	(0.026)
age2	0.263**	(0.045)
age3	0.446**	(0.052)
age456	0.468**	(0.054)
Intercept	9.179**	(0.086)
Equation 2 : job		
gender	0.105**	(0.035)
college	0.806**	(0.054)
highschool	0.502**	(0.038)
age2	0.591**	(0.049)
age3	0.856**	(0.050)
age456	0.931**	(0.057)
single	-0.394**	(0.046)
children	0.146**	(0.046)
Intercept	-0.004	(0.061)
Equation 3 : /mills		
lambda	-0.273**	(0.095)
N	7964	
Log-likelihood	.	
$\chi^2_{(6)}$	634.546	

Significance levels : ý : 10% ∗ : 5% ∗∗ : 1%

Table C.1 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. Abbreviations: OMT—Outright Monetary Transactions (Announcement), APP—Asset Purchases Programmes, APF—Asset Purchase Facility, CME—Comprehensive Monetary Easing, QQE—Quantitative and Qualitative Monetary Easing, LSAP—Large Scale Asset Purchase Program, MEP—Maturity Extension Program.

Table C.2 Estimates of the Effects of Nonstandard Monetary Policy Using VARs

Authors	Method (Country)	Type of Event	Effect on Real Economy and Inflation
Altavilla et al. (2016)	VAR (DE, ES, FR, IT)	OMT	Real GDP: 0.34%–2.01%, HICP: 0.28%–1.21%
Baumeister and Benati (2013)	TVP VAR (US, UK)	LSAP	Inflation: trough of −1% to −4% GDP gr: trough −10% to −12%, UR: peak 10.6%
Kapetanios et al. (2012)	TVP VAR (UK)	BoE LSAP	Real GDP: peak effect of 1.42%
Weale and Wieladek (2016)	Bayesian VAR (US, UK)	LSAP	Real GDP: 0.25%–0.58%, CPI: 0.32%–0.62%
Gambacorta et al. (2014)	Panel VAR (EA, non-EA countries)	Various	GDP: −0.25% to 0.25%, CPI: −0.12% to 0.10%
Darracq-Paries and De Santis (2015)	Panel VAR (EA countries)	3-year LTROs	GDP: peak of 0.8%, GDP Defl: peak of 0.35%
Babecka Kucharcukova et al. (2016)	VAR (EA, non-EA countries)	Spillovers from ECB QE	IP: −0.2% to 0.2%, HICP: −0.1% to 0.06%
Bluwstein and Canova (2016)	Bayesian SVAR (EA, EU countries)	Spillovers from ECB QE	IP: −0.1% to 0%, CPI: 0%–0.5%
Hachula et al. (2019)	SVAR (EA, EA countries)	LTROs	GDP: 0.1%–0.65%, CPI: 0%–0.45% UR: −0.21%–0.07%
Behrendt (2017)	SVAR (EA)	ECB QE	IP −0.0032%–0.0023%, HICP −0.0006%–0.0005%
Boeckx et al. (2017)	SVAR (EA, EA countries)	3Y LTRO, CBPP1	GDP: −0.35%–0.6%, HICP: −0.1%–0.3%

Notes: See also Andrade et al. (2016), Appendix B for other studies and details. Abbreviations: OMT—Outright Monetary Transactions, LSAP—Large Scale Asset Purchase Program, LTROs—long-term refinancing operations, CBPP1—Covered Bond Purchases Program.

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