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Essays in Empirical Macroeconomics

Presentata da: Antonio Marsi

Coordinatrice Dottorato

Maria Bigoni

Supervisore

Luca Fanelli

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Chapter 1

A machine learning estimate of the equity premium

Abstract

We explore equity returns predictability in the European stock market, using several machine learning techniques. We train and test the forecasting algorithms using monthly returns of equities contained in the EURO STOXX 50 index, from 1994 to 2018, as the target variable. Compared to similar studies performed using US data and lager samples, we get an higher performance, in terms of predictability, with linear methods rather than highly non-linear ones. In general the predictive ability of the machine learning algorithms is not particularly high, suggesting that equity returns in our sample are highly unpredictable, in line with the efficient market hypothesis.

1.1 Introduction

A longstanding question in the empirical finance literature is whether equity returns can be predicted. Seminal papers in this area are, among many others, Campbell and Shiller (1988) Pesaran and Timmermann (1995). The issue is relevant both for an investor who wants to optimally shape its portfolio of stocks and for a researcher who wants to study the efficiency of a financial market. According to the efficient market hypothesis (Fama(1970)) in an efficient stock market returns are unpredictable as current market value of stocks should already price all future relevant information. This means equity prices should follow a random walk. By exploring equity return predictability one can investigate also the degree of efficiency in the equity market. The topic is also of interest for those who wants to extract the predictable component of a return in order to build an estimate of the cost of capital (Duarte (2015)). The huge literature on empirical asset pricing is still divided on the fundamental question: are equity returns predictable? We will later review some studies suggesting that variables with predictive power can be actually found, while among the studies arguing for the non-predictability of equity returns Goyal and Welch (2008) stands out.

Recent developments in the machine learning literature makes it possible to study the predictability of equity returns using a vast set of candidate predictors all the same time. Machine learning techniques indeed are designed to construct predictive models when the number of predictors is extremely large, to the extreme case where the number of candidate predictors is greater than the number of observations available. Of course these algorithms are extremely appealing in the finance field, both for practitioners and empirical researchers, given the amount of data available and the typical difficulty encountered in predicting stock returns.

By using machine learning algorithms we can explore predictability of equity returns by taking an agnostic prior regarding the structure of the econometric model underlying the data. More precisely we don't have to select a priori which predictors to use and the functional form of the predictive model, and allow for linear and non linear functions. In this sense we can let the data speak by themselves. The drawback of this approach lies on the fact that we cannot draw any theoretical implications about the way in which future returns are determined. Gu et al. (2018), hereafter GKX, apply this idea to a large sample of US stocks, exploiting almost one thousand predictors. They show that highly non linear predictive algorithms (e.g. neural networks) can lead to good performances in terms of predictive power of the model.

In this paper we perform a very similar exercise by analyzing predictability of stock returns in European equity market. We focus on a rather small subset of equities, more precisely those contained in the STOXX 50 index. We compare several machine learning techniques. In our sample, the best performing algorithm is the Elastic Net, while complex non-linear methods such as Neural Networks are performing worse. This can be explained by the rather small size of sample we are using: as Neural Networks requires to estimate a large number of parameters, a small sample size makes it less efficient.

While US equity data have been largely explored in the literature, European data have been much less investigated. We fill this gap, being conscious of the smaller availability of data compared to US stock market. Nonetheless it is interesting to see whether a market with a shorter history and less investigated displays different pattern of predictability. We think that replicating main results of the huge literature on returns predictability of stock markets outside the US is important in order to validate the many results obtained in these studies.

A central question in the machine learning literature concerns the debate: "sparsity vs density". Simplifying, we can state that all ML algorithms deals with the large dimension of the predictor matrix in two ways: either by shrinking the number of predictors to be actually used in the final model, thus selecting the level of complexity of the model or by shrinking the size (and thus the associated variance) of the parameters of the model. In the first case the algorithm assumes the true model is *sparse*, while in the second case a *dense* model is assumed. This issue is deeply analyzed in Giannone et al. (2019), where the true level of sparsity/density of the underlying models is analyzed in several empirical applications,using Bayesian techniques, including the prediction of equity returns in the US market. Their analysis points to the result that the underlying predictive model in the stock-level data lies somewhere between a fully dense and a fully sparse model. This result is somehow in line with our results that selects the Elastic Net algorithm as the one with most predictive power. Elastic Net indeed combines a dense and a sparse representation of the data, thus taking a mixed stand of this paramount choice.

Some of relevant recent papers studying the predictability of equity returns by using stock-level characteristics are: Green et al. (2013) analyze 330 stock-level characteristics proposed in many studies in the literature; Freyberger et al. (2017) studies the predictive power of a set of 36 characteristics and concludes that only a bunch of them have predictive power and that taking into account non-linearity is fundamental; Harvey et al. (2016) instead identify 300 factors that have predictive power for future equity returns; Chordia et al. (2015) compares predictability of stock-level characteristics and betas on risk factors identified in the literature, concluding that characteristics have stronger predictive power; Light et al. (2017) suggests that Partial Least Squares (PLS) is the best technique to summarize the predictive content of stock-level characteristics, while our analysis suggests PLS under-performs several other techniques on the data we explore.

The remainder of the paper proceeds as follows: in section 2 we describe the data we are using and explain how we recursively split them in order to implement ML algorithms; in section 3 we briefly explain the ML methods we apply; in section 4 we present our results and compare the performances of the different methods.

1.2 Data and sample splitting procedure

1.2.1 Data

As target variable we use monthly returns of stocks included in the EURO STOXX 50 index, which includes 50 largest companies in Eurozone countries. Since composition of the index changes at least once a year, we have a total of 89 stocks, which are all stocks which entered in the index at least once since 1994. We use data from January 1994 to July 2018.[1] We try to construct a matrix of predictors for all the stocks used as similar as possible to that used by GKX. We manage to collect 45 stock level predictors, which are listed in Table 1.1. These predictors are taken from those used in the vast empirical asset pricing literature.[2] All data are taken from Thomson Reuters Datastream. Beyond stock level predictors we use 24 industry dummies[3] and 6 macro predictors (the spread between Italian and German 10 year sovereign rates, the 1 year German rate, the term spread (difference between 10 years and 1 year German rates), index return variance (monthly sum of squared daily return on the STOXX 50 index) and aggregate price-to-book value ratio and dividend yield of the EURO STOXX 50 index. The macro variables are also interacted with stock level predictors and industry dummies, therefore we have at the end a total of $(45 + 24) \times (6 + 1) = 483$ predictors. From 1994 to 2018 we have a total of 24317 observations. The approach we use to construct the matrix of predictors makes this analysis comprehensive of both the stock-level characteristics approach and the risk-factors approach, as we interact firm-level predictors with candidate risk factors (the macro predictors).

When observations of predictors are missing we impute them the median value of the cross section. When a certain predictor is missing for the whole cross section we impute the historical mean. We also treat outliers by squeezing tail values to 5 and 95 percentiles.[4]

[1] Though the index return is available since 1987, we only use data since 1994 due to data limitations.

[2] Compared to GKX we face the difficulty that, since most of the stock pricing literature uses US stock market data, we had to construct predictors on our own rather than have them taken from some previous paper.

[3] We categorize industries by using the first 2 digits of the SIC code.

[4] This procedure is applied by using only past values for computing percentiles, so that the forecasting is truly out of sample.

beta12	Beta computed on last 12 months	mvel1	Market value of equity
beta24	Beta computed on last 24 months	operprof	Operating profit margin
beta36	Beta computed on last 36 months	pchcurrat	% change in current ratio
beta12_sq	Beta computed on last 12 months, squared.	pchdepr	% change in depreciation
beta24_sq	Beta computed on last 24 months, squared.	pchgm	% change in gross margin
beta36_sq	Beta computed on last 36 months, squared.	pchquick	% change in quick ratio
acc	change in working capital/total assets	pchsale_pchinvt	% change in sales - % change in inventories
agr	Total assets growth	pchsale_pchrect	% change in sales - % change in A/R
baspread	Bid/ask spread	pchsale_pchxsga	% change in sales - % change in AG&A
bm	Book-to-market ratio	pchsaleinv	% change in sales-to-inventory ratio
cash	Total cash over total assets	quick	Quick ratio
cashdebt	Total cash over total debt	rd	Change in R&D
cashpr	Cash productivity	rd_sale	R&D-to-sales ratio
cfp	Cash flow over price	roaq	Return on assets
chinv	Change in inventory	roeq	Return on equity
cinvest	Corporate investment	salecash	Sales-to-cash ratio
convind	Convertible debt over total debt	saleinv	Sales-to-inventory ratio
currat	Current assets over current liabilities	salerec	Sales-to-receivable ratio
depr	Depreciation rate	sgr	Sales growth
dy	Dividend-yield	sp	Sales-to-price ratio
ep	Earnings-to-price ratio	tang	Debt capacity over firm tangibility
gma	Gross profits over total assets	chmom	Change in 6-months momentum
grcapx	Growth rate of capital expenditures		
hire	Growth rate of number of employees		
lev	Leverage		
lgr	Growth of long term debt		
mom12m	12 months momentum		
mom1m	1 month momentum		
mom36m	36 months momentum		
mom6m	6 months momentum		

Table 1.1: List of stock level predictors used.

1.2.2 Sample split for validation

Most of machine learning techniques require choosing a value for tuning parameters. These are parameters which govern the complexity of the model and its degree of sparsity/density. To set them optimally we need to minimize some loss function in a *validation* sample separate from the *training* one. In this way we avoid the risk of training a model which overfits "in-sample" and would thus perform bad for "out of sample" predictions. In the implementation of the several machine learning algorithms we employ the following **Time series validation**: with this method we take into account the multivariate time series nature of our data and we validate tuning parameters using observations which are always more recent to those used for training the model. We apply the following recursive procedure: we start iterations with a training window of 5 years (60 months) of data and use the subsequent 5 years of data for validation. We then use the selected model for predicting the following 12 months out of sample. In the next iteration we increase the training window by 12 months, keeping fixed the size of the validation window. Figure 1.1 explains this sample splitting procedure.

Given the time span of our sample and the splitting procedure, for each algorithm we perform 14 training iterations. The out-of-sample predictive accuracy of the several models will be therefore computed on the 14 separate test sample of 1-year size each. This recursive iteration will also give us an idea about the degree of convergence of the models towards an optimal one, as the size of the training sample increases and new, more recent, observations are included in the analysis. Anticipating the results, the algorithms we test do not display a clear convergence pattern, suggesting that 14 iterations are probably not enough to adequately train the models.

1.3 Estimated models

Let us first introduce some notation. We assume the asset pricing equation:

$$r_{i,t+1} = E_t[r_{i,t+1}] + u_{i,t+1} \tag{1.1}$$

where $r_{i,t+1}$ is stock i monthly return in month $t+1$. In other words monthly equity returns are made up of a predictable component plus an unpredictable one. Our aim is to forecast the predictable one. The true model to estimate is then:

$$r^*_{i,t+1} = E_t[r_{i,t+1}] = f(\mathbf{x}_{i,t}) + \epsilon_{i,t+1} \tag{1.2}$$

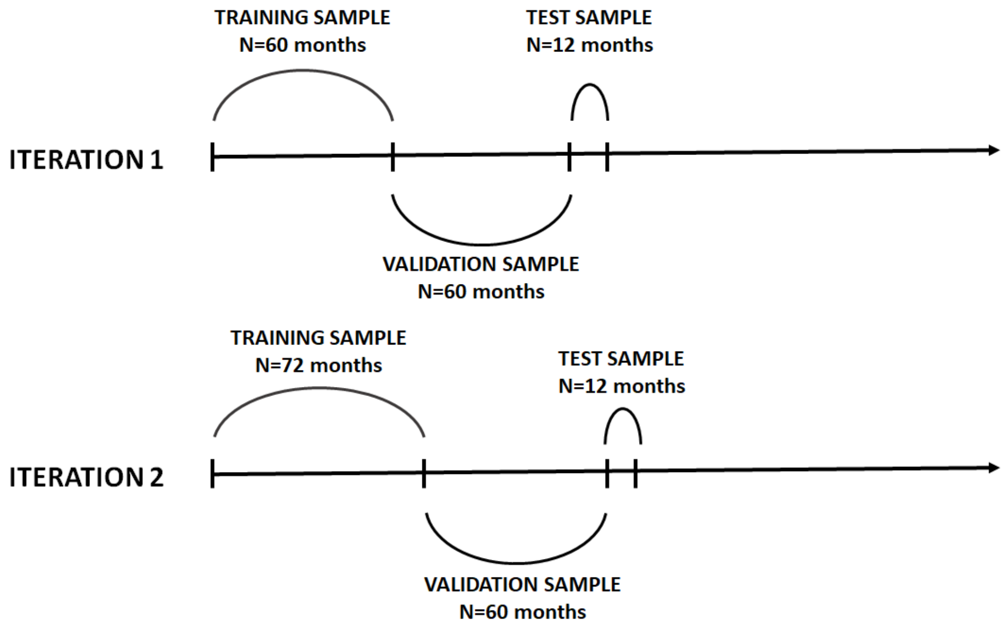

Figure 1.1: Sample splitting procedure.

where $x_{i,t}$ is a vector of predictors at the end of month t. By applying machine learning algorithms we take no stand a priori about the functional form of $f(x_{i,t})$, though different models will in fact assume different degrees of sparsity/density and linearity/non-linearity of the model.

Each of the methods explained below, starting from the simple OLS to complex Neural Networks, are estimated (or "trained" in Machine Learning jargon) by minimizing some loss measure. In some estimation we use the Mean Squared Error, in some other we use a Mean of a Huber Loss of this form:

$$H(e_t) = \begin{cases} e_t^2 \quad \text{if} \quad |e_t| \leq c \\ 2c|e_t| - c^2 \quad if \quad |e_t| > c \end{cases} \tag{1.3}$$

Using the Huber Loss brings the advantage of putting less weight on the forecasting errors on the tails of the error distribution. This is particularly useful when dealing with stock returns as they are notoriously characterized by heavy-tailed distributions. In our specification we use a value for c of 0.1.[5]

[5]Ideally, one would like to validate the parameter c of the Huber loss function. We don't do as it would have increase excessively the computational time of the algorithms we use, which is already quite significant.

1.3.1 Linear regression

We estimate first a linear regression model and evaluate its forecasting performance to provide a benchmark. This means assuming:

$$f(x_{i,t}) = \beta_0 + \beta' x_{i,t} + \epsilon_{i,t} \tag{1.4}$$

It's clear that having almost 500 covariates makes simple OLS estimation quite unfit for achieving good forecasting performance. The reason is that with OLS there is no way to avoid overfitting when the number of predictors is large. We therefore try also a specification where we select only 3 predictors that are expected to be quite powerful ones: 6-months momentum, dividend yield and book-to-market ratio.

1.3.2 Elastic Net, LASSO and Ridge Regression

Elastic Net falls in the category of Penalized Regressions, which consists in estimating the parameters of a linear model by imposing some restrictions on the estimation such that the sizes of estimated parameters are kept low. In practice it means estimating a linear model by minimizing:

$$L(\theta; \hat{\mathbf{e}}) = S(\theta; \hat{\mathbf{e}}) + P(\theta) \tag{1.5}$$

where $\hat{\mathbf{e}}$ is the $NT \times 1$ vector of forecasting errors, $S(\dot{})$ is loss function and can be either quadratic or Huber. $P(\dot{})$ is instead a penalty function, which in the Elastic Net model takes the functional form:

$$P(\theta) = \alpha\lambda \frac{1}{M} \sum_{j=1}^{M} |\theta|_j + (1-\alpha)\lambda \frac{1}{M} \sum_{j=1}^{M} \theta_j^2 \tag{1.6}$$

The penalty function in the elastic net model is a weighted average of the LASSO penalty (Tibshirani (1996)) and the Ridge Regression one (E. Hoerl and Kennard (1970)). The former shrinks parameters toward zero thus forcing the model to be a sparse one. Ridge Regression instead estimates a dense model: estimated parameters are shrunk but not to zero. Drastically simplifying, this category of models in fact takes a (quasi) Bayesian approach as the penalty function applies the idea that the researcher has a prior about the parameters θ_i. In the LASSO algorithm the prior assumes that θ_i is exactly zero with some probability, while in the Ridge Regression the prior is about the variance of the (centered) distribution of θ_i: it tends toward zero. Elastic Net allows these two types of priors to be mixed together.

The parameter λ governs the complexity of the model and thus should be chosen by validation. α sets the level of sparsity/density of the model and again is chosen by validation. We implement both an Elastic Net algorithm, where we let α unrestricted and validate it, a LASSO algorithm, where α is set equal to 1, and a Ridge Regression where α is set to zero.

1.3.3 Principal Component Regression

Principal Component analysis falls into the category of the so called *unsupervised learning* methods. It means that dimension reduction is obtained by using the predictors data only, without exploiting the target variable in order to train the model. The method allows to condense the information contained in a large matrix of predictors into a smaller one. The First principal component pc_1 is defined as the linear combination of the predictors that explain the highest fraction of variance of the sample of predictors:

$$\hat{pc}_{1,i,t} = \hat{\rho}_1' \tilde{x}_{i,t} \tag{1.7}$$

$$\hat{\rho}_1 = \arg\max_{\rho_1} \rho_1' (\sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{x}_{i,t}' \tilde{x}_{i,t}) \rho_1 \tag{1.8}$$

where $\tilde{x}_{i,t} = x_{i,t} - \overline{x}$ are demeaned predictors. The second principal component is then another linear combination of predictors that explain the higher variance of predictors and it is at the same time uncorrelated with the first principal component. The procedure is further iterated until k principal components are obtained, where k is set exogenously. Of course one can iterate the procedure until she reaches $k = M$, that is we have as many principal components as regressors.

The k principal components are then used in a simple linear regression to forecast the target variable. The regression is estimated on the training sample and used in the test sample to forecast the target variable. At this step the number of principal components to include in the regression k can me optimized by minimizing the prediction error in the validation sample. This is the *supervised learning* part of this methodology, as the target variable in the validation sample is used to tune the parameter k.

1.3.4 Partial Least Squares

Partial Least Squares (Wold (1975)) method is quite similar to Principal Component Analysis except for the fact that it is a *supervised learning* approach. The target variable is indeed used directly to construct linear combination of the predictors that explain the highest variance of the predictors and are related to the target.

First the target variable is regressed separately on each predictive variable:

$$r_{i,t+1} = \beta_{0,j} + \beta_j x_{i,j,t} + \epsilon_{i,j,t} \tag{1.9}$$

β_j is then used to construct a linear combination of all the predictors:

$$\hat{pls}_{1,t} = \sum_{j=1}^{M} \beta_j x_{j,t} \tag{1.10}$$

The same procedure is iterate by using the residuals of the regression in 1.9 in place of the actual predictors. In this way the contribution of each predictor to the linear combinations $\hat{pls}_{.,t}$ depends of the in-sample predictive content of the predictor. Again one can iterate the procedure till $k = M$.

The linear combinations are then used, as in the principal component regression, in a simple regression which is fit on the training sample and used in the test sample for forecasting. Again the validation sample is used to select the number of linear combinations to include in the regression. This type of predictive models which exploit the idea of condensing the matrix of predictors into few combinations, or some modified version of them, have proved quite successful on US data, as in Kelly and Pruitt (2013) and Giglio and Xiu (2017).

1.3.5 Random Forest

Random Forest algorithm (Breiman (2001)) is an evolution of Tree Regression algorithms. A Tree algorithm splits the predictor space into K non-overlapping regions $R_1, ..., R_K$. In each region fitted value of the target variable is the mean of it in the region: $\hat{y}_k = \frac{\sum_{i=1}^{n} y_i \mathbb{I}(x_i \in R_k)}{\sum_{i=1}^{n} \mathbb{I}(x_i \in R_k)}$. Regions are defined by finding critical values of the predictors such that by fitting y with the mean over the region the MSE is minimized. In practice the algorithm works as follows (Recursive Binary Splitting):

1. Choose a predictor $x_j \in X$ and a value x_j^* such that two regions are defined: $R_1 : x_j \leq x_j^*, R_2 : x_j > x_j^*$. The predictor and its critical value are chosen such that the MSE is minimized by using the fitting procedure described above.

2. Choose a region R_k, a predictor x_j and a value x_j^*, split the region R_k into 2 subregions accordingly and fit the target variable mean to each region. Again the split is made to minimize prediction error.

3. Repeat step 2 recursively until a stopping criterion is met.

Figure 1.2 shows an example of a tree with 2 predictors, and 5 "leaves" (number of regions formed).

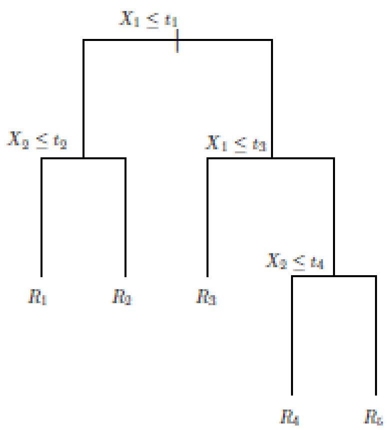

Figure 1.2: A simple tree.

The number of *leaves* is a tuning parameter (letting $K = n$ would make the tree perfectly fitting the data) and should be find using validation. Optimal size of the tree, hence the number of *leaves*, is usually chosen by minimizing a loss function that penalizes for the number of *leaves*. The penalty coefficient is then chosen using out of sample validation data, similarly to penalized regressions. This process is called *pruning* a tree.

An alternative is to use *bagging*. With bagging, several bootstrap replicates of the training set are created. For each of them a large tree is fit to the data. Observations which are left out of the bootstrap sample (o average one third of them) are used to compute prediction errors ("Out of Bag" errors). Predictions and OOB errors are averaged across bootstrap samples. Choosing a large number of bootstrap replications, B, does not create the problem of overfitting, thus it can be set to very large values at the cost of reducing marginal benefit and increasing computational cost.

Random Forest performs a Bagging algorithm with trees, but adding a feature that allows to further reduce the variance of predictions. It does so by reducing the correlation between predictions from different tress in different bootstrap samples: in each bootstrap sample only a number m of randomly chosen predictors is used to build the tree. In this way trees are not correlated.

In Random Forest the tuning parameters are B, number of bootstrap replications, and m, number of predictors used for each tree. Since these parameters does not imply smaller/larger complexity of the model, we do not validate them using the splitting procedure described above. For B, we set a value large enough (500). For m, we use the value usually set in the literature $\sqrt{M}$, where M is the number of predictors.

1.3.6 Neural Networks

Neural Networks (NN) are quite sophisticated Machine Learning algorithms that aim at mimicking the way neurons work in the brain. The idea is to make predictions using a linear combination of non-linear combinations of the predictors. The most simple NN is a linear regression, which is a NN with no *hidden layer*. Figure 1.3, depicts a Neural Network with p predictors and 1 hidden layer with M nodes. For each node of the hidden layer, predictors are linearly combined:

$$Z_j = \beta_0 + \sum_{i=1}^{p} X_i \tag{1.11}$$

After that, an nonlinear *activation function* is applied:

$$Z_j^* = activ(Z_j) \tag{1.12}$$

The predicted outcome is then a linear combination of the "activated" nodes:

$$Y = \alpha_0 + \sum_{j=1}^{M} \alpha_j Z_j^* \tag{1.13}$$

As you can see this method implies estimating a large number of parameters. For a network like the one described above, it requires estimating $(p+1) \times M + 1$ coefficients. As usual, coefficients are estimated by minimizing a loss function, we use a standard quadratic loss. When estimating a neural network two types of challenges need to be overcome:

1. First, the loss function to be minimized could be very complex, given the high number of parameters and the highly nonlinear structure of the network, which makes the surface of the loss function non-convex. For non trivial networks the minimization is highly computationally intensive, almost unfeasible in some cases. This requires adding some features that ensure a rather fast and efficient optimization. We use the following ones:
   - We use a *stochastic gradient descent algorithm*. At each iteration of the loss function minimization, a random subset of observations is used to compute the gradient, used to optimally move in the parameter space toward the global minimum. We set the algorithm to use one fifth of the observations in the training sample at each iteration. This method sacrifices an optimal gradient computation in order to significantly speed up computations.
   - The *learning rate* governs the length of the step made at each iteration in the parameter space, in the direction indicated by the gradient. By setting a large number we would gain computational fastness at the cost of increasing the risk of skipping global minima. We use a learning rate equal to 1×10^{-4}.
   - To further avoid skipping minima when the algorithm approaches them, we use the ADAM, adaptive moment estimation algorithm by Kingma and Ba (2015), which forces a reduction in the learning rate as the gradient approaches zero.
2. Second, regularization techniques should be used to avoid overfitting, we employ two of them:
   - We use a $L1$ penalty parameter in the loss function, analogue to the λ in the LASSO objective function, i.e. the penalty function is the sum of the absolute values of the model parameters. We tune this parameter using the validation procedure explained above.
   - We use an *early stopping* algorithm: at each step of the minimization algorithm, a validation set error is computed. The minimizing algorithm is stopped when the validation

set error stops decreasing, even if the global minimum using the training sample is not yet reached.

Regarding the activation function, we follow GKX and use a ReLU function:

$$ReLU(x) = \begin{cases} 0 \quad \text{if} \quad x < 0 \\ x \quad \text{otherwise} \end{cases} \tag{1.14}$$

We try several structures of the networks, avoiding too complex networks, given the rather small size of our sample:

- NN-A.1 1 hidden layer - 2 nodes
- NN-A.2 2 hidden layers - 4,2 nodes
- NN-A.3 3 hidden layers - 8,4,2, nodes
- NN-B.1 1 hidden layer - 16 nodes
- NN-B.2 2 hidden layers - 16,8 nodes

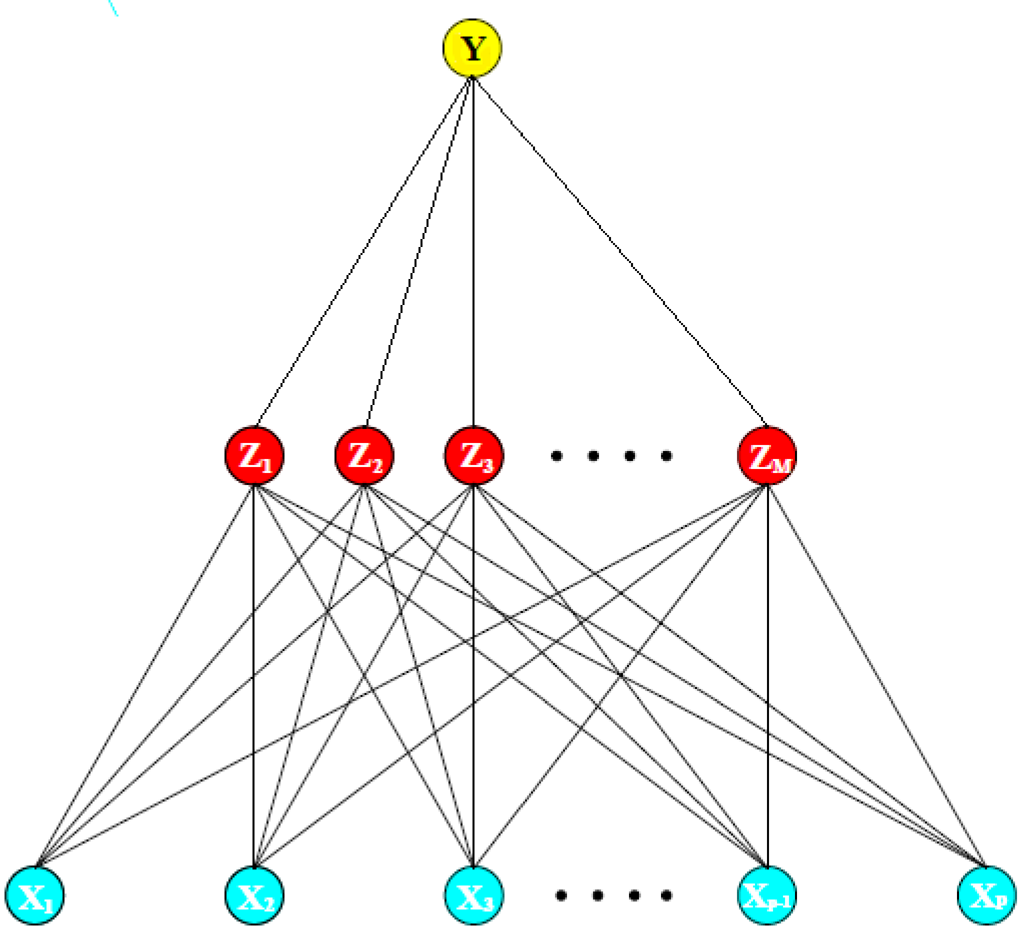

Figure 1.3: Example of a neural network. Figure taken from Hastie et al. (2017).

1.4 Empirical results

Table 1.2 shows the predictive performance of the different algorithms on our sample. The performance is measured using the Out of Sample R-squared:

$$R^2_{OOS} = 100 \cdot (1 - \frac{\sum_t \sum_i (\hat{r}_{i,t} - r_{i,t})^2}{\sum_t \sum_i r^2_{i,t}}) \tag{1.15}$$

This measure of predictive performance compares the forecasting errors of each model with a benchmark prediction $\hat{r}_{i,t} = 0$, which is the same measure employed by GKX. The reason for using this zero-prediction as a benchmark instead of an historical mean, which is usually employed to setup the denominator of an Out of Sample R-squared, relies on the fact that for net stock returns the zero-prediction usually performs better than the historical mean, thus using it makes this measure more conservative. R^2_{OOS} goes from $-\infty$ to 100. Negative values of the statistic implies that the model is performing worse than the benchmark prediction of zero return. A zero value means the two model equally performs, while positive values means the model forecasts better than the zero-prediction, to the extreme case when the R^2 is 100, perfect forecast.

Obviously evaluating out-of-sample performance of the model is a completely different exercise from an in-sample prediction exercise. Let us just consider that a simple in-sample regression of the returns of the full set of predictors delivers a huge 14% R-squared, showing us that the covariates have indeed some "predictive content", while their true forecasting power some very different topic.

Results overall show ML algorithms perform quite bad in forecasting monthly returns of the stocks contained in the EURO STOXX50 index. The only algorithms which provide a positive out-of-sample R^2 are the Lasso and Elastic Net, though a very small one.

Table 1.3 shows the values of the test statistic of the Diebold-Mariano test (Diebold and Mariano (1995)), as modified by Harvey et al. (1997), used to compare the predictive performance of the several predictive models employed.

Figure 1.4 plots the the out of sample R^2 computed in each test sample (each test sample is made of 12 months observations) across the iterations. Dotted lines depicts the zero threshold. We

	OLS	OLS-3	LASSO	RR	ELNET	PCR	PLS	RF
$R^2_{OOS}(\%)$	-381.61	-1.17	0.025	-9.69	0.0358	-0.386	-4.11	-9.69
	NN.A.1	NN.A.2	NN.A.3	NN.B.1	NN.B.2			
$R^2_{OOS}(\%)$	-6.66	-0.64	-7.40	-26.94	-19.03			

Table 1.2: Out of sample R squared, using different ML methods.

can notice the high variability in the predictive performance of all algorithms, which suggests the several models are not particularly reliable. The simple OLS including all predictors preforms very bad at each iterations. LASSO, ELNET and PCR are the most stable models, with the R^2 on single test samples never reaching negative values smaller than -10. The very bad performance of PLS and RF are partially explained by Figure 1.4: we observe highly negative R^2 for the first iterations, while it reaches more satisfactory values towards the final iterations. Evidently, these algorithms suffer the small availability of data and converge towards positive R^2 with larger training samples. Finally RR displays a lot of variability across iterations. The comparison of its performance with LASSO and ELNET relates to the density/sparsity issue. As Giannone et al. (2019) suggests, the true model is probably not sparse, but some degree of sparsity helps to exclude certain “trash predictors” which makes predictions too volatile and little stable.

Figure 1.5 plots the tuning parameters selected in the algorithms through validation, across the iterations along the sample. Interestingly, LASSO selects only between 0 and 15 predictors among the 483, suggesting that most of the information contained in the predictors matrix is useless. This does not necessarily imply that the true model is sparse, but rather that we are not able to exploit the predictive content of each relevant predictor, probably because the small sample size, thus it results optimal to only use a bunch of predictors.

Elastic Net always selects an α parameter, which governs the sparsity/density of the predictive model, always between 0.25 and 1. This again suggest the true model is not completely dense, which explains the bad performance of the Ridge Regression. It’s worth noticing also the difference

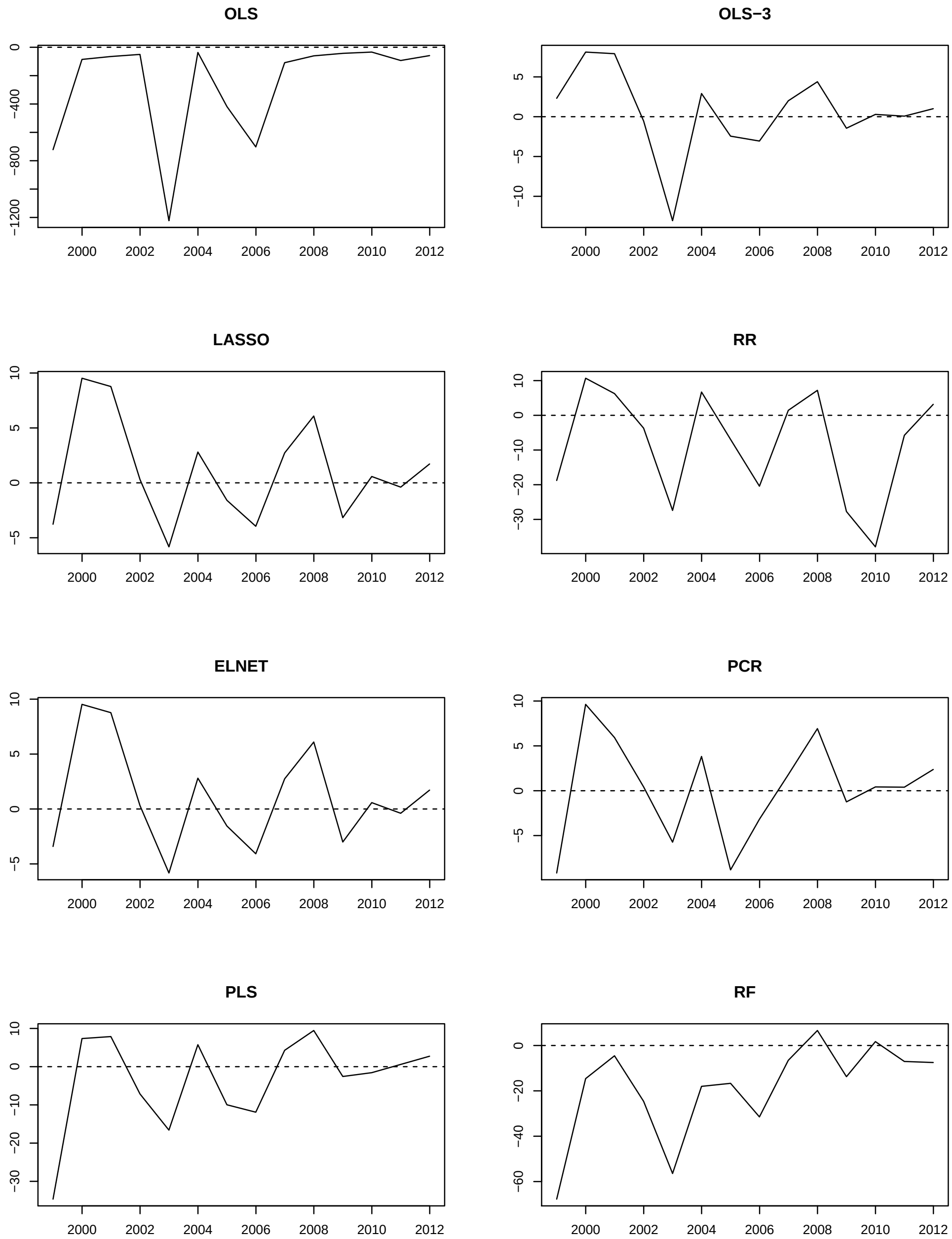

Figure 1.4: Out of sample % R^2 across iterations. On the x-axis years of end of the training sample are reported.

in the number of relevant factors identified by the PCR and the PLS regressions. PLS identifies almost always one single relevant factor while PCR around 10 on average.

Figure 1.6 depicts the number of iterations of the minimization algorithm used for estimating

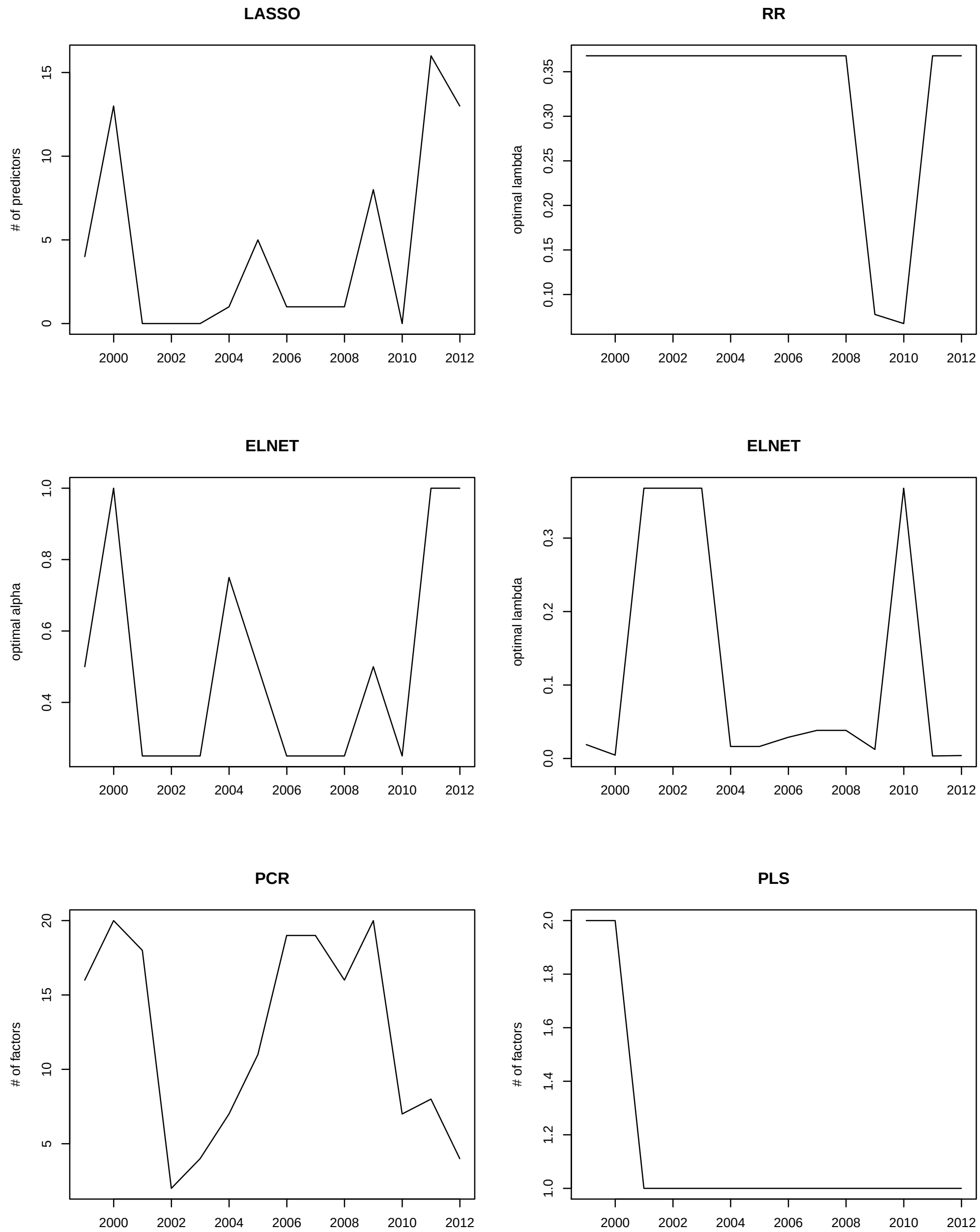

Figure 1.5: Tuning parameter selected through validation. On the x-axis years of end of the training sample are reported.

neural networks. Figure 1.7 shows out-of-sample R^2 across test samples. The high variability suggests the algorithms are not so reliable. We can also notice for the networks with an high number nodes, some convergence to an higher R^2 as the size of the training sample increases, again showing that most involved algorithms need more data to be fitted properly.

Overall it seems that the time span we are using is not big enough to guarantee a convergence of the trained algorithms to a stable and well performing forecasting model, as it is instead the case in GKX, where they use data from 1920.

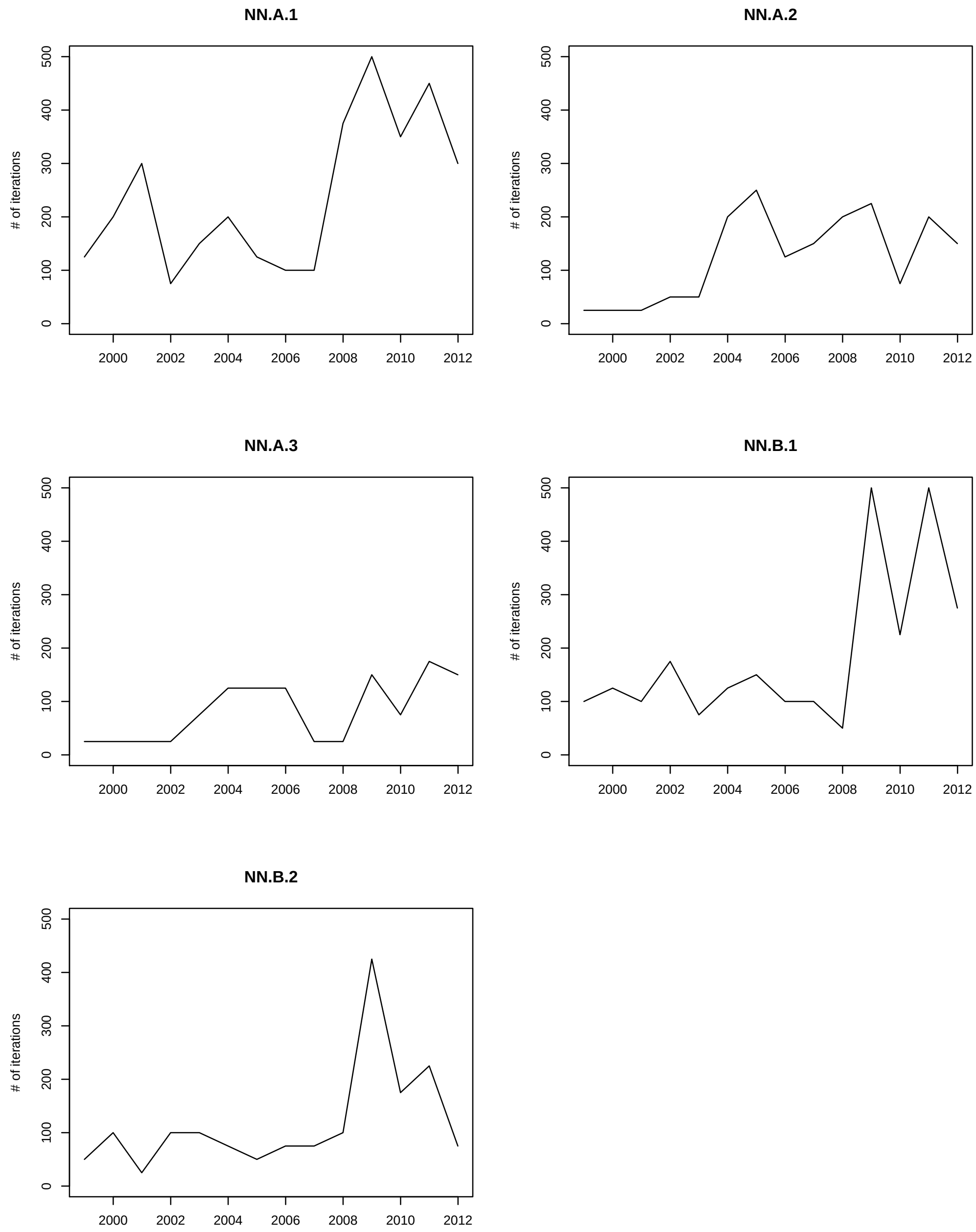

Figure 1.6: Optimal number of minimizing iterations selected through validation. On the x-axis years of end of the training sample are reported.

	OLS	OLS-3	LASSO	RR	ELNET	PCR	PLS	RF	NN.A.1	NN.A.2	NN.A.3	NN.B.1	NN.B.2
OLS		5.57***	5.58***	5.50**	5.58***	5.58***	5.55**	5.27**	5.48***	5.57***	5.47***	5.19***	5.31***
OLS-3			3.91***	-6.92***	3.82***	2.33**	-4.45***	-10.40***	-9.7***	1.15	-9.7***	-25.4***	-18.6***
LASSO				-7.06***	0.14	-2.03*	-5.39***	-10.66***	-13.63***	-2.03**	-13.62***	-27.55***	-20.52***
RR					7.06***	6.70***	7.03***	-7.06***	2.19**	6.93***	1.76*	-12.89***	-7.01***
ELNET						-1.69*	-5.37***	-10.83***	-13.76***	-1.92**	-13.37***	-27.92***	-19.96***
PCR							-4.90***	-10.17***	-12.16***	-0.77	-12.91***	-26.46***	-20.78***
PLS								-9.82***	-3.19***	4.99***	-4.46***	-23.74***	-16.71***
RF									7.58***	10.57***	7.78***	-2.29***	1.91**
NN.A.1										12.19***	-1.28	-21.97***	-13.78***
NN.A.2											-19.6***	-30.97***	-24.73***
NN.A.3												-25.80***	-18.29***
NN.B.1													9.57***
NN.B.2													

Table 1.3: Diebold-Mariano test statistic for comparing models' forecasting performance. A positive number means that the model in the column outperforms that in the row.

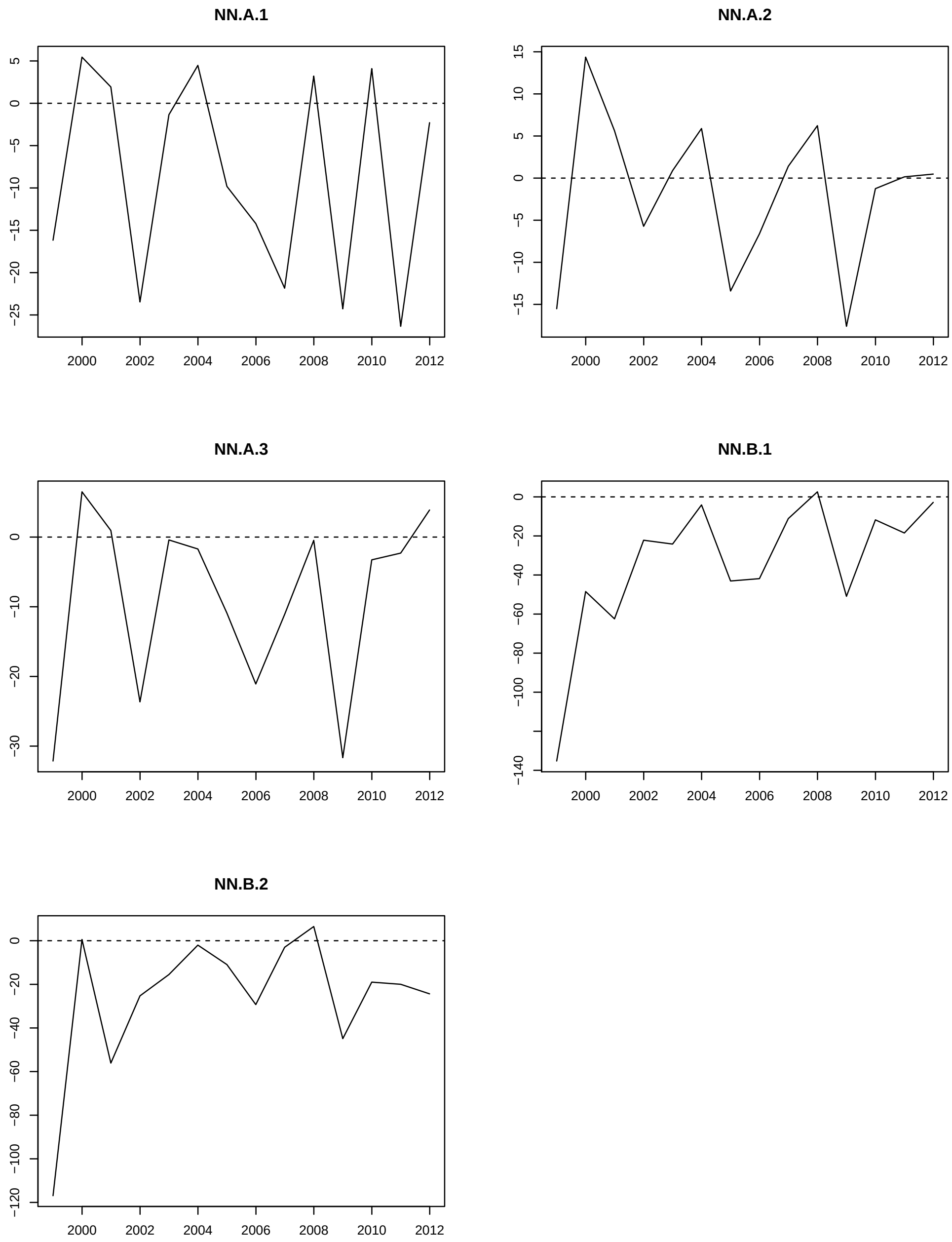

Figure 1.7: Out of sample % R^2 across iterations. On the x-axis years of end of the training sample are reported.

1.5 Conclusion

In this paper we have investigated the predictability of stock-level equity returns using a large set of firm-level characteristics, interacted with macroeconomic factors. We have applied several machine learning algorithms in order to test their forecasting ability of monthly returns of 89 stocks contained, throughout the last 30 years, in the EURO STOXX50 equity index. We contributed to the vast literature on equity returns predictability by applying a set of algorithms to European data rather than US data, which have been investigated extensively. The final objective of this exercise if twofold: first we want to test once more the well-known efficient market hypothesis, which posits that equity returns are not predictable if markets are deep enough; second, by applying several and significantly different algorithms, we analyze which is the most convenient framework, regarding the structure of the underlying model, when using a large set of candidate predictors.

Results points to the following conclusions:

- In general, even quite sophisticated machine learning techniques do not display a strong ability to forecast future monthly equity returns. The larger out of sample R^2 is obtained when using Elastic Net: 0.04%, barely above zero.
- For European data, the short time span of the sample we are using is an issue, as algorithms which require to estimate a large number of parameters suffers the small sample size. For this reason, algorithms which perform some degree of variable selection outperforms the others.
- Given the point above, results would suggest the underlying model is quite sparse, though we interpret the relative success of sparse models as a tool to face the small availability of data. In line with Giannone et al. (2019), results from the Elastic Net algorithm suggest a average degree of sparsity is the best choice.

Chapter 2

Unconventional monetary policy in an unconventional proxy-SVAR for the Euro Area: effects in a fragmented bond market

Abstract

We analyze how the ECB unconventional monetary policy heterogeneously affect countries across the Euro Area using a novel proxy-SVAR specification which takes into account possible interdependence among core and periphery specific spreads. To do this, we exploit Overnight Indexed Swap rates to decompose sovereign yields across Eurozone with the objective of understanding how QE affected the country-specific components of long term rates. Furthermore, we propose a novel flexible identification strategy in a proxy-SVAR context which proves useful for isolating different channels behind the transmission of QE to real economic variables.

2.1 Introduction

When hitting the Zero Lower Bound, Central Banks lose their ability to stimulate the economy through conventional monetary policy, i.e. by cutting the short term rate. They therefore need to focus on the long term rate in order to further influence the economy. To do so several unconventional tools are available to central bankers such as forward guidance and quantitative easing (QE).

With forward guidance, the central bank commits to keep the short term rate low for an extended period of time, thereby influencing the long term rate through agents' expectations and thus economic activity (Eggertsson and Woodford (2003)). With QE the Central Bank directly purchases large amounts of long term bonds and keeps them in its balance sheet, thereby lowering the long term rate through several channels which we will briefly review later.

After all major Central Banks around the world, the ECB as well started a QE program in 2015, which involved the purchase of long term sovereign bonds, split across Euro Area countries according to the economic size of the countries. [1] The peculiarity of QE in the Euro Area is given by the fragmentation of the sovereign bond market, with different yield curves across European countries, the main distinction being between core and periphery countries.

This fragmentation posed peculiar challenges to the ECB, which faced the dilemma on how should its policies affect country-specific components and common components. Should the ECB have focused on reducing the spreads on peripheral countries rates with respect to core countries' rates or was it more important to reduce the Eurozone-wide term premium? Moreover, did the purchase of core sovereign debt contribute to an increase in its scarcity, making it more expensive to safely store liquidity in the Euro Area? (Courè (2017)) In the view of Caballero and Farhi (2018) a scarcity of safe assets could impede economic activity.

To address these questions we exploit Overnight Indexed Swap (OIS) rates in a SVAR framework as a measure of a Euro Area long term risk-free rate and use country specific spreads to build time series of country specific risk/safety premia. This strategy allow us to clean country specific long

[1] More precisely, purchases are split according to the *capital key* of Euro Area countries, that is their share in the capital of ECB. This is basically proportional to their GDP.

term sovereign rates from the Eurozone common components, namely the "expectation hypothesis component" and the term premium.

By using OIS rates we can build a periphery risk premium and a core safety premium, and estimate the effects of QE on these premia and their persistence over time. Furthermore, we study heterogeneous effects of monetary policy across core and peripheral countries in a novel way, since by modeling spreads together in the SVAR we take into account possible interdependence among them. This may stem from the fact that a riskier sovereign debt of the periphery makes safe assets scarcer and thus leads to an increase in the safety premium on core sovereign debt.

We first address this question by estimating a proxy-SVAR at daily frequency, using high-frequency surprises in long term rates around ECB press conferences during the QE period as external instruments. Results show that the on-impact effect of QE announcements significantly increases the spread between long term OIS rates and the corresponding German rates (a measure of the safety premium) and seems weaker in reducing the spread between Italian and OIS rates (a measure of the risk premium). This result raises some questions on the optimality of the design of QE in the Euro Area. In fact an increase in the expensiveness of safe sovereign debt in the Eurozone could have impeded its transmission to real economic activity.

Similar results are found by estimating a proxy-SVAR at monthly frequency, from which we also detect a significant increase in economic activity and consumer prices following an expansionary QE shock.

Ideally, we would like to have a counter-factual experiment in which we can measure what would have been the effect of QE on GDP and inflation if it was designed to not affect the convenience yield on safe bonds, but only to reduce OIS rates and risk premia. Though this exercise is very challenging, we provide some evidence by estimating a proxy-SVAR at monthly frequency, where A and B matrices are fully and separately identified. This allows us to estimate the extent to which the impact on the common component, the periphery spread and the core spread were important for the final effect on real economic variables.

Structural VARs are largely used to estimate the effects of monetary policies. The usual identification issue in SVARs has been initially solved by imposing a recursive ordering on the simultaneous relationships among the endogenous variables in the SVAR (Christiano et al. (1999)). The typical assumption imposed in this literature is that real economic variables react to monetary policy shocks with a lag, while the central bank adjusts the policy rate instantaneously to real economy shocks.

To avoid imposing such *a priori* restrictions, which have been largely questioned in the empirical monetary policy literature, we can exploit information from external instruments in a so called proxy-SVAR approach (Gertler and Karadi (2015),Mertens and Ravn (2013),Stock and Watson (2012), Stock and Watson (2018)). In this context we can identify the instantaneous effects of monetary policy on the other variables, and then build impulse responses, without the need to impose any additional restriction, except from assuming the exogeneity of the instrument with respect to the other structural shocks.

In this paper we propose a novel identification strategy, based on proxy-SVARs, which overcomes the limit of the "partial shocks" identification logic that characterizes the monetary policy literature. We consider a more flexible proxy-SVAR framework which allows us to apply external instruments techniques in a flexible "AB-model" setup, which permits to jointly identify:

- Simultaneous relationships among the endogenous variables (matrix A).
- Contemporaneous effects of the structural shocks on the the endogenous variables (matrix B).

The "AB-model" has been extensively used in studies of fiscal policies effectiveness (Blanchard (1989), Blanchard and Perotti (2002)) but its potential benefits have been less explored in the monetary policy literature. This separate identification of the two sets of structural parameters allows us in turn to:

- Identify the dynamic causal effect of a monetary policy shock on a set of variables.
- Isolate the channels through which the policy have transmitted, controlling for indirect effects coming from simultaneous structural relationships among variables.
- Isolate the importance of each channel for the transmission to real economic variables.

This empirical analysis leads us to identity a contractionary component in the QE shock, which partially offsets the expansionary effects of the QE in the Euro Area. We interpret this contractionary channel as resulting from the scarcity effect induced by the large purchases of safe German bonds, which made them more expensive. On the contrary the main expansionary channels is estimated to be the reduction in long-term risk free OIS rates, while the reduction in peripheral sovereign spreads is estimated play a negligible role for the transmission of QE to Euro Area economic activity.

The rest of the paper proceeds as follows. In section 2 we briefly review the related literature. In section 3 we explain the usual identification strategies exploited in monetary SVARs with external instruments. In section 4 we deal with the relationship between QE policies and safe assets' scarcity, and estimate a daily proxy-SVAR to estimate the effects of QE on the safety premium on German bonds. In section 5 we estimate the macroeconomic effects of QE by estimating a proxy-SVAR at monthly frequency. Finally, in section 6 we explain how we use a flexible $AB-SVAR$ to isolate the transmission channels of QE in a core/periphery perspective.

2.2 Related literature

This paper speaks to several strands of the literature. First of all our identification strategy constitutes a novelty in the related econometric literature: to the best of our knowledge, this is the first paper to separately identify the matrices A and B in a proxy-SVAR, in particular in the monetary policy literature. We thus contribute to the existing literature on proxy-SVARs, which has recently developed quite intensively. Stock and Watson (2018) provide a comprehensive analysis of the use of external instrument for identifying structural macroeconomic shocks. Gertler and Karadi (2015) is the application of the proxy-SVAR more relevant to our purposes. They use high-frequency variations around monetary policy decisions as instruments for conventional monetary policy shock, in order to estimate its effects of financial and real variables. Their identification strategy allows to estimate only the column of the matrix of structural parameters related to the monetary policy shock, i.e. a "partial shocks" identification. In other words, the are able to identify the effects of monetary policy on the other variables, not the opposite. Angelini and Fanelli (2019) provide a framework in which the use of external instruments not only makes this partial identification possible, but helps the researcher in the identification of the full matrix of structural parameters. The number of *a priori* restrictions needed to obtain this full identification is lower than what it would be without the use of the external instrument. To obtain this result they augment the SVAR with the instrument, instead of using it in an IV setup to estimate the structural parameters of interest.

Moreover, this paper contributes to the huge literature on the effects of central banks large scale asset purchases on real and financial variables. Regarding the Asset Purchase Program of the ECB the literature is more limited as it started years after other major central banks. Still, there are already many studies addressing the topic, outstanding examples areAltavilla et al. (2015), Andrade et al. (2016),Gambetti and Musso (2017) and Altavilla et al. (2019).

Gambetti and Musso (2017) exploit a non-linear VAR with time varying parameters and stochastic volatility and estimate the APP announcement on 22^{nd} January 2015 to have been successful in increasing HICP (Harmonized Index of Consumer Prices) though with some lag. They estimate zero instantaneous impact, 1% increase after 8 months, persistent for at least 3 years. The impact on euro area GDP growth is however more concentrated on the short term, with an estimated increase of 0.3% after 8 months, vanishing after 18 months. Regarding the effects on financial variables, the APP announcement lowered 10-year composite euro area yield by -11 basis points instantaneously, by -25 basis points after 4 months, while it increased it by +40 basis points after 6 months. The effect on 1-year rate is -8 basis points after 4 months and zero after 12 months. The estimated impact on long term inflation expectations is positive but not significant.

Andrade et al. (2016) use a proxy-SVAR methodology, in a daily VAR setup, showing that the impact on 10-year AAA rated sovereign yields persists for about one year. They also document that APP announcement led to an increase in inflation expectations: comparing data from the ECB Survey of Professional Forecasters of January 2015 (right before the APP announcement) and April 2015 we observe an increase of 1-year ahead inflation expectation by 55 basis points, while long term inflation expectations increased by 9 basis points. Expected GDP growth increased by 45 basis points.

Altavilla et al. (2019) build a new dataset (Euro Area-Monetary Policy Database, EA-MPD) containing high-frequency market surprises during all ECB governing council meetings. They exploit the fact that ECB decisions are announced in two separate steps (the press release and the press conference) to build four factors interpretable as Target, Timing, Forward Guidance and QE factors. Altavilla et al. (2019) are the first ones to extensively use OIS rates to build a unique risk-free yield curve for the Euro Area. They also exploit the new database to assess the impact of ECB monetary policy on asset prices, finding a persistent and significant reduction in all Euro Area sovereign rates in response to QE shocks.

Finally, our paper addresses the issue of the effects of QE in a fragmented bond market and it possible unintended consequences. It thus relates to a literature focusing especially of possible scarcity effects of the program on the pool of safe sovereign bonds. Aggarwal et al. (2020) for instance study the effects of ECB measures on safe asset scarcity, in particular the securities lending program launched in 2016 to overcome possible side-effects of the APP. They however have in mind a "short term" definition of safe asset scarcity, while here we employ a "long term" measure which detects the expensiveness of safe assets with respect to a reference risk-free rate. In this way we can analyze as well the persistence of any scarcity-effect.

2.3 Identification of monetary SVARs using external instruments

Consider the following Structural VAR:

$$K(L)Y_t = c + \varepsilon_t \tag{2.1}$$

where $K(L) = K_0 - K_1 L - ... - K_p L^p$ is the lag polynomial, c is a vector of constants and ε_t is a $(n \times 1)$ vectors of independent structural shocks, with zero mean and identity variance/covariance matrix: $E(\varepsilon_t \varepsilon_t') = I_n$.

The SVAR in (2.1) corresponds to the reduced form:

$$\Pi(L)Y_t = \mu + u_t \tag{2.2}$$

where $\Pi(L) = I - \Pi_1 L - \ldots - \Pi_p L^p$ is the lag polynomial, and $E[u_t u_t'] = \Sigma$. Reduced form parameters are related to the structural ones, such that $\Pi_j = C_0 K_j$, $\mu = C_0 c$, where $C_0 = K_0^{-1}$. Reduced form disturbances are related to structural shocks through:

$$u_t = C_0 \varepsilon_t \tag{2.3}$$

or, alternatively:

$$K_0 u_t = \varepsilon_t \tag{2.4}$$

C_0 contains the parameters quantifying the total impact of structural shocks on the variables in Y_t, while K_0 parameters represent estimated simultaneous relationships among variables.

The reduced form parameters can be estimated from the data available to researcher, the challenge is to recover from them the structural parameters. In particular, we get an estimate $\hat{\Sigma}$ of the variance-covariance matrix Σ, which is used to estimate the structural parameters. Whether to specify the SVAR either in the K_0 or in the C_0 form depends on where it results more convenient for the researcher to place restrictions on the structural parameters. (see Amisano and Giannini (1997))

Without further restrictions, the matrix C_0 is not identified. In fact it contains n^2 parameters, while the system of equations $C_0 C_0' = \Sigma$ provides the researcher with only $\frac{n(n+1)}{2}$ moment conditions.

Assume the following partition of the vector of variables $Y_t = \begin{bmatrix} p_t \\ x_t \end{bmatrix}$, where p_t is the monetary policy instrument, and x_t is the $(n-1) \times 1$ vector containing all other variables, e.g. inflation and economic activity.

The standard solution used initially in the monetary SVAR literature to solve the identification issue (see Christiano et al. (1999) for a review), is to assume a triangular structure for the matrix C_0, making the model exactly identified. The recursive structure implied by a triangular C_0 comes at a cost, since it requires assuming that the variables in x_t do not simultaneously react to monetary policy shocks. This is particularly implausible for financial variables, but it is difficult to justify for real economy variables as well, also in light of results coming from DSGE literature.

Beyond the identification issue, if we are interested in studying unconventional monetary policy rather than conventional one, we lack of a clear policy instrument. In a conventional monetary policy setting, p_t is the short term rate, which the central bank controls directly. In a Zero Lower Bound environment the short term rate is constant and equal to zero (or slightly negative), central banks lose their ability to lower it further and need to implement unconventional measures. The measure of the policy instrument must also change accordingly. A possible solution has been provided by the "shadow rate" literature (see Wu and Xia (2016)). The shadow rate is meant to be a measure of the short term rate which is not bounded below by the zero threshold. An alternative is to use a long term rate, though while the short term rate is under direct control of monetary policy authority, a long term rate reacts to many other shocks, regardless of the central bank reaction function. This makes the identification of exogenous monetary policy shocks challenging.

A way to tackle the issues explained above is by using a proxy-SVAR (Gertler and Karadi (2015),Mertens and Ravn (2013),Stock and Watson (2012), Stock and Watson (2018)). The idea is to use information from instruments external to the variables included in the VAR to identify the shock of interest and thus the structural parameters related to it. Call f_t an instrument (or a vector of instruments) for the latent monetary policy shock $\varepsilon_{p,t}$. It satisfies the two conditions:

$$E[f_t \varepsilon_{p,t}] = \phi \neq 0 \quad \text{relevance} \tag{2.5}$$

$$E[f_t \varepsilon_{x,t}] = 0 \quad \text{exogeneity} \tag{2.6}$$

where $\varepsilon_{x,t}$ denotes the vector of all structural shocks featured by the system but the monetary policy one. Under these assumptions, the first column of C_0, call it C_p, can be fully and consistently estimated. A standard approach in the literature is to use high frequency surprises in interest rates around monetary policy decisions for instrumenting monetary policy shocks (Gertler and Karadi (2015)), short term for conventional policies, long term for unconventional ones. The assumption behind this choice of the instrument is that if the window around which the variations are measured is small enough (typically a day or smaller), then the variations in interest rates must be solely due to the monetary policy shock. This assumption would be violated if some other news possibly affecting interest rates would come out systemically in the same day or in the same hours of the monetary policy decision. This is not the case for Euro Area (Altavilla et al. (2019)). This strategy has been largely employed in the event-study literature. Another assumption behind this choice for the instrument is that markets are fast and good in pricing monetary policy decisions, but this is surely the case in modern deep financial markets. [2]

We employ the external instrument in the SVAR by augmenting the set of endogenous variables with the instrument itself (Angelini and Fanelli (2019) Caldara and Herbst (2019)). [3] We therefore impose the exogeneity and relevance conditions in the matrix of structural parameters. The augmented set of variables becomes:

$$\tilde{Y}_t = \begin{bmatrix} p_t \\ x_t \\ f_t \end{bmatrix} \tag{2.7}$$

and the augmented SVAR is:

$$\tilde{K}(L)\tilde{Y}_t = \tilde{c} + \tilde{\varepsilon}_t \tag{2.8}$$

which implies the following partition of $\tilde{C}_0 = \tilde{K}_0^{-1}$:

$$\tilde{C}_0 = \begin{pmatrix} C_{pp} & C_{px} & 0 \\ C_{xp} & C_{xx} & 0 \\ \phi & \mathbf{0} & \sigma_\omega \end{pmatrix} \tag{2.9}$$

[2] One possible issue related to this identification of monetary policy shocks relates to the possible risk of capturing some *information effect* (Nakamura and Steinsson (2018)). When central banks announce a monetary policy decision, they also disclose, implicitly and explicitly, their information and projections about future developments of the economy. If this private information of the central bank induce market's participants to revise their expectations, this can be a confounding factor in the high frequency responses of rates observed. To check for this, we use use the strategy employed by Jarociński and Karadi (2020) and set to zero the surprise instrument when we observe a "opposite than expected" reaction in the stock market index (we use the STOXX50 index). For instance, if an expansionary monetary policy shock is observed (a decrease in the 5-year bund rate) and at the same time we observe a decrease in the stock index, we label this as an information shock and set the instrument equal to zero. Results do not differ significantly from the baseline estimation.

[3] An alternative strategy would be to implement an IV approach, in order to extract from the reduced form disturbances the exogenous component (see Stock and Watson (2018),Gertler and Karadi (2015)). In this way C_p is identified after a two-stages regression. By augmenting instead the set of variables with the instrument, we use it to gain on the number of restrictions required for a full identification of the matrix C_0.

The zero-restrictions imposed in the block (3,2) of the $\tilde{C}_0$ matrix represent the exogeneity assumption, while the ϕ parameter (or vector of parameters) is the counterpart of the first stage parameters in the TSLS approach and mirrors the relevance condition related to the instrument. As shown by Angelini and Fanelli (2019), augmenting the SVAR with the instrument and setting the proper restrictions on it is enough to identify the column of C_0 corresponding to the instrumented variable. In this way we are able to identify the first column C_p, which contains the total simultaneous impact of the identified monetary policy shock on the other variables. Beyond that, this strategy allows us to obtain not only this *partial* identification of C_p, but a *full* identification of C_0. To fully identify C_0 we need to impose some more restrictions beyond the ones implied by the exogeneity of the external instrument. In other words by using the instrument we are able to obtain a full identification with a lower number of restrictions than those that would be necessary without the instrument.

2.4 QE and safe asset scarcity

The aim of QE is to lower the long term yield, in order to boost investment and economic activity. There is a large literature investigating the possible channels through which QE can affect long term yields. Krishnamurthy and Vissing-Jorgensen (2011) review them extensively. In a nutshell, two are the main channels:

- Through the *signaling channel* the central bank is affecting the expectations about the future path of conventional monetary policy: by implementing the QE the central bank displays to market participants its will to commit to an expansionary monetary policy for a long period of time. This is akin to a forward guidance policy, but the commitment can be stronger with QE. Indeed by keeping long term bonds in its balance sheet the central bank exposes itself to duration risk, thus it would suffer a loss from any future increase in the short term rate.

- Through the *portfolio rebalancing channel* the central bank can directly affect the prices of the securities purchased, by a reduction in the risk premia. For this channel to operate, some form of segmentation should exist. In this way the price of risk can be affected by central bank purchases, which alter the demand/supply in the bond market.

We are interested in understanding how heterogeneous has been the impact of QE on Euro Area sovereign bond markets, considering a core/periphery dichotomy. This is important in order to provide an ex-post evaluation on the way the QE was designed, in particular on how the purchases of government bonds were split among Eurozone countries. The ECB purchased sovereign bonds from the different countries according to their capital key, that is according to the GDP of the countries. This is clearly a design aimed at focusing on the Eurozone-wide component of yields. We ask whether this was optimal for the final transmission of QE to economic activity. In other words: would have been more effective to focus on reducing country specific premia?
A second question relates to the issue of safe assets scarcity: did QE actually alleviate or worsen scarcity of safe sovereign bonds in the Euro Area? Again this question relates to how the APP was designed, involving the purchase of very large amount of core countries government debt.
To analyze how QE affects long term yields across Euro Area countries, let us decompose an interest rate on a zero-coupon bond with residual maturity M, issued by country j as follows:

$$y_{t,M,j} = E_t\left[\sum_{i=1}^{M} r_{t+M}\right] + tp_{t,M} + cp_{t,j,M} \tag{2.10}$$

where r_t is the ECB short term rate, $tp_{t,M}$ is the term premium and $cp_{t,j,M}$ is the country-specific premium. QE can affect all these 3 components of a long term yield, through several channels. By the *signaling channel*, QE is a way through which the central bank commits to keep short term rates low for a long period of time, thus influencing the first component of $y_{t,M,j}$, the *expectation hypothesis* component.

The term premium can be affected through the *portfolio re-balancing channel*, by which QE affects the price of risk, duration risk in this case, in the market. These first two components are common across all Euro Area countries, since they are linked to the short term rate set at Euro Area level. $cp_{t,j,M}$ is a country specific premium which could be either positive or negative. A positive premium should be interpreted as deriving from a country specific default/re-denomination risk, which is the case for countries of Euro Area periphery. A negative premium on the contrary can be interpreted as a *convenience yield* on the safest sovereign bonds, for which there is a specific demand as it serves the purpose of a safe asset, or quasi-money (Gorton (2017)).

We measure the common Euro Area component using Overnight Indexed Swap rates, that is expected to be a proxy for the first two components of $y_{t,M,j}$ in (2.10):

$$OIS_{t,M} = E_t\left[\sum_{i=1}^{M} r_{t+M}\right] + tp_{t,M} \tag{2.11}$$

In a OIS contract a fixed rate for M periods is swapped against the EONIA rate. This means that the fixed rate is pricing both the expectation over future overnight rate and the term premium. Given that this contract is usually collateralized, any risk component should be negligible. By taking spreads of sovereign bonds versus the OIS rate at the correspondent maturity, we get a measure of the country specific premium $cp_{t,j,M}$. Figure 2.1 show country-specific spreads for some Euro Area countries.

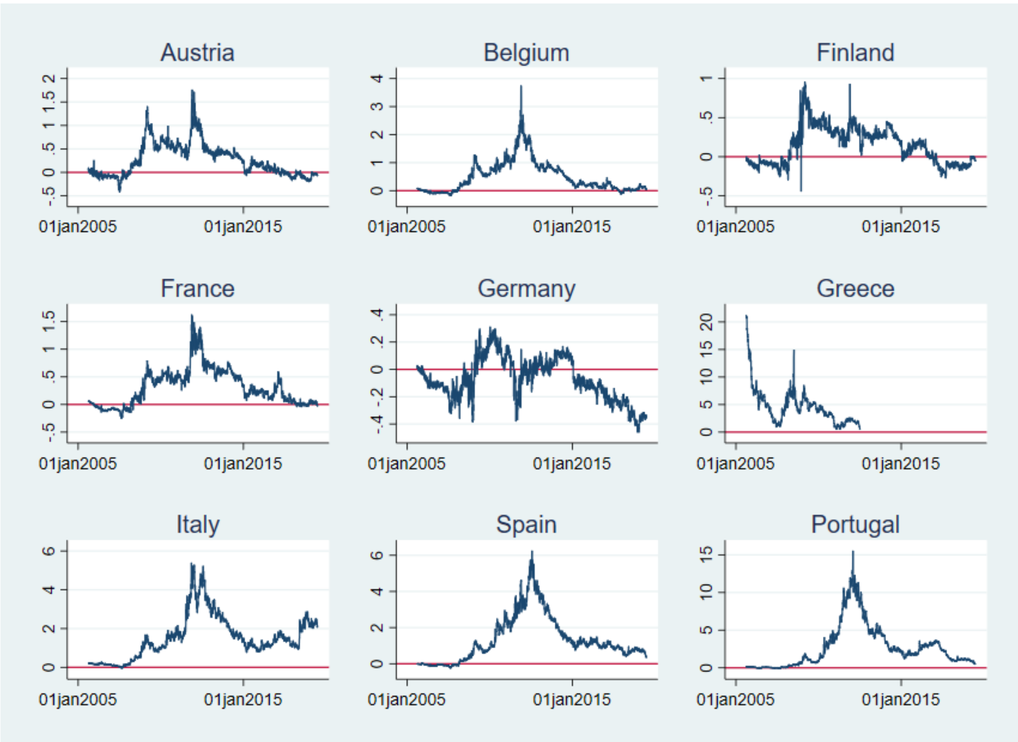

Figure 2.1: 10-year spreads between sovereign rates and OIS rate.

To evaluate the effects of QE on periphery and core specific components we run a proxy-SVAR at daily frequency. At this stage we are only interested in a partial identification of the $\tilde{C}_0$ matrix, that is to identify the parameters of the first column C_p (see equation (2.9) in previous section).

We run the SVAR using the following endogenous variables:

- The 10-year OIS rate.
- The average of the 10-year sovereign spreads of Italian and Spanish bonds, computed with respect to the 10-year OIS rate. This constitutes our measure of the peripheral countries risk premium.
- The 10-year spread between OIS rate and German rate, as a measure of the safety premium (or convenience yield) or core countries debt.
- Other variables commonly used in this type of financial SVARs (see Altavilla et al. (2019)): the log of the STOXX50 index, the 2-year Inflation Linked Swap rate (which measures inflation expectations at 2-year horizon) and the log of the EUR/USD exchange rate.

To measure the safety premium on safe assets we exploit German rates, as German bonds are widely considered the most safe in the Eurozone, so we use it as a proxy for the premium paid by investors to hold very safe assets. Regarding the periphery risk premium we focus on Italy and Spain as they are by far the two largest sovereign bond markets of Euro Area periphery. [4]
As external instrument we use high-frequency variations in the 10-year Italian rate around ECB press conferences, taken from the database made available by Altavilla et al. (2019). This choice is motivated by the fact that Italian rates are those who displayed the higher variability on relevant days in which the QE was announced. Some of the endogenous variables display a clear trend over the sample considered, so we run the VAR by allowing for a deterministic trend. We run the VAR using 3 lags, selected by minimizing the AIC and HQ criteria.

Figure 2.2 shows the estimated impulse response functions to a QE shock, normalized to lower the 10-year OIS rate by 10 basis points on impact. The estimated shock has a quite short lasting effect on the 10-year OIS rate, whose reduction lasts less than three months. The impact on the periphery risk premium is sizable on impact but very short lived. On the contrary we estimate

[4]We don't include Portugal and Greece as their economic size is marginal. Moreover, Greece is an outlier as it partially defaulted on its debt during the crisis.

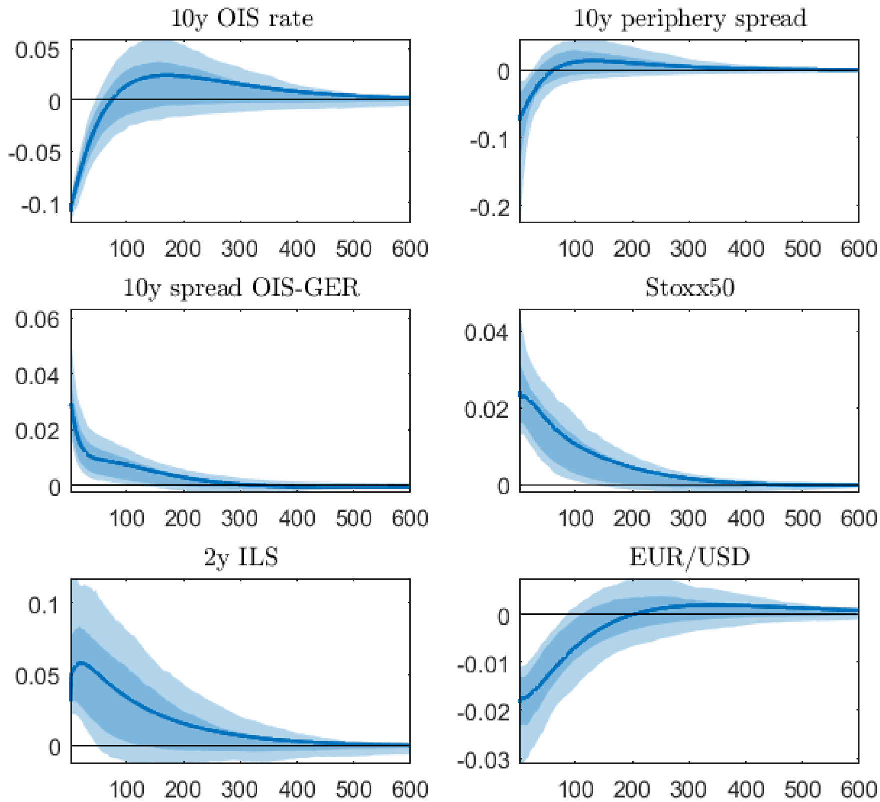

Figure 2.2: Impulse responses to an APP shock, normalized to lower 10-year OIS rate by 10 basis points. Shaded areas shows 90% bootstrap intervals computed using moving block bootstrap. Darker areas show 68% confidence intervals.

a significant and more persistent effect of the convenience yield on German bonds, which lasts almost 1 year. The response of the other variables is that expected in response to an expansionary monetary policy shock: an increase in the stock market index, an increase in the 2-year ahead inflation expectations and a depreciation of the Euro with respect to the US dollar.

In the augmented SVAR framework explained in section 3, the relevance of the external instrument is checked by looking at the ϕ parameter (see equation (2.9)). In our estimation ϕ is significantly different from zero, with an associated t-statistic of 19.5, so we don't face any issue of weak instrument which would undermine the whole estimation.

These results raise some questions on the way the APP has been designed as it mostly affected the safe rates by increasing the convenience yield part of them. This issue becomes even stronger in recent days as the QE has been extended but the amount of safe German debt outstanding is becoming even scarcer. Whether this poses significant issues for the Eurozone economy is not yet clear. In the next section we will focus on the macroeconomic effects of the QE, by carrying out a full identification on a SVAR at monthly frequency. Moreover, by using a flexible AB specification, we will try to decompose the different transmission channels in a novel and innovative way.

2.5 Macroeconomic effects of QE

We now turn to the estimation of the macroeconomic effects of QE in the Euro Area. We will first estimate a macroeconomic SVAR and obtain a partial identification to measure the overall effects. We will then use an innovative strategy to isolate the relative importance of core vs periphery channels.

To analyze the effectiveness of APP in a core/periphery perspective, we run a baseline VAR with 6 endogenous variables:

- The 10-year OIS rate.
- The average of the 10-year sovereign spreads of Italian and Spanish bonds, computed with respect to the 10-year OIS rate. This constitutes our measure of the peripheral countries risk premium.
- The 10-year spread between OIS rate and German rate, as a measure of the safety premium (or convenience yield) or core countries debt.
- The log of the Euro Area industrial production index, cleaned from seasonal effects and excluding construction.
- The log of the HICP index of consumption prices.
- The CISS index, constructed by the ECB to measure systemic risk and financial distress. [5]

[5] The CISS index (Holló et al. (2012)) aggregates five market-specific sub-indices created from a total of 15 individual financial stress measures. It is designed to increase when stress is detected in several market segments at the same time, that is when risk is more systemic.

- The IMF index of commodities prices.

As external instrument we use, as in the previous section, the high-frequency variations of the 10-year OIS rate around ECB press conferences, from 2014 to 2018. We run the VAR with 2 lags, selected by looking at the AIC criterion. We also allow for a deterministic trend as variables display a clear trend.

Since we are dealing with variables that are usually observed with different frequency (namely GDP and Inflation for which we have monthly observations and interest rates for which we have daily observations), we aggregate daily variables at monthly level using the same strategy adopted by Gertler and Karadi (2015). For interest rates and spreads we take the monthly average of daily observations. This poses a problem for the instrument, since the day of the ECB meeting normally lies in the middle of the month. We therefore aggregate the instrument to the monthly level in two steps. First we impute for each day when the instrument is zero because there has been no ECB meeting the value of the instrument on the last previous relevant day. We then compute the monthly average of this new daily observations. In this way the observation of the instrument for e.g. January 2017, will be a weighted average of the observed high frequency variations of the 10-year Italian rate around press conferences of December 2016 and January 2017.

Figure 2.3 shows impulse response functions to the estimated APP shock, obtained by partial identification. Results partially confirm what we observed at daily frequency. The shock is normalized to lower the OIS rate by 10 basis points on impact, but the decrease becomes non significant soon after. The point estimate of the response of the periphery risk premium implies a strong and persistent decline in sovereign risk premia. The effect is however not significant at 90% confidence level. The increase in the convenience-yield on German bonds is instead confirmed at monthly frequency, and it lasts almost one year. The effects on macroeconomic variables are those expected. We observe an increase in the industrial production index, an increase in the price-level and a reduction in the systemic-risk index.

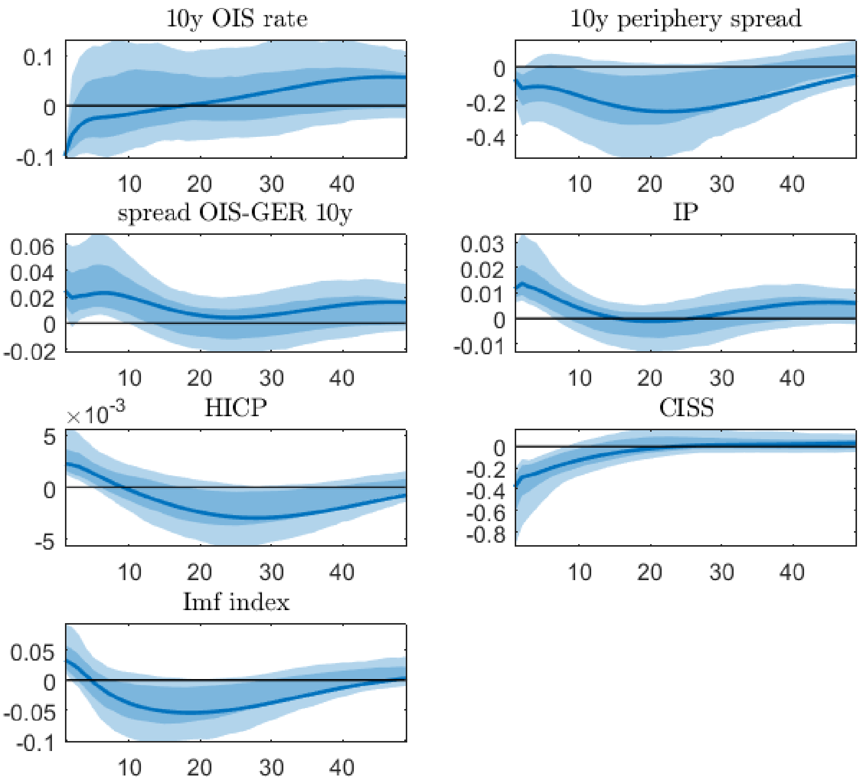

Figure 2.3: Impulse responses to an APP shock, normalized to lower 10-year AAA rate by 10 basis points. Shaded areas shows 90% bootstrap intervals computed using wild bootstrap. Darker areas show 68% confidence intervals.

2.6 A flexible SVAR to isolate transmission channels

The partial identification of the SVAR at monthly level allows us to estimate the overall effect of APP on macroeconomic variables and its persistence. We have highlighted in the previous sections how sovereign rates have responded to APP announcements, decomposing them into three components: a risk-free reference rate, a risk premium on peripheral countries rates and a convenience yield on core countries rates. We now would like to know how important has been the reaction of each of these three components for the final transmission of the unconventional measure to the real economy. To do this we will exploit again the proxy-SVAR methodology in an innovative way. We perform a decomposition of impulse response functions, where for each impulse response function we obtain the contribution of each shock to it. This is typically done in fully-identified SVARs where multiple structural shocks are estimated. In our case however, we have a single QE shock, which we expect to operate through the three above-mentioned components of sovereign rates.

In this section we develop a framework useful for analyzing the three channels described above, treating them as three separate shocks, originating from the single QE shock. To simplify the narrative, I will first first explain the framework in a context with the lowest possible number of variables in the VAR. The estimation we then carry out using the set of variables used in the previous section will simply be a generalization of the framework described here.

Call m_t the vector of variables directly affected by the QE shock, through which the shock is channeled to macroeconomic variables. In our context this will be a 3×1 vector containing the OIS rate (p_t), the spread IT-OIS (r_t) and the spread OIS-GER (s_t):

$$m_t = \begin{bmatrix} p_t \\ r_t \\ s_t \end{bmatrix} \tag{2.12}$$

Call g_t the vector of other macro variables. For simplicity let's assume it contains only a single measure or economic activity. Finally, call f_t the instrument for the QE shock, $\varepsilon_{QE,t}$.

We can rewrite the three shocks related to the three variables in m_t, each of them as a function of the single QE shock:

$$\eta_{p,t} = b_{pp}\varepsilon_{QE,t} \tag{2.13}$$

$$\eta_{r,t} = b_{rp}\varepsilon_{QE,t} \tag{2.14}$$

$$\eta_{s,t} = b_{sp}\varepsilon_{QE,t} \tag{2.15}$$

or, in compact form:

$$\eta_t = b_{m,QE}\varepsilon_{QE,t} \tag{2.16}$$

we can then write the AC-SVAR using the AB specification:

$$Y_t = \begin{bmatrix} m_t \\ g_t \\ f_t \end{bmatrix} \tag{2.17}$$

$$\Pi(L)Y_t = \mu + u_t \tag{2.18}$$

$$Au_t = B\varepsilon_t \tag{2.19}$$

$$\begin{bmatrix} A_{mm} & a_{mg} & 0 \\ a_{gm} & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u_{m,t} \\ u_{g,t} \\ f_t \end{bmatrix} = \begin{bmatrix} B_{mm} & 0 & 0 \\ 0 & b_{gg} & 0 \\ \phi & 0 & \sigma_\omega \end{bmatrix} \begin{bmatrix} \varepsilon_{m,t} \\ \varepsilon_{g,t} \\ \omega_{f,t} \end{bmatrix} \tag{2.20}$$

where:

$$B_{mm} = \begin{bmatrix} b_{pp} & 0 & 0 \\ b_{rp} & b_{rr} & 0 \\ b_{sp} & 0 & b_{ss} \end{bmatrix} \quad \varepsilon_{m,t} = \begin{bmatrix} \varepsilon_{QE,t} \\ \varepsilon_{r,t} \\ \varepsilon_{s,t} \end{bmatrix} \tag{2.21}$$

and A_{mm} has ones on the main diagonal.

Using this specification we obtain two advantages:

- Variables are instantaneously affected by the QE shock only through the three variables in m_t. In this way we can truly decompose the QE shock into three separate components.
- By modeling the parameters in the A matrix, we possibly allow all variables, to simultaneously react to the QE shock, but only indirectly as a reaction to the η shocks.

Of course, depending on the size of the vector Y_t, we will need to impose some other zero-restrictions in the A matrix, in order to achieve identification of the structural parameters. We will later explain all the restrictions on the A matrix we impose in our baseline estimation.

Regardless of the restrictions we impose in A, let's denote $D = A^{-1}$ the inverse of A. It will look like follows:

$$F = A^{-1} = \begin{bmatrix} F & 0 \\ 0 & 1 \end{bmatrix} \tag{2.22}$$

where F is a full 4×4 matrix. Finally $C = FB$. Given the structure of B, the first column of C, which will be used to derive impulse responses to the QE shock, will be:

$$C_{\cdot 1} = \begin{bmatrix} b_{pp}F_{\cdot 1} + b_{rp}F_{\cdot 1} + b_{sp}F_{\cdot 1} \\ \phi \end{bmatrix} = \begin{bmatrix} b_{pp}F_{\cdot 1} \\ \phi \end{bmatrix} + \begin{bmatrix} b_{rp}F_{\cdot 1} \\ \phi \end{bmatrix} + \begin{bmatrix} b_{sp}F_{\cdot 1} \\ \phi \end{bmatrix} = \tilde{C}_p + \tilde{C}_r + \tilde{C}_s \tag{2.23}$$

With this decomposition we can build three separate impulse response functions of all variables, as if we had identified three separate shocks:

$$IRF^p_{QE}(h) = \Psi(h)\tilde{C}_p \tag{2.24}$$

$$IRF^r_{QE}(h) = \Psi(h)\tilde{C}_r \tag{2.25}$$

$$IRF^s_{QE}(h) = \Psi(h)\tilde{C}_s \tag{2.26}$$

where $\Psi(h)$ is the matrix of the MA representation of the VAR obtained from the $VAR(1)$ representation of the $VAR(p)$. Therefore we can decompose the impulse response of the variable g to the QE shocks:

$$IRF_{g,QE}(h) = IRF^p_{g,QE}(h) + IRF^r_{g,QE}(h) + IRF^s_{g,QE}(h) \tag{2.27}$$

Table 2.1 summarizes the restrictions we impose on the A matrix to achieve identification. Arrows in the Table indicates the direction in which contemporaneous causality is assumed to operate. The rationale behind the imposed restrictions is summarized in the following statements:

- Financial variables (interest rates and the CISS index) respond instantaneously to real economic variables and not the opposite.
- The safety premium on German bonds reacts to the risk premium on Italian bonds, not the opposite.
- Inflation does not react instantaneously to industrial production (sticky prices).

	10Y AAA	10Y IT-OIS	10Y OIS-GER	IP	HICP	CISS	IMF
10Y AAA rate	·	$\Leftarrow$	$\Leftarrow$	$\Leftarrow$	$\Leftarrow$	$\Leftarrow$	$\Leftarrow$
10Y IT-OIS	·	·	$\Rightarrow$	$\Leftarrow$	$\Leftarrow$	$\Leftarrow$	$\Leftarrow$
10Y OIS-GER	·	·	·	$\Leftarrow$	$\Leftarrow$	$\Leftarrow$	$\Leftarrow$
IND. PROD.	·	·	·	·	$\Leftarrow$	$\Rightarrow$	$\Leftarrow$
HICP	·	·	·	·	·	$\Rightarrow$	$\Leftarrow$
CISS	·	·	·	·	·	·	$\Leftarrow$
IMF INDEX	·	·	·	·	·	·	·

Table 2.1: Summary of the directions of contemporaneous causality implied by the restrictions on the A matrix. A (left) right pointed arrow indicates causality goes from variable on the (horizontal) vertical list.

- All variables reacts instantaneously to the IMF index of commodities prices, not the opposite.

Figure 2.4 shows the decomposition of the obtained impulse responses into the three channels explained above. The estimated QE shock is normalized to lower by 10 basis points the 10-year OIS rate. The first aspect to comment concerns the estimated "total" impulse responses, depicted by the black line. Overall, they are very similar to those obtained from partial identification of the QE shock (Figure 2.3). This suggests the set of restrictions we imposed on the matrices A and B are quite plausible. The only exception concerns the response of the HICP price index, for which we estimate a lagged decline with no increase on-impact.

In what follows we will mainly focus on the obtained decomposition of impulse responses at short horizons, namely in the first 6-12 months after the shock. In fact, from Figure 2.3 we have seen that all the estimated effects of the QE shocks on the variables included in the VAR tend to vanish after few months. Having this in mind, we also acknowledge the fact that the estimated magnitude of the three "channels" of the QE is less to be trusted at long horizon. With this approach we shelter from the main drawback of this analysis, i.e. we don't have proper confidence bands for the three estimated "channels".

In a nutshell, this decomposition analysis highlights the presence of a contractionary component of the QE shock, possibly related to the "scarcity effect" and an expansionary component related to the reduction in long term OIS rates. The reduction in the risk premium on peripheral debt does not seem instead to play a sizable role.

The "shock" associated to the 10-year OIS ($\eta_{p,t}$ in equation (2.13) generates the red component of impulse responses depicted in Figure 2.4, which represents the quantity $IRF^{p}_{QE}(h)$ in equation (2.27). This channel behaves like the expansionary component of the QE. It lowers the OIS rate on impact, though the effect is reversed at long horizons. It is responsible for a massive and persistent decline in the risk premium on peripheral bonds. It lowers the convenience yield on German bonds for the first months after the shock. Furthermore, it is responsible for the observed increase in industrial production and the decrease in the index of systemic risk. Quite strikingly though, the effect on consumer prices is opposite, as it pushes them toward a persistent decline.

The "shock" associated to the 10-year OIS-GER spread ($\eta_{s,t}$ in equation (2.15) generates the blue component of impulse responses depicted in Figure 2.4, which represents the quantity $IRF^{s}_{QE}(h)$ in equation (2.27). This "shock" behaves like the contractionary component of the QE shock: it increases substantially the convenience yield on German bonds at short horizons, it increases the long term OIS rate and the risk premium on peripheral debt. It partially offsets the positive impact on industrial production of the $\eta_{p,t}$ "shock". Again the impact on consumer prices is instead reversed, the "shock" is inflationary. These observed responses points to the conclusion that the direct impact of QE purchases of safe German bonds, which increased the convenience-yield on them, has given origin to a contractionary component in the transmission of QE to real economic activity.

Finally, the "shock" associated to the 10-year periphery spread ($\eta_{r,t}$ in equation (2.14) generates the green component of impulse responses depicted in Figure 2.4, which represents the quantity $IRF^{r}_{QE}(h)$ in equation (2.27). This "shock" does not contributes substantially to the observed impulse response functions.

The observed decomposition of impulse responses points to the conclusion that the direct impact of QE purchases of safe German bonds, which increased the convenience-yield on them, has given origin to a contractionary component in the transmission of QE to real economic activity. This is a possible identification of the “scarcity” channel described in section 4. On the other hand, this analysis suggests that the expansionary effect of QE has mainly to do with the reduction of long term OIS rates, that is the Euro Area common component of sovereign rates, while the reduction in the sovereign spreads of the periphery did not play an important role for boosting economic activity.

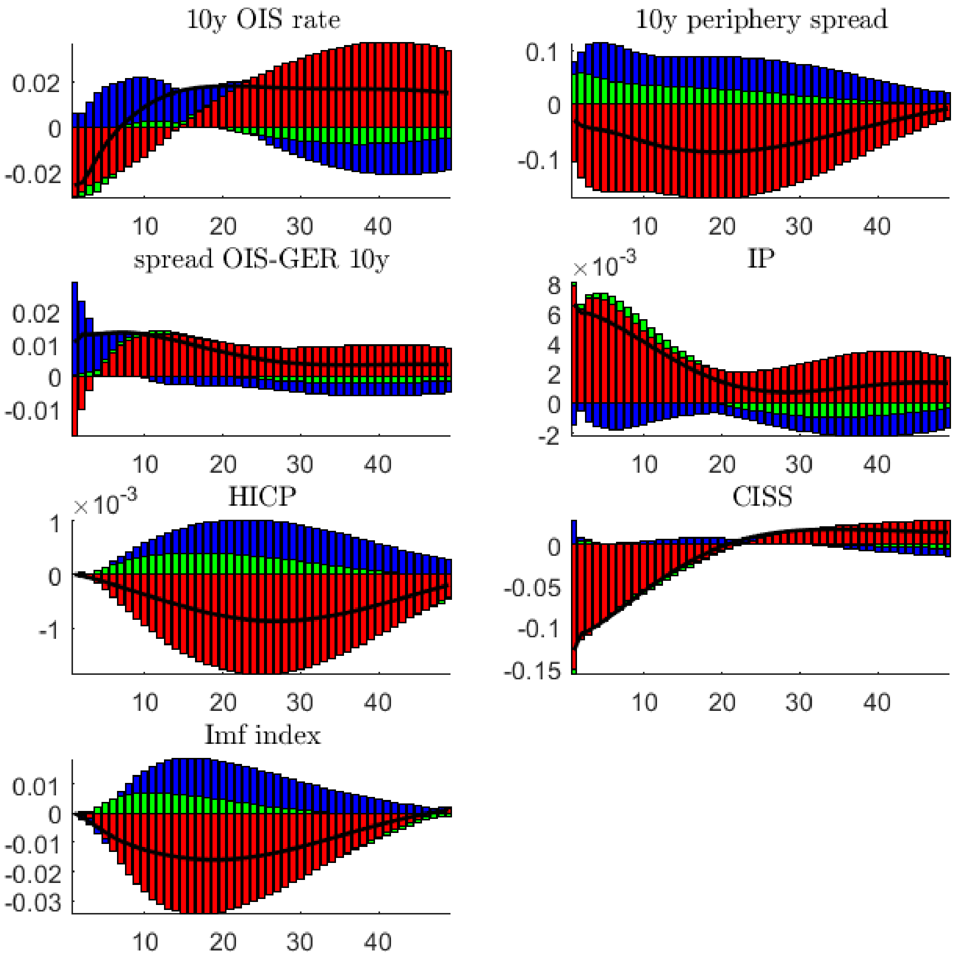

Figure 2.4: Estimated IRFs to a QE shock (black line), obtained thorough identification of A and B matrices, and their decomposition into the three channels: 10-year OIS rate channel (red), 10-year IT-OIS channel (green), 10-year OIS-GER channel (blue).

2.7 Conclusion

In this paper we have analyzed the effects of the QE implemented by the ECB: the Asset Purchase Program, started in 2015. We have done so by employing a core/periphery perspective. First, by mean of a proxy-SVAR estimated at daily frequency, we have shown that the QE has decreased the long-term risk-free rate, measured by the 10-year OIS, and reduced sovereign spreads of the periphery. We also estimated a significant increase in the convenience-yield associated to long-term German bonds. This is a good measure of the expensiveness of German bonds, which originates from their scarcity. This increase in the convenience-yield following the QE is an issue which should be further explored, as it could impede the effectiveness of the QE in boosting the Euro-Area economy, in lights of the possible contractionary effects of safe-assets scarcity (Caballero and Farhi (2018)).

To analyze deeply this issue, we run a proxy-SVAR at monthly frequency which allows to trace out the dynamic causal effects of QE on output and inflation of the Euro Area. We estimate an increase in industrial production and consumer prices following an expansionary QE shock. We then employ an innovative methodology to disentangle three channels through which QE impacts the Euro Area economy:

- A channel referring to the response of the Euro Area common component of sovereign rates, measured by the OIS rate at long maturity.
- A channel referring to the response of peripheral countries sovereign spreads.
- A channel referring to the response of the convenience yield on safe government bonds, measured by the spread between OIS and the German BUND at long maturity.

To estimate these three channels we exploit the information contained in the external instrument, which is built by using high-frequency variations of sovereign rates around ECB press conferences during the QE period, i.e. after 2014. The external instrument is used to achieve identification of a fully specified $AB-SVAR$ (Amisano and Giannini (1997)). This framework allows to separately specify simultaneous relationships among the variables and simultaneous effects of the structural shocks on the variables. By building properly the B matrix, we force the QE shock to affect instantaneously only through the three channels listed above. In this way we can decompose the impulse responses of the variables to the QE shock into three components associated to the three channels.

The analysis suggests that the response of the Euro Area economic activity to QE is made of a contractionary component, related to the increase in the convenience-yield of German bonds, and an expansionary component, related to the decrease of long term OIS rates. The channel referring to the reduction in peripheral sovereign spreads instead seems to play no role for the transmission of QE to real economic activity.

Overall, the expansionary component is estimated to dominate the contractionary component, thus generating the expansionary effects we estimated for the total QE shock. Nonetheless, we think that the presence of this contractionary component is an issue which should further analyzed. In fact, in light of the evidence presented, the design of the QE should be rethought in order to remove any contractionary component and improve its effectiveness. The topic is particularly relevant now, as following the crisis due to the Covid-19 pandemic, the QE is playing an ever more important role among the tools available to the ECB.

Chapter 3

Unconventional monetary policy in the Euro Area: a tale of three shocks

Abstract

To identify the effects of monetary policy, high-frequency (HF) surprises of relevant asset prices around central bank meetings are currently employed in the literature. This identification strategy assumes that these surprises reflect either a single unconventional "monetary shock" or, as recently suggested, jointly an unconventional monetary shock and a central bank "information shock". We argue that this is not actually the case for Euro Area monetary policy after 2008, for which we show that three shocks operate simultaneously around ECB press conferences. Besides the unconventional monetary shock and the information shock, we identify a third shock resulting from the ECB directly targeting the risk premia of peripheral countries. We call this novel shock "spread shock", and show that it permits to solve a puzzle we observe in HF co-movements of long term risk free rates and sovereign spreads around ECB press conferences. We identify the three shocks simultaneously through a novel methodology based on two steps. In a first step we appeal to a sign-restrictions approach to extract three proxies for the three shocks from HF variations of the Euro Area risk-free yield curve, and in a second step we use these proxies as external instruments in a proxy-SVAR framework and to run Local-Projection analyses. We trace out the dynamic causal effects of the three shocks on real economic activity and show that the spread shock represents a crucial ingredient of the transmission mechanism of Euro Area monetary policy after the Global Financial Crisis.

Keywords: Monetary Policy Shock, Structural VAR, ECB

JEL codes: E43, E44, E52,E58,G10

3.1 Introduction

Identifying the effects of monetary policy is a central question in the empirical macro literature. The endogeneity implied by the reaction function of the central bank has been historically tackled by assuming a lagged response of macroeconomic variables to exogenous innovations in the policy rate (see Christiano et al. (1999) for a review). In the empirical macro jargon, this means assuming a triangular structure in the matrix of structural parameters in a Structural Vector Autoregression (SVAR) context. This approach has proved weak for two main reasons. First, the assumption of no contemporaneous response of macro variables to policy shocks has been largely questioned in light of the predictions of monetary New-Keynesian models. Second and more importantly, after the global financial crisis, with advanced economies stuck at the Zero Lower Bound, a "Taylor rule" approach is no longer defensible (Rossi (2019)). With unconventional monetary policies the relevant policy instrument is the long term rate, which is affected by many other variables beyond monetary policy decisions, namely expectations about the future state of the economy, risk aversion, etc. Identifying exogenous variations in long term rates which reflect monetary policy actions proves challenging in this context. The recent crisis induced by the Covid-19 pandemic and the significant effects it will exert on the global economy suggests this issue will remain relevant in the following years.

Since Kuttner (2001), the use of high-frequency (HF) interest rate surprises within the central banks' announcements window has made the life of empirical monetary economists much easier as they allow to isolate unexpected variations in the policy rate or in the long term rate (Gürkaynak et al. (2005)). These variations can be then used to trace out the effects of exogenous monetary policy shocks (Gertler and Karadi (2015)). The central assumption in this literature is that whatever happens within the narrow window around announcements only reflects a single exogenous monetary policy shock.

In this paper we focus on the Euro Area (EA) and provide evidence of the presence of three independent shocks, rather than a single one, operating within ECB press conferences. We identify them by looking at HF co-movements of default-free long term rates, risk premia on EA periphery bonds and the stock market index. The three shocks are:

1. A "classic" monetary policy shock, which (if contractionary) raises the default-free Eurozone yield curve, lowers the stock market index and spills over to EA periphery risk premium, increasing it. We call it a *monetary shock* and it is meant to encompass all unconventional measures, from Forward Guidance to Quantitative Easing (QE), aimed at mainly targeting the risk-free yield curve. An increasing short/long term risk-free rate induces a drop in the stock market index as higher discount rates and lower expected dividends cause a downward revision in stock prices.

2. An *information shock*, as recently identified in the literature (Nakamura and Steinsson (2018),Jarociński and Karadi (2020), Andrade and Ferroni (2019)). By announcing policy decisions central banks simultaneously release private information, embedded in their forecast about the future state of the economy, thus affecting the expectations of market participants. Assume that an ECB press conference causes an upward revision in market participants expectations about the future path of the economy: this leads to an increase in the long term rate, an increase in the stock index and possibly a decrease in the periphery risk premium. Not taking into account this second shock, the *information shock*, could bias the estimates of the impact of monetary policy on macroeconomic variables and asset prices.

3. Finally, we identify a third and novel *spread shock*, which we interpret as the result of the ECB affecting directly the risk premia on peripheral countries and only indirectly the default-free yield curve. This can be either due to the communication carried out by the ECB or actual announcements regarding relevant policies. When this shock hits we observe a negative HF co-movement of default-free long term rates and periphery risk premium. We will explain throughout the paper the interpretation and the implications of this third shock and why we need to take it into account. Given the nature of this shock, its relevance is concentrated mostly in the period of the sovereign debt crisis and it aftermath, though the recent crisis due to the Covid-19 pandemic has highlighted again the need of a spread-targeting policy by the ECB.

This three-shocks description of the surprises around ECB press conferences allows to obtain a non-biased and comprehensive estimation of the financial and macroeconomic effects of unconventional monetary policy in the Euro Area. We can do so without the need to split the sample or focusing on specific measures adopted. On the methodological side, we apply a sign-restrictions approach to build three orthogonal factors extracted from HF surprises around all ECB press conferences. We then use the obtained factors as external instruments for the three shocks, using proxy-SVAR and local projection methodologies to trace out the dynamic causal effect of unconventional monetary policy.

Our central hypothesis that the risk-free yield curve is affected by policies targeting sovereign spreads is confirmed in the estimated daily proxy-SVAR, where we see that its response to the spread shock is highly persistent. We show also that the so identified spread shock has non-negligible effects on output and inflation which would not fully accounted for, by the monetary and information shocks alone.

The paper is organized as follows. In section 2 we explain the puzzle we face when looking at HF responses of periphery spreads to ECB announcements. In section 3 we explain the implications of the novel spread shock, while in section 4 we provide details on the methodology we use to identify the different shocks from HF surprises. In section 5 we analyze dynamic responses of asset prices to the identified shocks using a daily SVAR, while in section 6 we focus on the macroeconomic effects using local projections.

Related literature.

The use of high-frequency data to proxy for monetary policy shocks dates back to Kuttner (2001) and Cochrane and Piazzesi (2002), while in the seminal work of Gürkaynak et al. (2005) they first proposed to use factor (or principal component) analysis to extract time-series of monetary policy factors. Recently, a fast developing literature, to which this paper speaks, focuses on identifying multiple shocks around monetary policy events, including the information effect. Nakamura and Steinsson (2018) focuses on US data. Regarding the Euro Area the most relevant papers are Jarociński and Karadi (2020) and Andrade and Ferroni (2019) who disentangle information shocks from monetary policy shocks by looking at high frequency responses of the stock market and inflation expectations, respectively, and imposing the proper sign restrictions. We build on their method to identify our spread shock.

Leombroni et al. (2019) is the work to which this paper relates the most. They focus on the effects of ECB communication of the sovereign yields of the Euro Area, in a core/periphery perspective. They identify two shocks from HF variations around press conferences: an interest rate shock and a risk premium shock. The first shock comprehends surprises due to forward guidance and information effects from ECB communication and the announced future path for the short term rate. This shock is identified by principal component analysis of variations in the OIS rates along the yield curve. The risk premium shock is meant to capture the ECB policies affecting directly the risk premium and credit risk of peripheral countries. It is identified by taking the variations in the stock market index orthogonal to the first shock. We differ from this paper in two dimensions. First, the interest rate shock in Leombroni et al. (2019) contains both information and monetary effect, as they don't exploit co-movements of OIS rates and stock prices to disentangle the two components. Second, we identify the risk premium shock using a different strategy, by taking a stand on the expected co-movement of OIS rates and sovereign spreads.

Cieslak and Schrimpf (2019) assume three types of structural shocks affect HF variations of interest rates around monetary policy announcements: a monetary shock, an information shock and a risk premium shock. The latter refers to news affecting the price of risk in financial markets. To identify the three shocks they exploit sign restrictions on HF co-movements of the yield curve and stock prices. Similarly to Cieslak and Schrimpf (2019) we identify a risk shock, though while they interpret it as a realization of "fligh-to-safety" episodes which move down the yield of safe government bonds, we specifically focus on the risk premium on the sovereign bonds of Euro Area periphery and exploit the idea that this shock affects the risk-free yield curve through expectations.

A large literature has focused on estimating the effects of unconventional monetary policies in the Euro Area. Prominent examples are Altavilla et al. (2015), Altavilla et al. (2016), Gambetti and Musso (2017),Krishnamurthy et al. (2018), Dewachter et al. (2016). All these studies focus on specific types of unconventional measures separately, while our aim is to provide a comprehensive estimate for the whole lifetime of the Euro Area. Altavilla et al. (2019) moves in this direction, by building a set of factors extracted from HF variations of the risk-free yield curve around ECB meetings, following the studies made for US data by Gürkaynak et al. (2005), Swanson (2017). We will use the dataset built by Altavilla et al. (2019) for the construction of the proxies for the three shocks. Wright (2019), in a comment of the work by Altavilla et al., highlights the need to focus also on HF variations in sovereign spreads to fully characterize ECB policies and constructs a "save the Euro factor" which behaves very much like our spread shock. We move in the same directions, but we differ from Wright (2019) in two dimensions. First, we also take into account the presence of an information shock. Second, we show that the "save the Euro factor" is also embedded in the HF variations of the risk-free yield curve, thus it cannot be ignored even though one wants to focus on this kind of measure of policy shocks only, as in Altavilla et al. (2019). It other words, by looking at HF movements in the risk-free yield curve to estimate pure monetary shocks, one inevitably faces the issue that some of these variations are due to sovereign spread targeting policies, thus estimates can result biased.

Our paper closely relates to Hachula et al. (2019), in which they solve the issue of having different types of monetary policy shocks in the Euro Area by splitting the sample into two parts: a "phase 1" (2007-2014) in which they assume the ECB is targeting the periphery spreads; a "phase 2" (2014-2016) in which ECB is assumed to target the risk-free yield curve. Accordingly, they use HF variation in periphery yields for "phase 1" and HF variations in core countries yields for "phase 2" to achieve identification. Our approach allows to account for this multiplicity of structural shocks without splitting the sample and taking a *a-priori* stand on the dates in which either of the multiple shocks must be considered.

Finally, our paper contributes to the fast growing literature which exploits information from external instrument to identify dynamic causal effects in SVARs, following Gertler and Karadi (2015),Mertens and Ravn (2013),Stock and Watson (2012), Stock and Watson (2018). We use the

AC-SVAR method by Angelini and Fanelli (2019), which allows to simultaneously identify several shocks of the system. The simultaneous identification of multiple shocks related to monetary policy is not so usual in the monetary literature, thus we contribute to filling this gap. Sign restrictions have been combined with external instruments, using bayesian estimation techniques, in order to identify structural shocks, as in Jarociński and Karadi (2020). We use sign restrictions only in the step in which we extract external instruments from HF data, thus obtaining point identification and standard asymptotic inference for the parameters of the proxy-SVAR and local projections.

3.2 The OIS-spread puzzle and policy surprises

Monetary policy conduct by the European Central Bank in the Euro Area is characterized by some distinctive features which make it substantially different from that of other major central banks in the advanced economies. Although the mandate to which the ECB is committed is simple, that is to achieve an inflation target lower but close to 2%, reaching this goal has proven quite difficult for the monetary authority. Especially since the beginning of the Great Recession in 2008, it has been clear that the ECB should have been ready to undergo several types of "non-standard" measures to fulfill successfully its mandate. Besides the challenge implied by having reached the Zero Lower Bound, and the consequent need for the implementation of unconventional monetary policies, the ECB had to face the risks connected with the sovereign debt crisis. After 2010 we have observed a sharp increase in the risk premia associated with sovereign debts of Euro Area periphery countries reflected in higher spreads between periphery and core countries interest rates. These premia can be attributed to two main reasons: a decrease in the perceived ability of some countries to repay their sovereign debt, and an higher probability associated to a breakup of the Euro Area and to the consequent redenomination of sovereign debts in local currencies (Krishnamurthy et al. (2018)). The debt crisis has magnified the contradictions implied by an imperfect currency area with a fragmented sovereign bond market and the need for the ECB to take actions aimed at compressing risk premia (De Grauwe (2011)). After an initial inertia the ECB seemed to have started addressing the issue directly, with the governor Mario Draghi trying to reassure financial markets about the irreversibility of the monetary union in his famous "whatever it takes" speech on 26^{th} July 2012. More recently, in the aftermath of the Covid-19 pandemic outbreak, in the press conference on March 12^{th} the new governor Christine Lagarde has stated: "we don't close spreads", referring to the responsibility of the ECB to compress sovereign risk premia. The huge reaction of financial markets to this statement has shown the expectations were quite the opposite: markets participants were expecting the ECB to effectively close spreads. This event made crystal clear the role of the ECB in controlling sovereign spreads.

Accordingly, several studies tried to understand how effective were the measures taken by the ECB in reducing risk premia on sovereign bonds (Altavilla et al. (2015),Altavilla et al. (2016),Gambacorta et al. (2014) among others). To answer this question, one needs first to identify a clear measure of monetary policy shock, and then envisage how spreads react to this shock. Most of the studies which address this issue, assume *a priori* a direct effect of monetary policy on the spreads. For example, Altavilla et al. (2015) use an event study analysis and show that the QE launched in January 2015 effectively reduced spreads of periphery bonds. In an event study analysis the spread is regressed on relevant date dummies and other covariates. The identification of the monetary policy shock then boils down to identifying the relevant policy events, using a two-day, one-day or intra-day window. Although this approach has proved useful for providing *prima facie* evidence on the effects of monetary policy, a more "agnostic" approach is desirable, where an incontrovertible measure of monetary policy shocks is identified *ex ante* and only then its effects on the spreads can be traced out. This is the approach followed by Altavilla et al. (2019), who construct four measures of policy surprises in the Euro Area by extracting four factors from the set of HF surprises in Overnight Indexed Swap rates (OIS) at different maturities around ECB governing council meetings. They rotate the extracted factors and interpret them as: *target, timing, forward guidance and QE* factors. OIS yield curve constitutes the reference risk-free term structure of interest rates which is relevant for the ECB monetary policy. [1]

[1] OIS (Overnight Indexed Swaps) are derivatives in which a fixed leg of a given time-length (from 3 months to 10 years) is exchanged for a floating leg given by the EONIA rate. These contracts are used by investors for two objectives: bet on the future path of the short term rate and insure against duration risk. For this reason long term OIS rates are equivalent to the yield of a default-free long term bond, net of any difference coming from "convenience yields" on sovereign bonds.

Figure 3.1, which is taken from Altavilla et al. (2019), gives an idea of how intra-day variations of the 2-year OIS rate looks like during a day in which the ECB governing council meets, by looking at four different dates. It's very clear how variations are clustered around the press release and later the press conference. Since conventional policies are announced in the press release, all other types of shocks are gathered in the press conference. It's worth pointing out that variations often moves in an opposite direction with respect to the measure taken, as they are cleaned for expectations before the announcements. For instance, on 3^{rd} December 2015 we observe an increase in the OIS rate around the press conference, despite an increase in the size of the QE was announced. This happened because market participants were expecting an even larger increase.

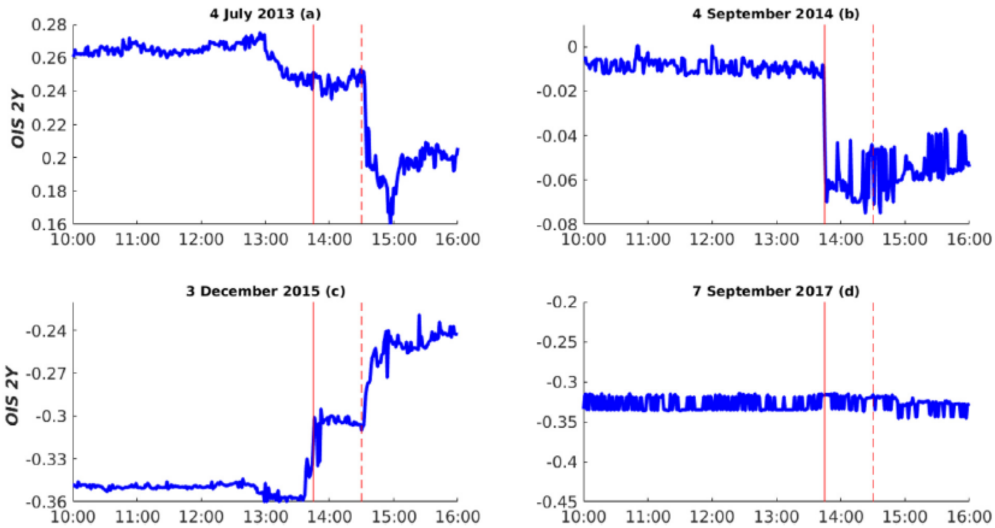

Figure 3.1: Examples of intra-day variations of the 2-year OIS around press release and press conference. Figure is taken from Altavilla et al. (2019).

Altavilla et al. (2019) regress the Italian rates at different maturities on these factors. Besides the effect of the QE factor in the 2014-2018 period, they get no clear-cut evidence that expansionary monetary policy by ECB reduced the spread Italy-OIS, which is a proper measure of peripheral countries risk premium. This can be seen in Table 3.1, where we show the results of a regression of HF variations of the 10-year spread ITA-OIS around ECB press conferences on variations of the 10-year OIS rate around the same press conferences, which can be interpreted as a measure of monetary policy surprises and basically accounts for both the FG and QE factors. We run the regression separately in three periods: 2002-2007 (PRE08), 2008-2013 (CRISIS) and 2014-2018 (QE). In the first period the regression coefficient is not statistically different from zero, which is not surprising given the very small variation of the ITA-OIS spread in this period. During the QE period, we instead observe the expected positive correlation between the OIS rate and the risk premium on Italian bonds. In the crisis subsample (2008-2013), however, we record a puzzling negative correlation, which at a first glance would lead to the counter-intuitive result that a restrictive policy actually reduces the risk premium. This makes the coefficient estimated over the full sample negative, though not significant.

	FULL SAMPLE	PRE08	CRISIS	QE
		(2002-07)	(2008-13)	(2014-18)
10-year OIS	-0.216	-0.026	-0.736**	0.687***
	(0.1232)	(0.0131)	(0.2427)	(0.1422)
constant	0.147	-0.076**	0.600	-0.511
	(0.3348)	(0.0281)	(0.7513)	(0.4059)
N	181	67	72	42
R2	0.02	0.06	0.12	0.37

Table 3.1: Dependent variable: 10-year spread ITA-OIS, surprises during ECB press-conference. Robust standard errors in parenthesis. $*p < 0.05, **p < 0.01, ***p < 0.001$.

Notice that by focusing on the surprises around the ECB press conference which takes place after the press release, we focus on market reactions to unconventional measures, as conventional policies (cuts/increases in the policy rates) are announced in the press release. However, similar results are obtained if we look at the surprises in the whole monetary event, i.e. press release plus press conference, see Table 3.2.

The puzzle can be seen also from Figure 3.2, in which we observe that a non-negligible fraction of episodes of negative co-movement between the 10-year OIS and the periphery risk premium,

	FULL SAMPLE	PRE08	CRISIS	QE
		(2002-07)	(2008-13)	(2014-18)
10-year OIS	-0.101	-0.02*	-0.611**	0.778***
	(0.108)	(0.009)	(0.212)	(0.144)
constant	-0.114	-0.0503*	0.454	-1.111*
	(0.328)	(0.022)	(0.723)	(0.471)
N	181	67	72	42
R2	0.005	0.067	0.105	0.422

Table 3.2: Dependent variable: 10-year spread ITA-OIS, surprises during ECB monetary events. Robust standard errors in parenthesis. $*p < 0.05, **p < 0.01, ***p < 0.001$.

proxied by the 10-year spread ITA-OIS.

One possible explanation for this puzzle may be found in the presence of an *information shock*. As shown by Nakamura and Steinsson (2018), Jarociński and Karadi (2020), Andrade and Ferroni (2019) and others, an increase (decrease) in the long term rate can be unrelated to a restrictive (expansionary) policy shock, but rather may reflect a disclosure of positive (negative) information about the future state of the economy by the central bank during the press conference. Under this scenario, a decrease in the long term OIS rate could well be a consequence of a negative information shock (i.e. a worsening of market expectations about future economic activity) rather than the result of an expansionary policy like a QE. A significant realization of an information shock could then generate the negative correlation we observe in Figure 3.2. In the next sections we show that accounting for an information shock is not enough to explain the puzzle. Moreover, the fact that episodes in which the spread IT-OIS and the OIS itself negatively co-moves are clustered in the 2008-2014 period suggests something more than an information shock should be accounted for, as there is no specific reason to believe that the information shock displays so much more variability during the crisis. In fact, estimates of the information shocks in the literature do not point to an increase of its variance during the crisis.

We provide an alternative explanation for the puzzle by considering a third type of shock, which we call *spread shock*, and explain in details in the next section.

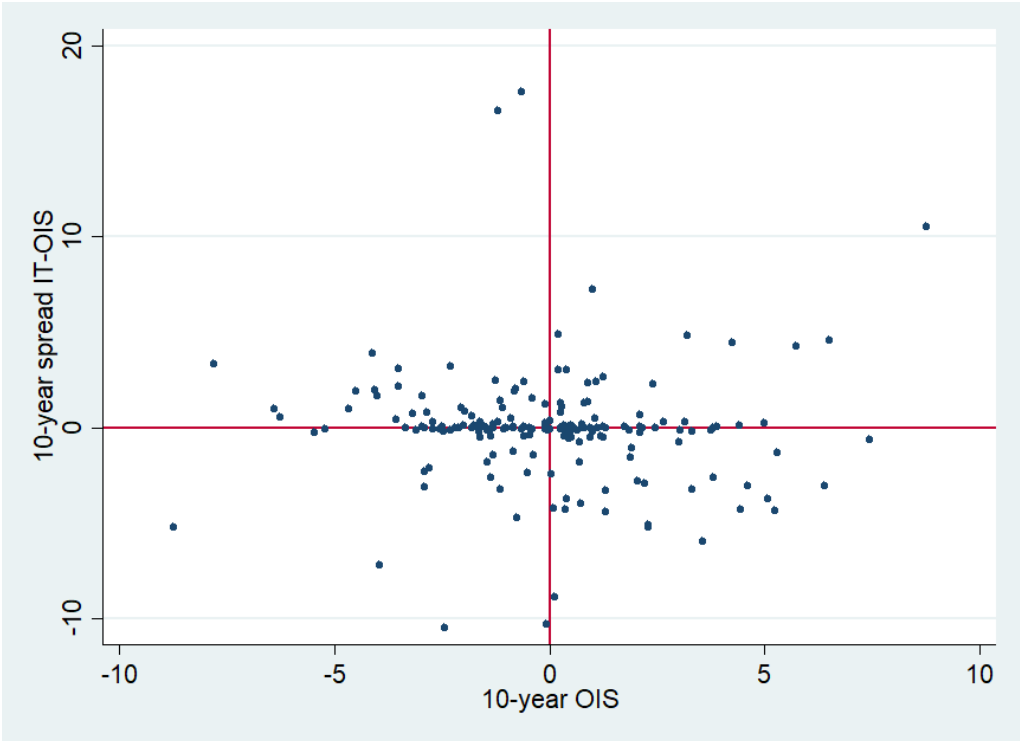

Figure 3.2: Scatter plot of surprises in 10-year OIS rate and 10-year ITA-OIS spread around ECB press conferences. Variations in basis points.

3.3 Spread vs OIS driven surprises.

We conjecture that all types of unconventional policies implemented by the ECB, that affect sovereign yield curves in the Euro Area can be summarized into two main categories:

- Through a "classic" monetary policy rule, the ECB affects the common Eurozone risk-free rate, measured by the OIS rate. It is worth stressing that by "classic" we don't mean "conventional". The ECB can affect the OIS rates at long maturities through unconventional measures, typically QE.[2] This type of policy spills over to the periphery risk premia. In particular, we expect an expansionary monetary policy, which reduces the OIS rates, to reduce the spreads as well. The mechanism through which this occurs are several: improved economic conditions can increase confidence of investors about sustainability of risky sovereign debts. Policies like QE are also expected to reduce the price of risk by taking some risk out of the market, through the *portfolio rebalancing effect.* Policies like LTROs (Long Term Refinancing Operations) are aimed at increasing the supply of long term loans by banks, thus reducing long term risk free rates. These liquidity injections have been used by commercial banks also to increase their exposure to risky sovereign debt (Crosignani et al. (2019)), again leading to a reduction in sovereign spreads.

  An example of this type of mechanism is observed on 22^{th} January 2015 when the QE was announced: we observe a similar reaction of the 10-year OIS rate, and the 10-year IT-OIS spread. (see Table 3.3). This is consistent with the idea that an expansionary unconventional monetary policy like the QE reduces risk premia.

- By a "spread-targeting" monetary policy aimed directly at affecting the spreads of peripheral countries, the ECB directly targets the periphery spread. This in turn can affect the OIS risk free rate, through a mechanism different from the one previously described. If this policy successfully reduces the spread, we can expect the OIS rate to increase rather than decrease. In fact market participants could revise their expectation about future policies needed to keep

[2]Notice that we refer to the OIS yield curve as the risk-free yield curve, simplicity. Clearly this definition is not completely appropriate, as long term OIS commands a risk premium as they incorporate some duration risk. A better definition would be the default/redenomination risk free yield curve.

spreads low. In particular they will revise their expectation about future OIS rates upwards, this will drive up long term OIS rates. Moreover, a successful reduction of risk premia could induce the market to revise their expectations about future real economic activity upwards and therefore long term OIS rates.

This is what we observe on the 6^{th} September 2012, when the details of the Outright Monetary Transactions (OMT) were announced by the ECB: a large reduction in the risk premium on Italian bonds associated to an increase in long term OIS risk free rate, as we can see from Table 3.3. [3]

	10-year OIS surprise	10-year ITA-OIS surprise
6^{th} September 2012: OMT announcement	0.12	-8.87
2^{nd} August 2012: OMT announcement	-6.09	38
22^{th} January 2015: QE announcement	-8.74	-14

Table 3.3: Surprises around ECB press conferences in the 10-year OIS rate and in the 10-year spread ITA-OIS on three relevant dates. Variations in basis points.

To sum up, we expect to observe a positive co-movement of long term OIS rate and the risk premium when a "classic" *monetary shock* hits, and a negative co-movement when the *spread shock*

[3] The actual OMT announcement took place on the 2^{nd} August 2012. This is actually quite a peculiar case because the OMT announcement has been initially interpreted as a decision that the ECB was not willing to fully protect countries in trouble. This is why we see a steep increase in the risk premium. This initial reaction was then counterbalanced in the subsequent days. What is interesting for us, though, is that this "restrictive" spread shock, is linked to a decrease in the OIS rate, as expected (see Table 3.3). "Il Sole 24 ore", the main financial newspaper in Italy, comments market reactions on August 3^{rd} by writing: "In the current situation, with high spreads and highly fragmented markets, the effects of monetary policy do not transmit to the whole Eurozone." In other words, the easing monetary policy, measured by the reduction in OIS rates, does not spill over to the Italian risk premium. Is it the case, or is it the other way round, i.e. the restrictive shock on Italian spread, measured by an increase in the latter, spilled over to OIS rates, reducing them? We want to explore this second interpretation. Another example is 26^{th} July 2012, the day the famous "whatever it takes" speech was carried out by Mario Draghi. That day we observe a large decrease in the periphery spreads, while the 10-year OIS rate increased, as expected in response to a spread driven monetary policy shock.

is instead at work.

Notice that by not taking into account the *spread shock* we might possibly incur into an omitted variable bias, which creates two kinds of problems. First, if one is interested in the estimation of the effects of "classic" monetary policy on the risk premia, the omission of the reverse effect of the "spread" shock on the risk free rate leads to underestimate the true effects. Second, even if we abstract from the periphery risk premia, using OIS rates surprises, or the factors constructed by Altavilla et al. (2019) from the OIS yield curve, as measures of monetary policy shocks could lead to systematic biased results when the "spread shock" is hitting. For instance, we would interpret an increase in the long term OIS rate as a restrictive monetary policy shock, while this can be the result of an "expansionary' spread shock", that is a reduction in the risk premium. This can in turn lead to biases in the estimates of the effect of monetary policy shocks on e.g. real economic activity and inflation. Given the short life of the Euro Area and the high importance played by unconventional MP in its lifetime span, this appears to be a relevant issue.

3.4 Extracting multiple factors from high-frequency surprises

To identify the multiple shocks embedded in HF surprises around ECB announcements and evaluate their dynamic effects on macro and financial variables, we use a two-step identification procedure. In the first step we use HF data to extract a set of orthogonal proxies. These proxies are then used in a second step as external instruments in a high-frequency proxy-SVAR and in a low frequency IV-LP (Instrumental Variable-Local Projection). In this section we explain the first step.

First, we ignore the possible presence of a *spread shock* and assume two shocks affect the OIS yield curve in the narrow window around ECB press conferences: a *monetary shock* and an *information shock*. We therefore follow an approach similar to Andrade and Ferroni (2019) and Jarociński and Karadi (2020) to extract two proxies for these two shocks. Later on we will account for a third *spread shock*. We do so in order to show that the two-shocks analysis in not enough to explain the puzzle depicted in Figure 3.2.

We collect in the vector δ_t the HF variations around press conference of OIS rates at 3-month 1,2,5,10 years maturity and of the STOXX50 index. We then assume this vector δ_t is explained by two factors, collected in f_t, and consider:

$$\underset{6\times 1}{\delta_t} = \underset{6\times 2}{\Lambda}\underset{2\times 1}{f_t} + \underset{6\times 1}{e_t} \tag{3.1}$$

where Λ is the matrix of factor loadings and e_t is a vector of disturbances. In the matrix form:

$$\underset{T\times 6}{\Delta} = \underset{T\times 2}{F}\ \underset{2\times 6}{\Lambda'} + \underset{T\times 6}{e} \tag{3.2}$$

To estimate f_t and Λ we decompose the correlation matrix of δ_t, using a maximum-likelihood estimation of the factors. Equation (3.2) is still valid for any orthonormal matrix $\underset{2\times 2}{H}$ such that:

$$\Delta = (FH)(\Lambda H)' + e = F^*\Lambda^* + e \tag{3.3}$$

where the orthonormal matrix H rotates the factor and changes the loadings accordingly. We select H, among the infinite possible orthonormal matrices, such that the following sign restrictions are satisfied:

$$\begin{bmatrix} \Delta OIS_{3m,t} \\ \Delta OIS_{1y,t} \\ \Delta OIS_{2y,t} \\ \Delta OIS_{5y,t} \\ \Delta OIS_{10y,t} \\ \Delta STOXX50_t \end{bmatrix} = \begin{bmatrix} + & + \\ + & + \\ + & + \\ + & + \\ + & + \\ - & + \end{bmatrix} \begin{bmatrix} f_{monetary,t} \\ f_{info,t} \end{bmatrix} \tag{3.4}$$

In practice, we are forcing the monetary factor to load positively on the OIS yield curve and negatively on the STOXX50, while the information factor loads positively both on the OIS yield curve and the STOXX50.

The algorithm which estimates factors through sign restrictions is quite standard and follows the literature started by Uhlig (2005). At each iteration a 2×2 orthonormal matrix is randomly generated and Λ^* is computed. After the signs of each column are normalized, sign restrictions are checked. We repeat the iteration until 1000 valid Λ^* matrices are obtained. To select among the 1000 randomly generated Λ^* satisfying the imposed sign restrictions we use the Median-Target method by Fry and Pagan (2011): for each Λ^* we compute the sum of the squared standardized distance of each of its elements from the element median value, we then select the matrix Λ^* for which this measure is minimized. This method ensures that the estimated factors are orthogonal.

As in Jarociński and Karadi (2020) the disentanglement of the information factor from the monetary factor in entirely grounded on the different co-movement of OIS rates and the stock index when either of the two shocks is hitting. This assumption is fed into the estimation procedure through the signs in the last row of matrix Λ^* in equation (3.4).

Figure 3.3 depicts the estimated factors. Figure 3.4 depicts the loadings of the two factors on the OIS yield curve, obtained by regressing variables in Δ on the two estimated factors. Not surprisingly, the information factor loads mainly on the 1-2 years segment of the yield curve, the horizon at which private information of the ECB is expected to matter most.

If we look at Figure 3.5 we see that the monetary factor loads in opposite directions on the OIS

Figure 3.3: Estimated monetary and information factors over the sample. Factors are standardized to have zero mean and unit variance.

and on the spread IT-OIS yield curve, i.e. a positive value of the monetary factor (a restrictive policy) is associated with a decrease in the spread IT-OIS. Moreover, the estimated information factor however does not load significantly on the spread curve. These results show that accounting for an information shock is not enough to describe the puzzle explained in section 2. We need therefore to introduce a third shock into the picture.

We augment the vector δ_t with the variations around ECB press conferences in spread IT-OIS yield curve (2,5,10 maturity) and the vectors of factors with the new *spread factor*. Therefore we have:

$$\underset{T\times 9}{\Delta} = \underset{T\times 3}{F} \underset{3\times 5}{\Lambda'} + \underset{T\times 9}{e} \tag{3.5}$$

Table 3.4 summarizes the assumed signs of the loadings of the three factors of the HF variations

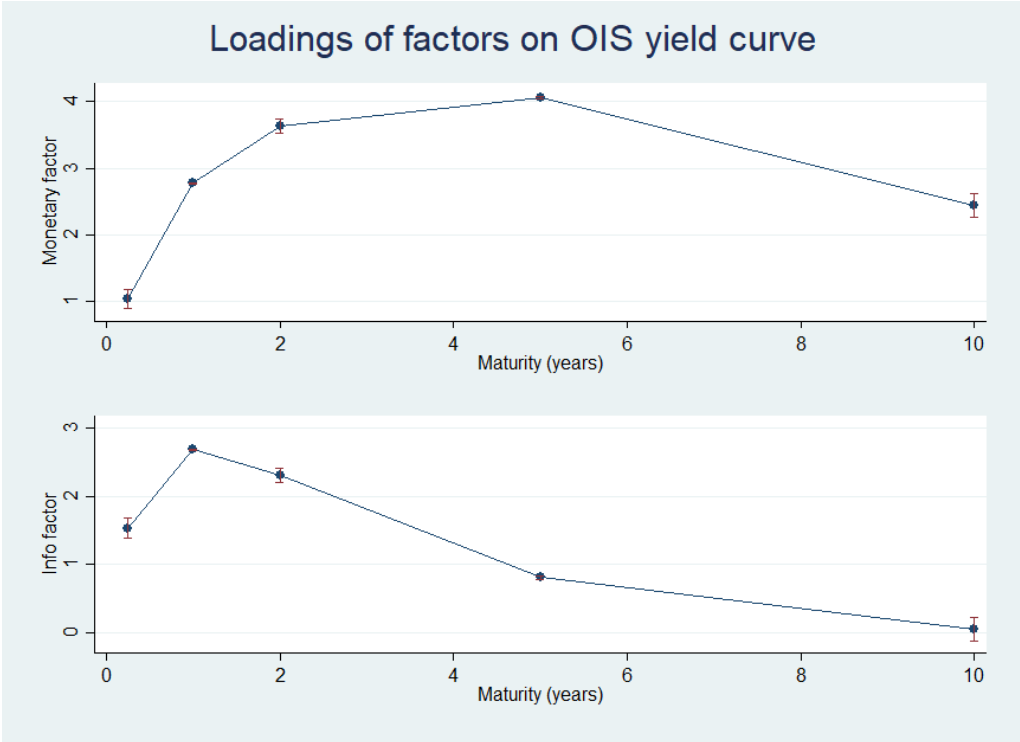

Figure 3.4: Monetary and information factor loadings, obtained by regressing OIS variations on the two factors. Red bands show 95% confidence intervals.

contained in vector δ_t. Equation (3.4) then changes to:

$$\begin{bmatrix} \Delta OIS_{3m,t} \\ \Delta OIS_{1y,t} \\ \Delta OIS_{2y,t} \\ \Delta OIS_{5y,t} \\ \Delta OIS_{10y,t} \\ \Delta IT-OIS_{2y,t} \\ \Delta IT-OIS_{5y,t} \\ \Delta IT-OIS_{10y,t} \\ \Delta STOXX50_t \end{bmatrix} = \begin{bmatrix} + & + & + \\ + & + & + \\ + & + & + \\ + & + & + \\ + & + & + \\ + & - & -- \\ + & - & -- \\ + & - & -- \\ - & + & + \end{bmatrix} \begin{bmatrix} f_{monetary,t} \\ f_{info,t} \\ f_{spread,t} \end{bmatrix} \tag{3.6}$$

An issue comes from the fact that the signs imposed to identify the information and the spread factors are the same. This causes an identification problem that we solve in two ways. First, we impose that the variance of the spread factor during the crisis (2010-2014) is at least 1.74 times

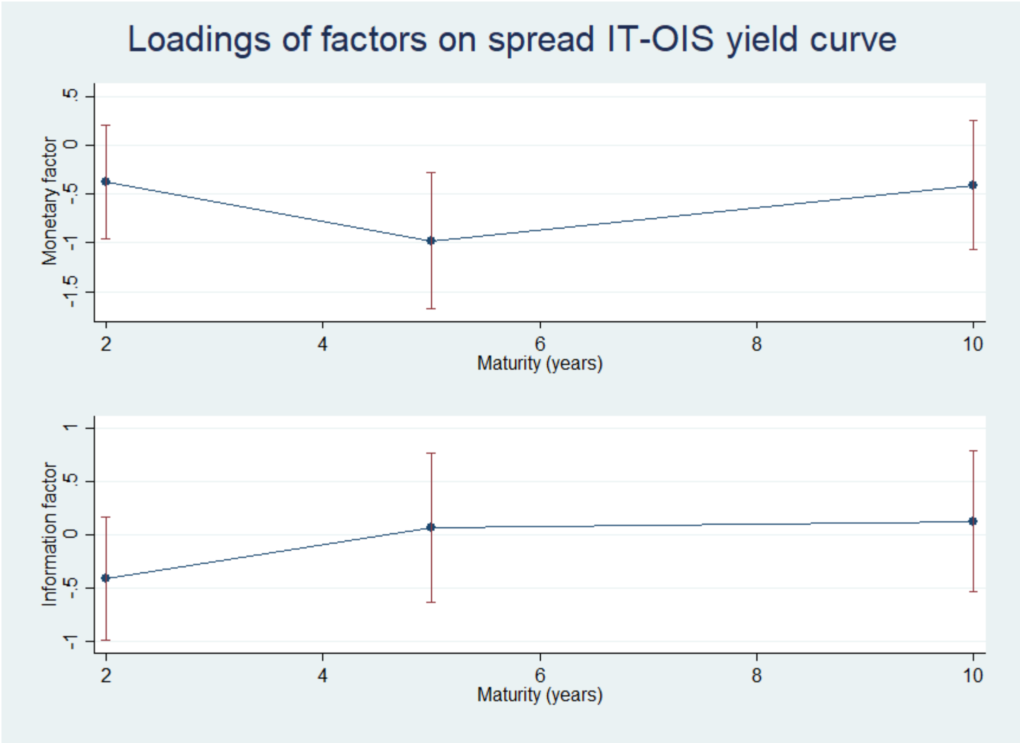

Figure 3.5: Monetary and information factor loadings, obtained by regressing spread IT-OIS variations on the two factors. Red bands show 95% confidence intervals.

	Monetary factor	Info factor	Spread factor ($Var_{10-14} >> Var_{08-10,14-18}$)
OIS yield curve	$+$	$+$	$+$
Spread IT-OIS curve	$+$	$-$	$--$
STOXX50	$-$	$+$	$+$

Table 3.4: Sign restrictions for 3-factors rotation.

larger that outside this time span. [4] This restriction is justified by the fact that before 2010

[4] In order to test the null-hypothesis $H_0 : \sigma^2(f_{spread}, 10-14) = \sigma^2(f_{spread}, 08-10, 10-14)$ against the one-sided alternative $\sigma^2(f_{spread}, 10-14) > \sigma^2(f_{spread}, 08-10, 10-14)$, we have to use the test statistic: $\frac{S_A^2}{S_B^2}$ where S_A^2, S_B^2 are the sample variances of the spread factor in the 10-14 and in the 08-10,14-18 sample respectively. This test statistic is distributes as an F distribution with (m, n) degrees of freedom, where m is the sample size of A minus 1, and n the sample size of B minus 1. Given the size of our two samples we compare the test statistic with an $F(59, 126)$, then H_0 is then rejected if $\frac{S_A^2}{S_B^2} > 1.74$. For this reason we use the 1.74 threshold for the ratio between

sovereign spreads were not an issue and the ECB was not expected to influence them.

Second, we impose that the loadings associated to the spread factor on the IT-OIS spread curve to be larger (in absolute value) than the loadings of the information factor on the spread curve. This additional restriction is a natural implication of the nature of the spread shock we explained above: as it is intended as a consequence of measures taken by the ECB to directly influence the spreads, it should affect sovereign spreads more than any other shock. This additional set of restrictions is less standard than the sign restrictions. Similar strategies have been already employed in the literature. For example Antolín-Díaz and Rubio-Ramírez (2018) and Caggiano et al. (2020) use similar "narrative restrictions", where they constrain some shocks to be more relevant at specific dates. Swanson (2017) as well employs a "variance restriction" to identify a QE factor in the US. Furlanetto et al. (2019) employ a restrictions on the relative magnitude of the response of certain variables in the SVAR to the shocks of interest, as we do for the spread shock.

These two additional constraints are inserted into the algorithm estimating the factors similarly to the more standard sign restrictions. More precisely, at each iteration the signs of Λ^* are checked, as well as the variance of f_{spread} and the absolute value of loading coefficients of the spread factor. The generated Λ^*, F^* are kept only if all these restrictions are satisfied.

Figure 3.6 plots the estimated factors using these restrictions. Figures 3.7 and 3.8 depict factor loadings on the OIS and the spread IT-OIS curves. Figure 3.9, 3.10, 3.11 show how HF variations in the 10-year OIS rate, the 10-year spread IT-OIS and the STOXX50 index are decomposed into components due to the three shocks. Some features are worth noting. The three factors decomposition fits the 10y-OIS and the 10y-spread variations quite well, while the residual component of the Stoxx50 variations is quite large. Most of the 10y-OIS variations are due to the monetary factor, but the spread factor plays an important role in the years of the crisis. Large variations in the 10-year spread are mostly explained by the spread factor, while the monetary factor explains

the two variances.

a small but significant fraction of the same variations.

Table 3.5 shows the fraction of variance of HF variation in these three variables explained by the three factors: the overall R^2 and the fraction of the explained variance which is attributable to each of the three estimated factors.

Figure 3.6: Estimated monetary, information and spread factors over the sample. Factors are standardized to have zero mean and unit variance.

R^2	Monetary factor	Information factor	Spread factor
Δ OIS 10y 78%	67.9%	4.7%	27.4%
Δ IT-OIS 10y 84%	6.3%	22.6%	71%
Δ STOXX50 29%	51.5%	6.5%	42%

Table 3.5: % of the variance of HF variations explained by the three factors. The first column shows the overall R^2. The last three columns shows the percentage of the explained variance due to each of the three estimated factors.

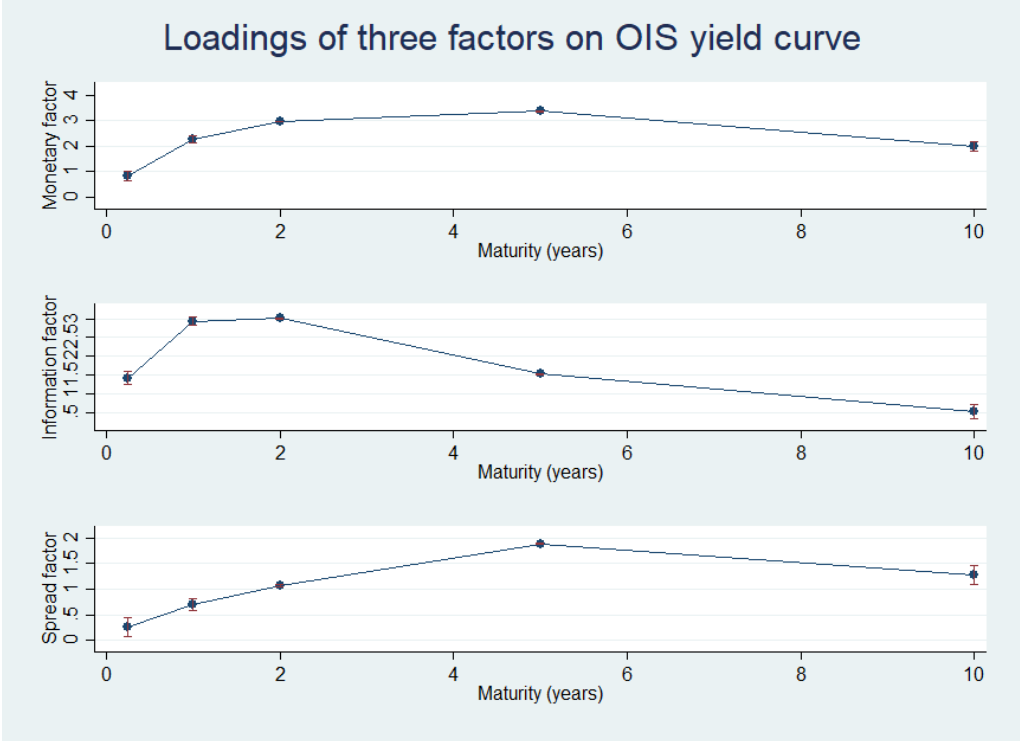

Figure 3.7: Monetary, information and spread factor loadings, obtained by regressing OIS variations on the three factors. Red bands show 95% confidence intervals.

We will use the estimated factors as external instrument in a proxy-SVAR at daily frequency. Notice again how the methodology we apply differs from that of Jarociński and Karadi (2020), which estimate the latent factors by imposing sign restrictions directly in the structural parameters of a bayesian proxy-SVAR. In a frequentist approach this would mean obtaining set identification instead of point identification and related confidence intervals. By using sign restrictions only in the constructions of the external instruments we instead can obtain point identification in the proxy-SVAR and rely on standard asymptotic inference. In this regard we are closer to Andrade and Ferroni (2019), though they use daily variations in the inflation-linked-swap rates to disentangle monetary and information shocks, while we exploit higher-frequency variations in the STOXX50 index.

Though we can rely on standard inference by using this two-step identification procedure, we still cannot ignore the degree of uncertainty implied by our model selection restrictions imposed in the factor estimation procedure. In Appendix C we discuss this issue in details and report the level of

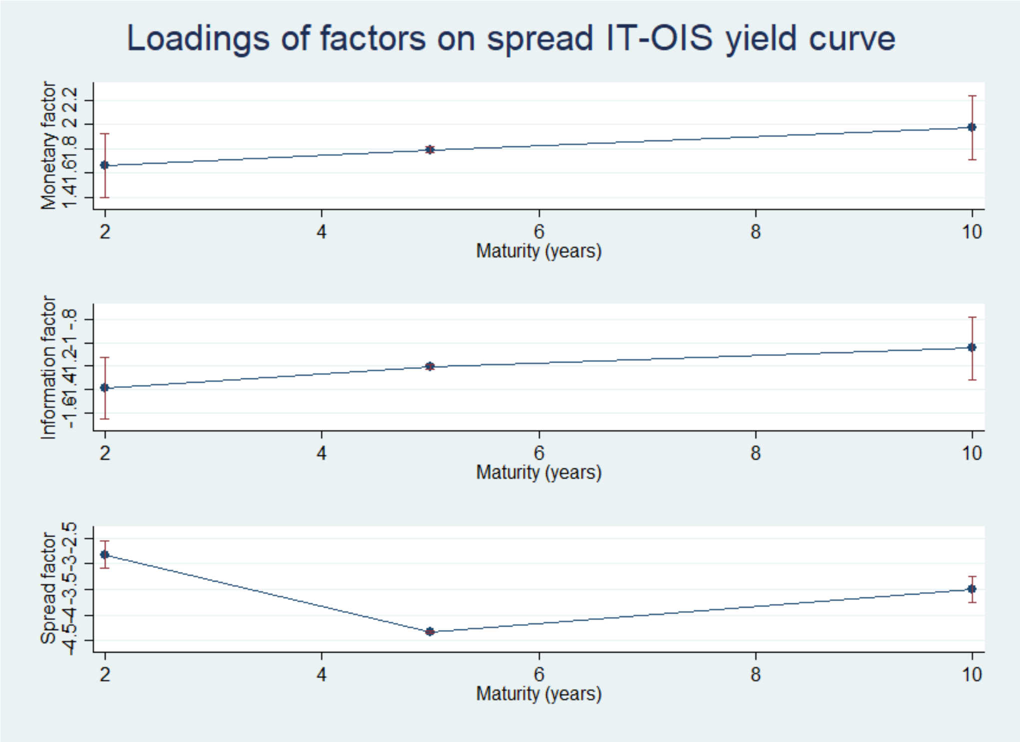

Figure 3.8: Monetary, information and spread factor loadings, obtained by regressing spread IT-OIS variations on the three factors. Red bands show 95% confidence intervals.

uncertainty surrounding our estimated factors.

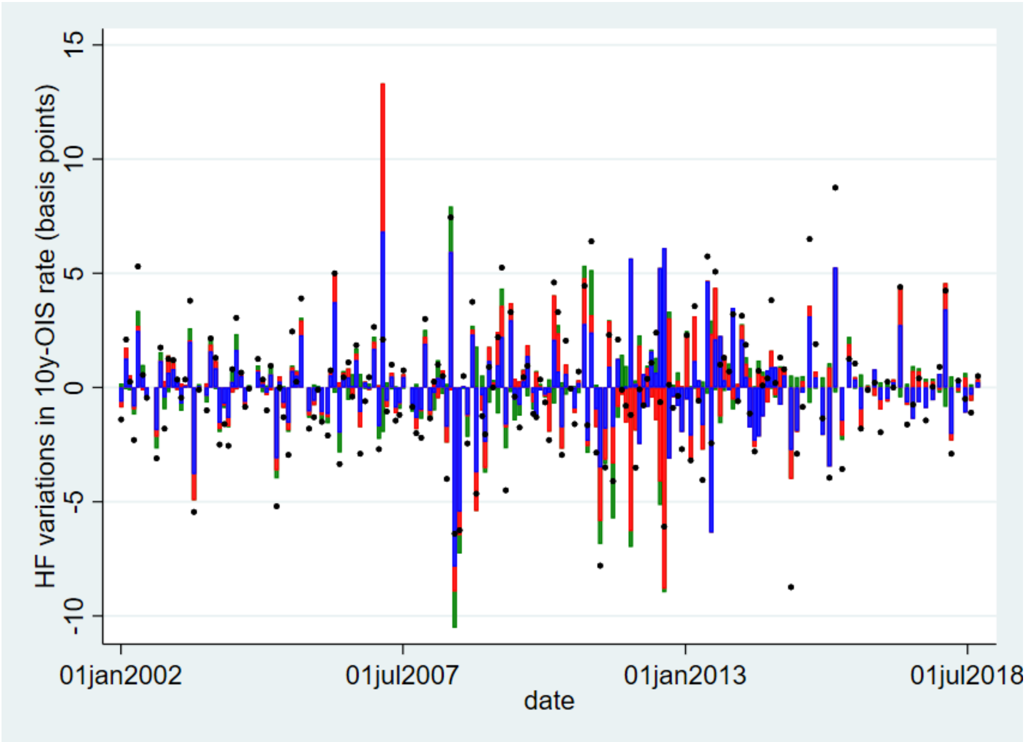

Figure 3.9: Decomposition of HF variations in the 10-year OIS rate around press conferences in the three factors: monetary factor (blue), spread factor (red) and information factor (green). Black dots show actual variations of the 10y-OIS.

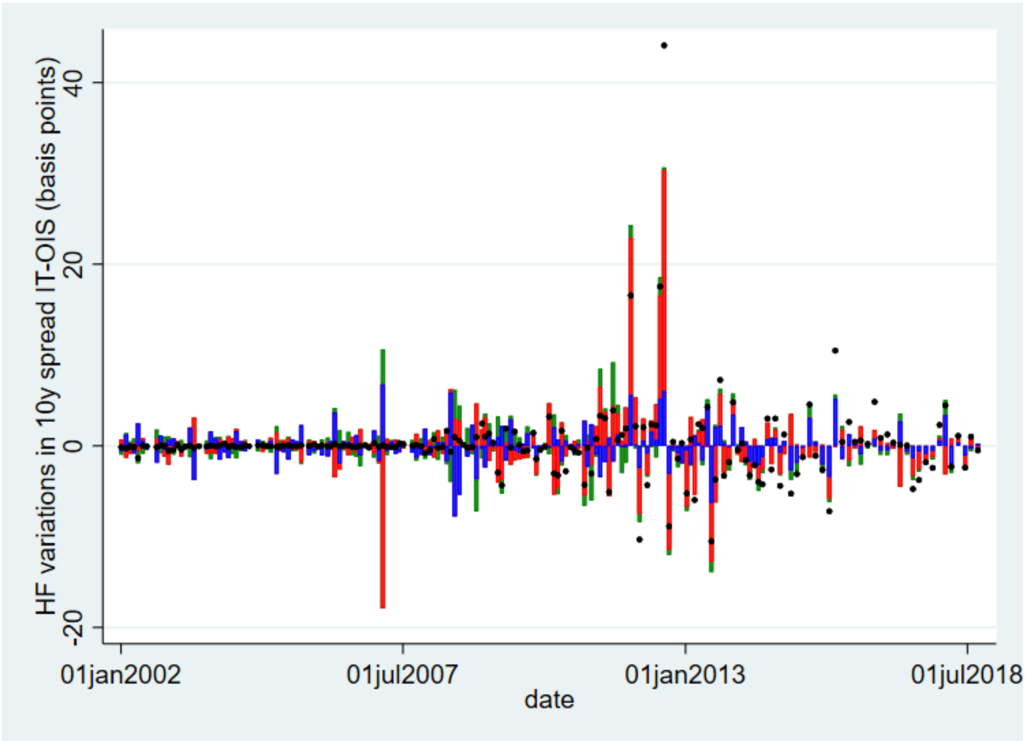

Figure 3.10: Decomposition of HF variations in the 10-year spread IT-OIS around press conferences in the three factors: monetary factor (blue), spread factor (red) and information factor (green). Black dots show actual variations of the 10-year spread IT-OIS.

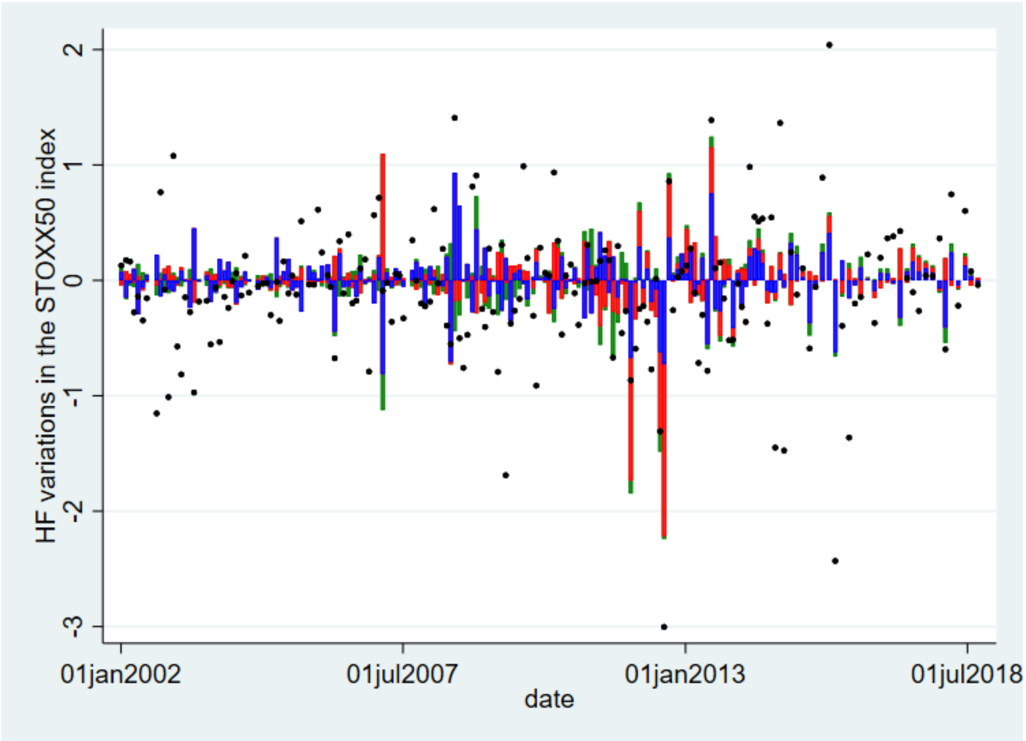

Figure 3.11: Decomposition of HF variations in the STOXX50 index around press conferences in the three factors: monetary factor (blue), spread factor (red) and information factor (green). Black dots show actual variations of the STOXX50.

3.5 Simultaneous identification of three shocks in a financial proxy-SVAR

We trace out the dynamic causal effects of the three shocks by using the three factors identified in previous section as external instruments for three shocks in a proxy-SVAR. We do so by following the methodology of Gertler and Karadi (2015),Mertens and Ravn (2013),Stock and Watson (2012), Stock and Watson (2018). Furthermore, we compare the obtained impulse responses to those obtained when ignoring the *spread shock*. We start by estimating a financial SVAR at daily frequency.

By using the approach of Angelini and Fanelli (2019), we can estimate the SVAR with multiple instruments and multiple instrumented shocks. To identify the three structural shocks of interest (monetary, spread and information shocks), we append the external instruments to the original set of variables, at the same time placing a proper set of restrictions.

We will estimate the SVAR with two different specifications. First we will ignore the novel spread shock and identify two shocks only: a monetary shock and an information shock. In this case we will use as instruments the two factors extracted in section 4, when ignoring HF surprises on the risk premium on Italian bonds. (see equation (3.4)) We will then estimate the SVAR by identifying the full set of three shocks by using the set of factors extracted in equation (3.6). By carrying out this two estimations we can compare results when considering the spread shock and when not, thus we will be able to evaluate the importance of including the spread shock in order to fully characterize ECB policies.

From the reduced form VAR, reduced form innovations are obtained:

$$\Pi(L)y_t = \mu + u_t \tag{3.7}$$

y_t is the set of endogenous variables and u_t the vector of reduced-form innovations. Let us split the vector y_t into two parts: r_t contains the three variables associated with the three shocks we are interested to identify, i.e. a long-term risk free rate, the stock market index and the risk premium on peripheral countries; x_t contains all the other variables included in the VAR. When considering only two shocks the periphery risk premium will then be included in x_t rather than in

r_t. Accordingly, the vector u_t is made of two sub-vectors: $u_{r,t}$ and $u_{x,t}$.

In our SVAR, reduced from innovations are linked to structural shocks through:

$$u_t = C\varepsilon_t \tag{3.8}$$

Following Angelini and Fanelli (2019) we augment the reduced form innovations of the VAR with the set of instrument f_t, getting the augmented representation of (3.8) :

$$\tilde{u}_t = \tilde{C}_t + \tilde{\varepsilon}_t \tag{3.9}$$

which we can decompose into:

$$\begin{bmatrix} u_{r,t} \\ u_{x,t} \\ f_t \end{bmatrix} = \begin{bmatrix} c_{rr} & c_{rx} & 0 \\ c_{xr} & c_{xx} & 0 \\ \phi & \mathbf{0} & \sigma_f \end{bmatrix} \begin{bmatrix} \varepsilon_{r,t} \\ \varepsilon_{x,t} \\ \omega_t \end{bmatrix} \tag{3.10}$$

$\varepsilon_{r,t}$ contains the structural shocks that we want to estimate. The bold zero represents the imposed exogeneity condition on the instruments. σ_f is a diagonal matrix with the standard deviations on the instruments measurement errors ω_t. In the three-shocks estimation ϕ is a 3×3 matrix which collects the relevance parameter which link the instruments to the identified shocks. To achieve identification of the c_{rr}, c_{xr} parameters, we need to impose at least 3 zero-restrictions on the ϕ matrix. In the 2-shocks estimation ϕ is 2×2 and it suffices to have one zero-restriction to achieve identification of the 2-shocks.

Our set of endogenous variables in r_t contains the 5-year sovereign AAA-rates yield, constructed by the ECB by averaging yields from Euro Area sovereign rates with triple A rating, the log of the STOXX50 index and the 10-year spread IT-OIS in the three-shocks specification. x_t contains the 2-year inflation-linked swap rate and the log of the Eur-Usd exchange rate. This set of variables is the same of that used by Altavilla et al. (2019), but for the periphery risk premium, which we add to the system. We estimate the reduced form VAR using three lags (selected by minimizing the AIC criterion) and allowing for a deterministic trend. Figure 3.12 plots the time series of the endogenous variables employed; by a visual inspection we can see that they are highly non-stationary and especially some of them display a clear trend in the sample considered.

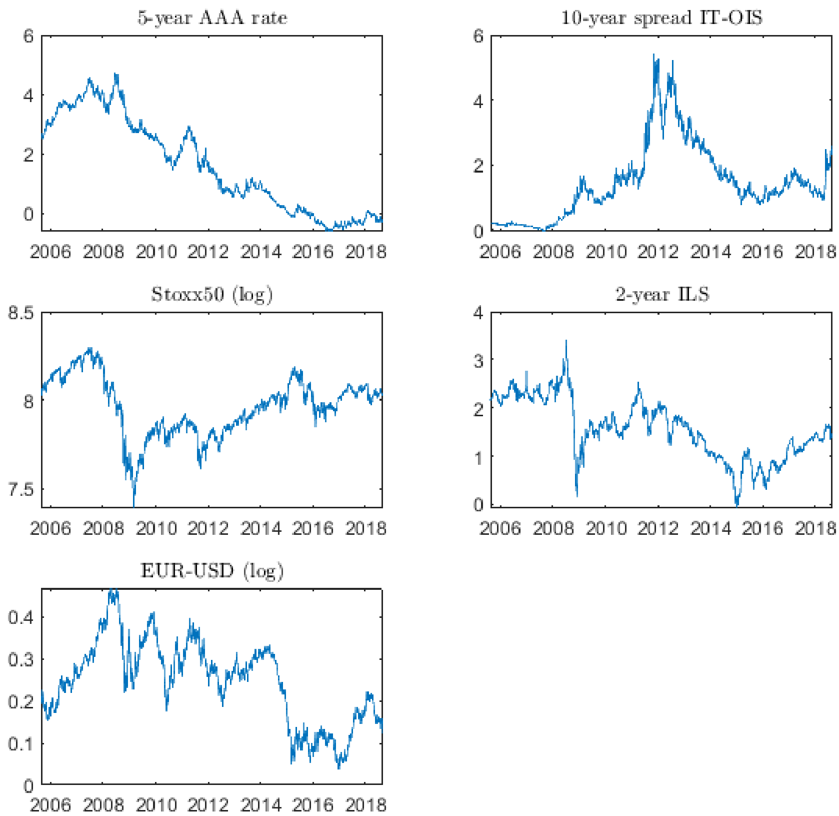

Figure 3.12: Time series of endogenous variables used in the daily proxy-SVAR.

The three identified shocks are:

$$\varepsilon_{r,t} = \begin{bmatrix} \varepsilon_{monetary,t} \\ \varepsilon_{info,t} \\ \varepsilon_{spread,t} \end{bmatrix} \tag{3.11}$$

while the three instruments we use are:

$$f_t = \begin{bmatrix} f_{monetary,t} \\ f_{info,t} \\ f_{spread,t} \end{bmatrix} \tag{3.12}$$

We impose five zero-restrictions on the ϕ matrix:

$$\phi = \begin{bmatrix} \phi_{11} & 0 & 0 \\ 0 & \phi_{22} & \phi_{23} \\ 0 & 0 & \phi_{33} \end{bmatrix} \tag{3.13}$$

This structure for the ϕ implies that each instrument is assumed to be correlated only with the single shock to which it refers. The only exception is the information factor which is assumed to be correlated with the spread shock as well. This departure from a diagonal ϕ is made in order to account for possible imperfections in the procedure we carry out to disentangle the spread shock and the information shock (see section 4).

In the two-shocks specification, ε_t, f_t and ϕ simplifies to:

$$\varepsilon_{r,t} = \begin{bmatrix} \varepsilon_{monetary,t} \\ \varepsilon_{info,t} \end{bmatrix} \quad f_t = \begin{bmatrix} f_{monetary,t} \\ f_{info,t} \end{bmatrix} \quad \phi = \begin{bmatrix} \phi_{11} & 0 \\ 0 & \phi_{22} \end{bmatrix} \tag{3.14}$$

Figure 3.13 displays impulse response functions to a monetary shock, normalized to lower by 10bp the 5-year AAA rate, identified by ignoring the spread shock. Figure 3.14 shows the same impulse responses when also including the spread shock into the analysis. Confidence intervals are computed using the Moving Block Bootstrap (Kunsch (1989)), as suggestd by Jentsch and Lunsford (2019). The monetary shock in the two specifications has very similar effects on all variables, in terms of their magnitude and persistence. It is however rather clear the different effect on the peripheral risk premium. In the 2-shocks specification the monetary shock has no statistically significant effect on the risk premium, neither at the 68% nor at the 90% level. When including the spread shock into the analysis we instead observe the expected reaction of the risk premium, which reacts to the monetary shock with a decrease more or less of the same magnitude of the decrease in the risk-free rate. Interestingly, the effect is also very persistent and it lasts more than the reduction in the risk-free rate.

Figure 3.15 plots the impulse responses to the novel spread shock, normalized to lower the spread IT-OIS by 10bp. Firstly, the positive effect on the 5-year risk-free rate is consistent (5bp increase) and quite persistent as well. This results gives importance to our choice to take this shock into account, as it has non-negligible and long-lasting effects on the risk-free yield curve,

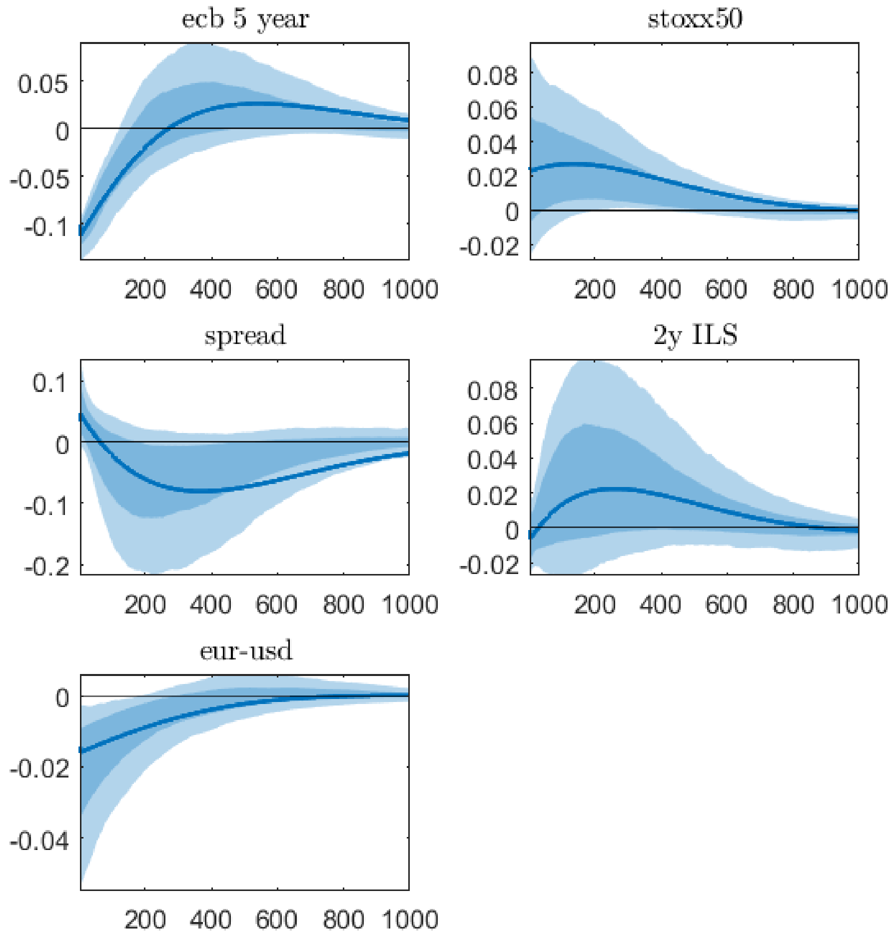

Figure 3.13: Estimated impulse responses to a monetary shock when ignoring the spread shock. Shaded areas depict 90% bootstrap confidence intervals, darker areas 68% confidence intervals.

which is usually used alone to measure monetary policy shocks. We don't observe significant effects on either the stock market or the 2-year ahead inflation expectations, measured by the inflation-linked swap rate. This results may suggest that this type of shock is not relevant for explaining macroeconomic fluctuations in the Euro Area, though the analysis at the monthly level which we will carry out in the next section points to the opposite result.

Finally, Figure 3.16 displays impulse response functions to an information shock, normalized to lower by 10bp the 5-year AAA rate, identified by ignoring the spread shock. Figure 3.17 shows the same impulse responses when also including the spread shock into the analysis. In both

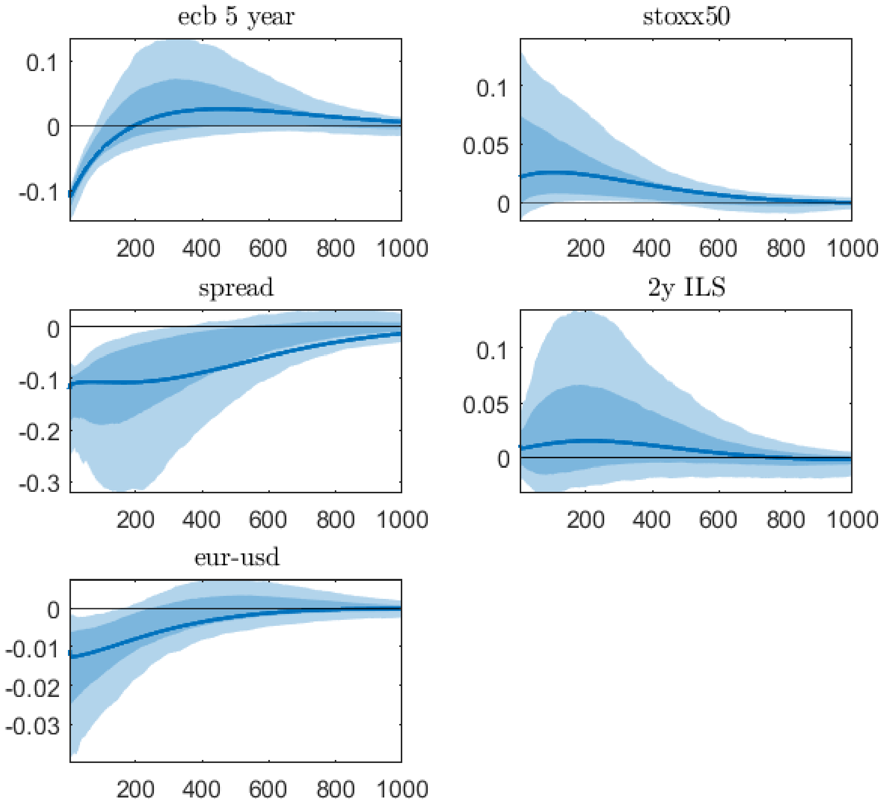

Figure 3.14: Estimated impulse responses to a monetary shock. Shaded areas depict 90% bootstrap confidence intervals, darker areas 68% confidence intervals.

specifications the variability of the estimated impulse responses makes the effects of the shock not significant at all. The simultaneous identification of the multiple shocks exploited here points to the conclusion that the information shock is a negligible issue in the analysis of monetary policy in the Euro Area. This is particularly true when also including the spread shock into the picture. Although, similarly to Jarociński and Karadi (2020)we use the reaction the stock market to disentangle the information shock from the monetary shock, these results contrasts with what found by them, which however look at very short maturity rates (3 month-future) and at the full monetary event (press release + press conference).

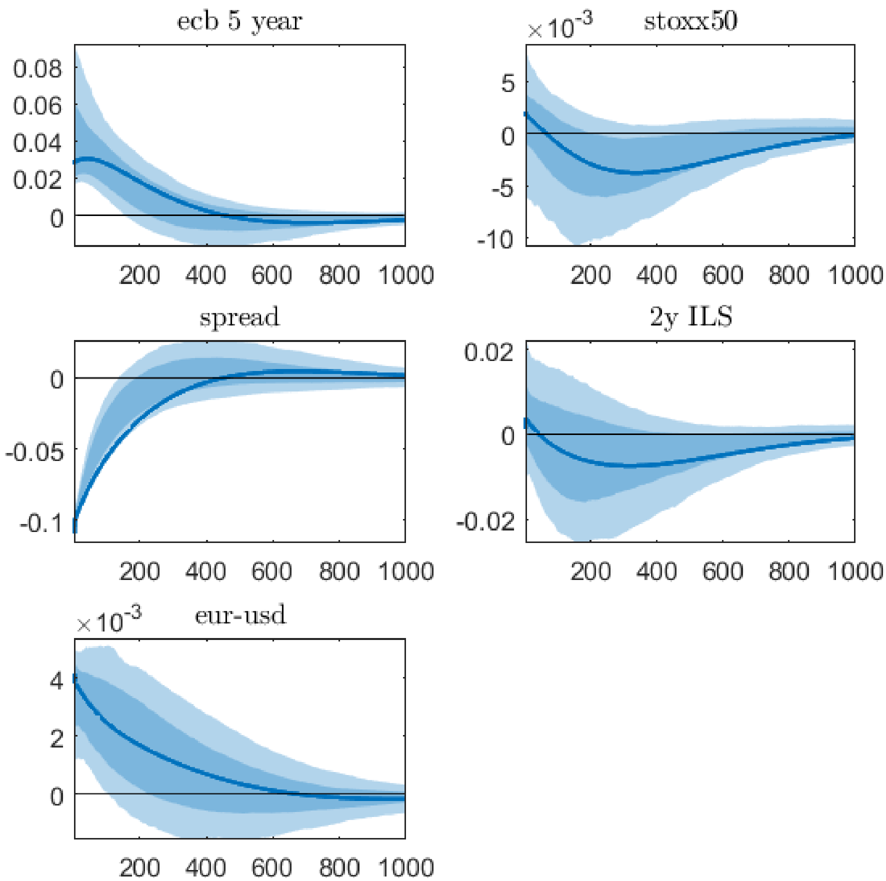

Figure 3.15: Estimated impulse responses to a spread shock. Shaded areas depict 90% bootstrap confidence intervals, darker areas 68% confidence intervals.

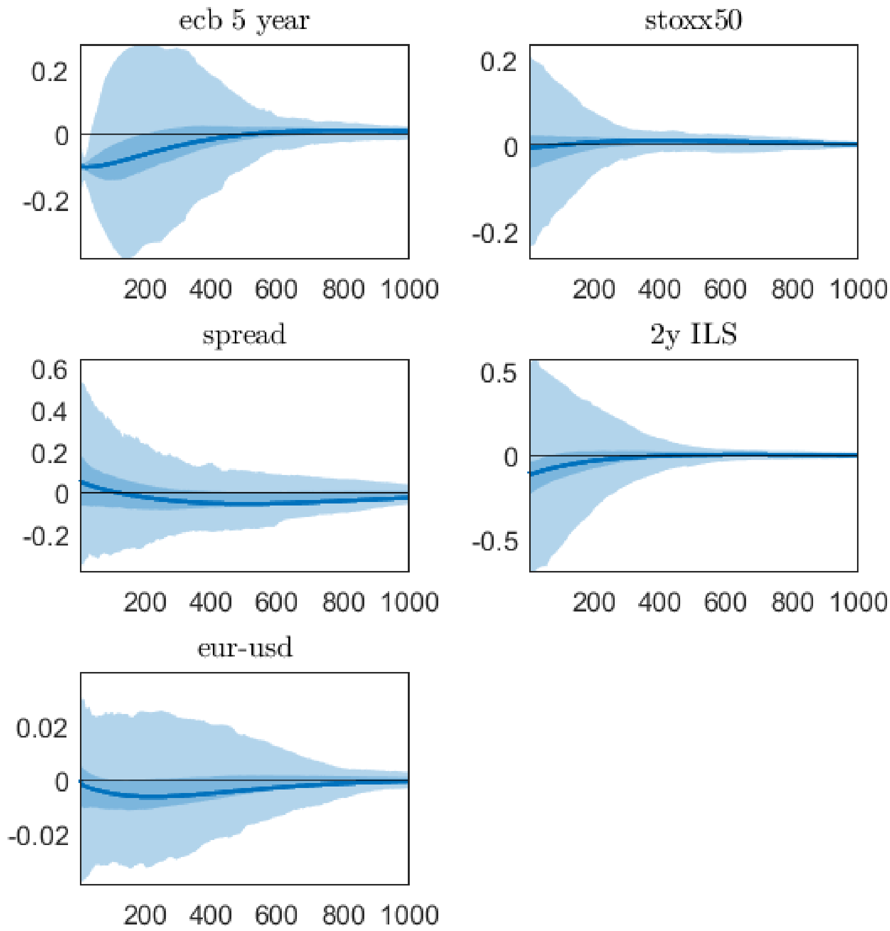

Figure 3.16: Estimated impulse responses to an information shock when ignoring the spread shock. Shaded areas depict 90% bootstrap confidence intervals, darker areas 68% confidence intervals.

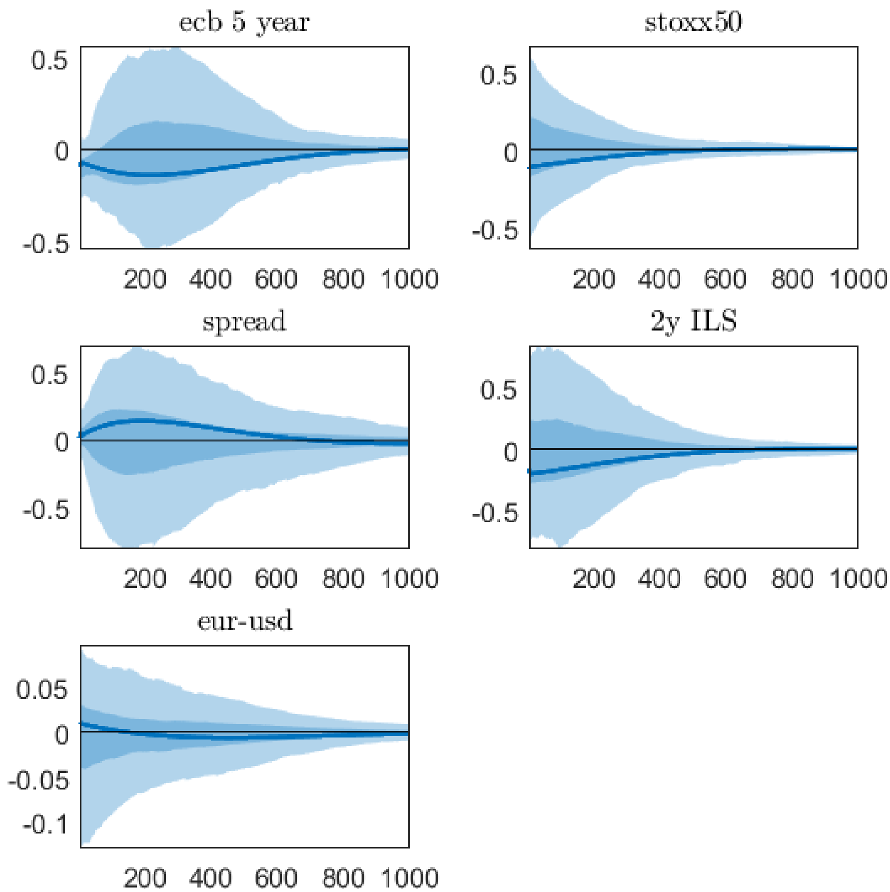

Figure 3.17: Estimated impulse responses to a information shock. Shaded areas depict 90% bootstrap confidence intervals, darker areas 68% confidence intervals.

3.6 Macroeconomic effects of policy shocks.

We turn now to the identification of the macroeconomic effects of the three shocks, in particular of the newly identified *spread shock*, which is meant to be a synthetic measure of all the policies implemented by the ECB aimed at controlling the risk premium on peripheral countries debt. As explained in Foroni and Marcellino (2016), estimating a low-frequency VAR on time series obtained by aggregating HF data generated by an HF data-generating-process creates important problem for identification. We think this is the case in our application, as the shock is estimated at daily frequency. Macro variables are instead observed at monthly frequency, so we need to aggregate the shock. In this regard we will follow the approach of Gertler and Karadi (2015): each observation of the proxy for the shock is assumed to last 30 days, or less if a press conference is held before. We then take the monthly average of the resulting daily series to get the monthly proxy. To avoid incurring in the issues explained by Foroni and Marcellino (2016), we estimate the dynamic causal effects of the shocks by running local projections (Jordà (2005)), using the estimated spread factor as an external instrument, one at a time.

At this point we are assuming that the true data-generating-process operates at daily frequency. The magnitude of the bias induced by the aggregation procedure depends on the number of true lags in the daily VAR DGP. Of course the three-lags structure assumed in the previous section is an approximation meant to deal with a possible much more complicated DGP. In this regard the number of relevant lags could be much larger, thus creating stronger issues in the estimation of a VAR aggregate at monthly frequency.

We run local projections using as endogenous variables: the 5-year ECB AAA rate (monthly average), the 10-year spread IT-OIS, the log of the Euro Area industrial production index (excluding construction), the log of the STOXX50 index, the log of the HICP index, the CISS index of systemic risk and financial distress constructed by the ECB and the IMF index of commodities prices. Figure 3.18 depict monthly time series. [5] We estimate local projections regressions using 12 lags and allowing for a time trend.

Figure 3.21 shows estimated impulse responses to a spread shock, normalized to lower the the

[5]This set of variables is similar to the one used by Baumgärtner and Klose (2019)

10-year spread IT-OIS by 10 basis points on impact. The estimated reduction in the Italian risk premium is quite short-lived (10 months) and it is accompanied by an increase in the 5-year AAA rate of similar duration. The shock causes a significant increase in output and a persistent increase in the price index. This latter result is particularly interesting as for the other two shocks we struggle to detect the expected transmission to inflation, as we can see from figures 3.19 and 3.20. In particular we estimate a quite strikingly persistent decline in consumer prices following an expansionary monetary shock normalized to lower the 5-year AAA rate by 10 basis points. These results confirms the idea that policies like the QE have struggled to inflate the economy.

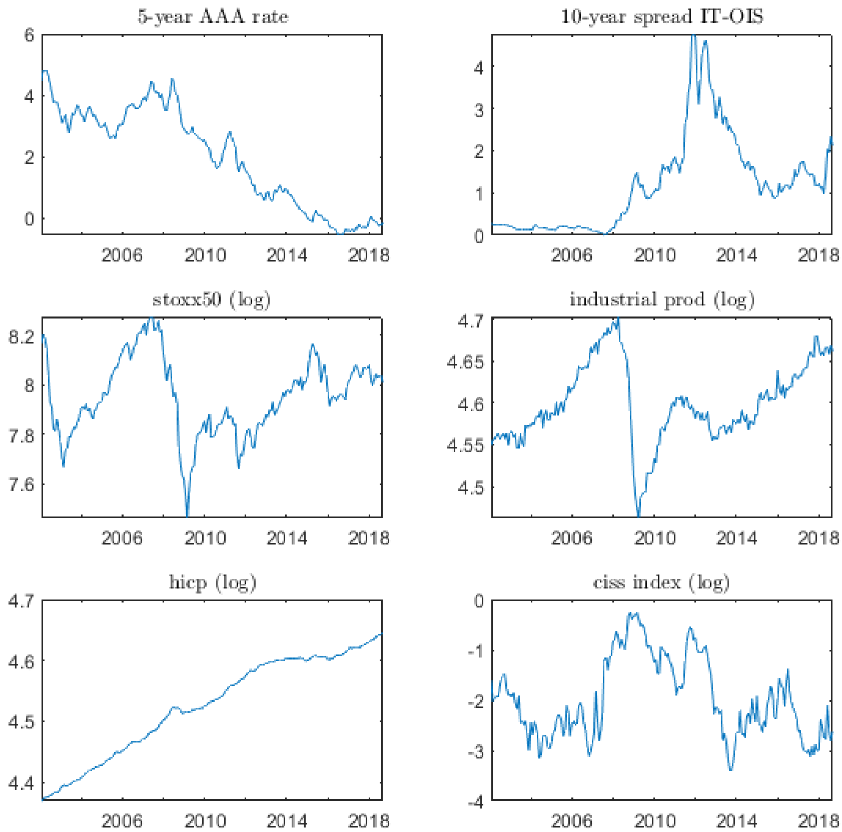

Figure 3.18: Time series of endogenous variables used in the local projections at monthly frequency.

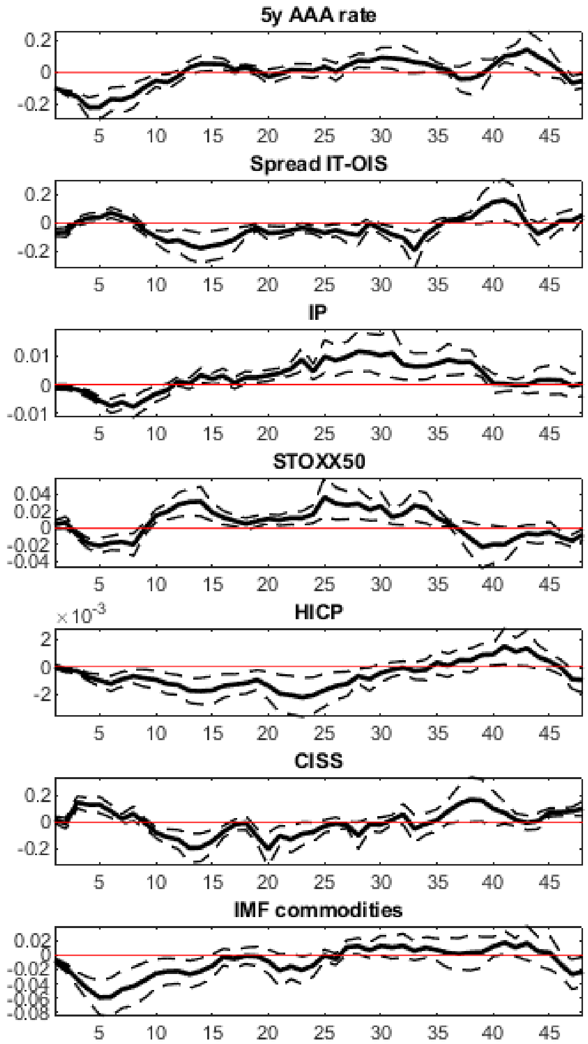

Figure 3.19: Estimated impulse responses to a monetary shock. Dotted lines depict 95% robust confidence intervals.

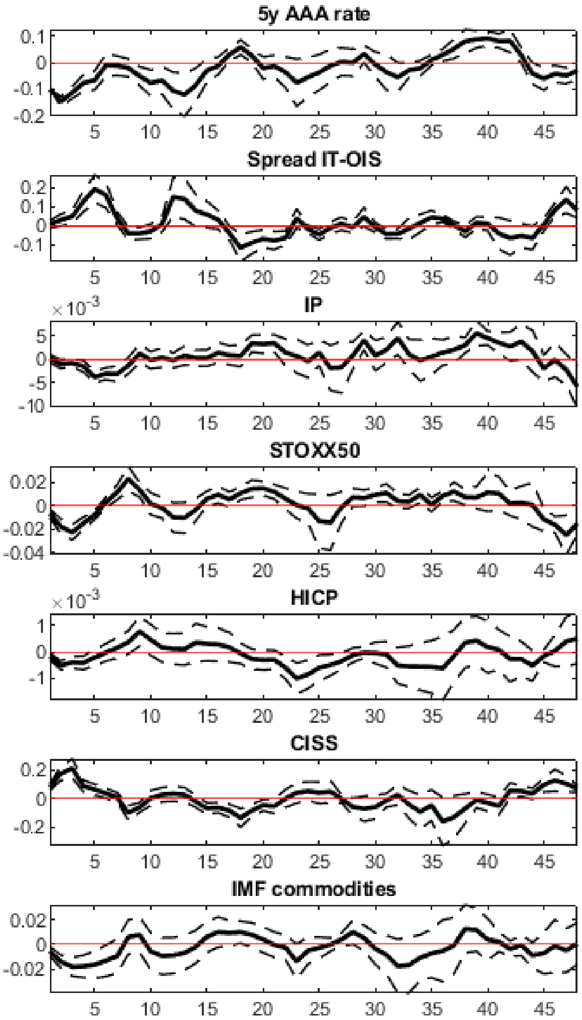

Figure 3.20: Estimated impulse responses to a information shock. Dotted lines depict 95% robust confidence intervals.

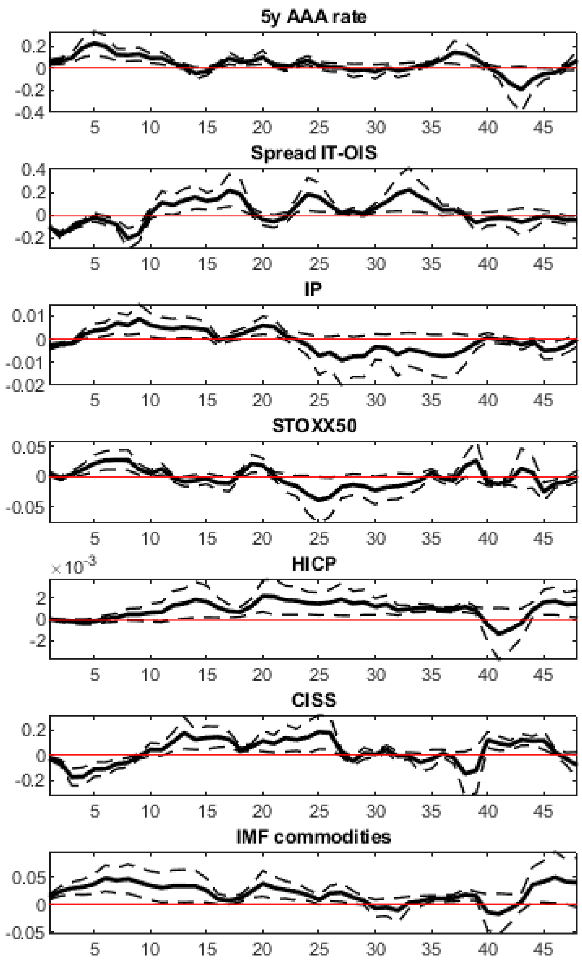

Figure 3.21: Estimated impulse responses to a spread shock. Dotted lines depict 95% robust confidence intervals.

3.7 Conclusion

The years of the sovereign debt crisis and the recent global crisis due to the Covid-19 pandemic has made very clear the important role of the ECB in stabilizing economic activity by using a set of unconventional tools, including the direct targeting of sovereign spreads. It is therefore essential to effectively decompose monetary shocks into components related to more traditional policy rules to those related to spread-targeting policies. This paper takes an explicit stand on this idea.

When looking at HF co-movement of long term OIS rates and Euro Area peripheral countries risk premia around ECB press conferences we detect a puzzle, as the expected positive correlation is not observed for a significant fraction of monetary policy events, especially in the aftermath of the crisis following 2008. The puzzle cannot be resolved by only allowing for a central bank information type of shock, acting simultaneously with the monetary shock. We solve the puzzle by allowing for a third shock, called a *spread shock*, which results from the ECB directly affecting risk premia of EA periphery, with indirect consequences on long term OIS rates. This procedure allows us to separately identify:

- A monetary shock, meant to capture all unconventional policies/announcement aimed at reducing the long term risk-free rate, measured by OIS rate.
- An information shock, in the spirit of Nakamura and Steinsson (2018).
- A novel spread shock, which synthesizes all policies/announcements by the ECB aimed at reducing pressures on the risk premia on peripheral countries.

We address the challenge of identifying these three simultaneous shocks by implementing a sign restriction approach, exploiting the fact that we expect them to affect both risk-free yield curves and the yield curves of peripheral countries which carry a risk premium. Reactions of the stock market are also exploited to disentangle the shocks. This strategy allows us to obtain proxies for the several shocks to be used in a proxy-SVAR and local-projections context.

We have shown that the *spread shock* has significant effects on relevant Euro-Area macroeconomic variables and seems to have been more effective than the other two types of shocks in boosting inflation in the Eurozone.

.1 Daily frequency analysis, one shock at a time

In this section we repeat the analysis of dynamic causal effects of the three shocks at daily frequency. This time we perform identification of the impulse responses by identifying the shocks one at a time, using again a proxy-SVAR approach. As we have only one instrument for each specification we can use the IV methodology to estimate the shock of interest, as in Gertler and Karadi (2015). Structural parameters are obtained in this approach using a two-stage-least-squares method which allows to isolate the component of the innovations in the policy indicator which is exogenous to the other shocks of the system. Notice that for the monetary shock and the information shock we use the 5-year AAA rate as the relevant policy indicator, while for the spread shock we use the 10-year IT-OIS spread.

Figure 22 compares the estimated responses to a monetary shock, when using the three factors decomposition for obtaining the instruments and when using only two factors, thus ignoring the spread shock. In other words, in the estimation on the left we instrumented the 5-year AAA rate with the first factor identified from equation (3.6), where the three shocks description is employed. On the right side instead we show impulse responses from the proxy-SVAR estimated by instrumenting the 5-year AAA rate with the first factor identified in equation (3.4), when the spread shock is ignored.

We obtain the expected response of the IT-OIS spread, which reacts to an expansionary monetary shock, normalized to lower by 10bp the 5-year risk-free rate, by decreasing by the same magnitude. The effect is quite persistent and lasts almost 1 year. In the right column, where the spread shock is ignored, the spread reacts in the opposite way at the beginning, while the effect is insignificant on longer horizons. Interestingly, in both cases the 2-year inflation-linked swap rate does not react significantly, suggesting this type of unconventional policies have struggled to move inflation expectations.

Figure 23 compares in the same fashion the responses to a negative information shock, normalized to lower by 10bp the 5-year risk-free rate. A negative information shock which lowers the long term rate. Quite surprisingly, the increase in the spread IT-OIS is much higher (20bp) when the spread shock is taken into account than when it is ignored (5bp increase). A negative information shock is estimated to reduce inflation expectations in both cases, but the magnitude of the effect decreases when including the spread shock.

Finally, Figure 24 plots the responses from the estimated spread shock, normalized to lower the IT-OIS spread by 10bp. The shock is estimated to have no significant effect on the stock index and on inflation expectations, which is instead captured by the other two shocks. It's worth noticing that the estimated effect of the spread shock on the 5-year safe rate is significant and quite persistent. This results justifies our assumption that the risk-free yield curve is affected by spread shock, and therefore that is must be taken into account when extracting factors from HF variations in the OIS yield curve.

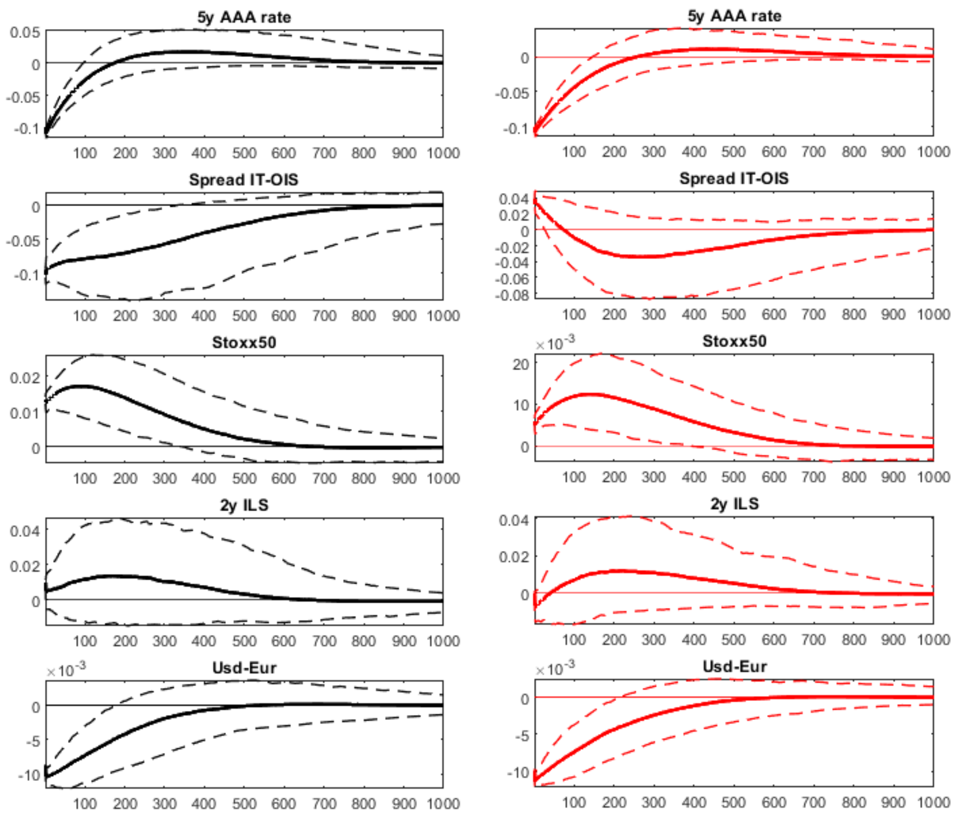

Figure 22: Estimated impulse responses to a monetary shock, taking into account the spread shock (left figure, black) and ignoring it (right figure, red). Dotted lines depict 90% bootstrap confidence intervals.

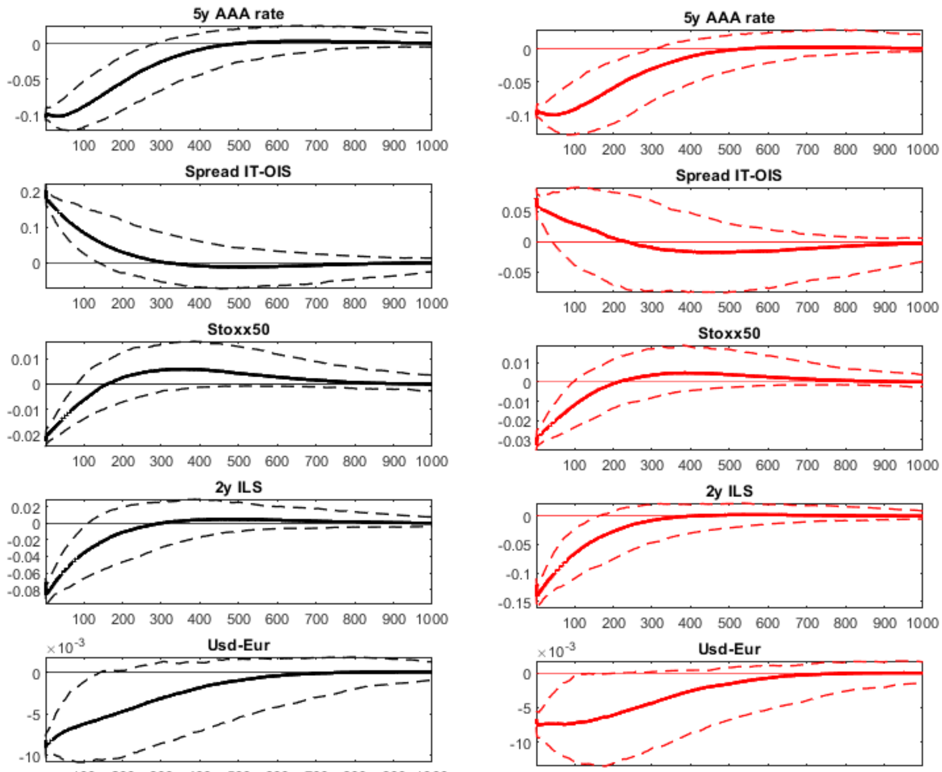

Figure 23: Estimated impulse responses to a information shock, taking into account the spread shock (left figure, black) and ignoring it (right figure, red). Dotted lines depict 90% bootstrap confidence intervals.

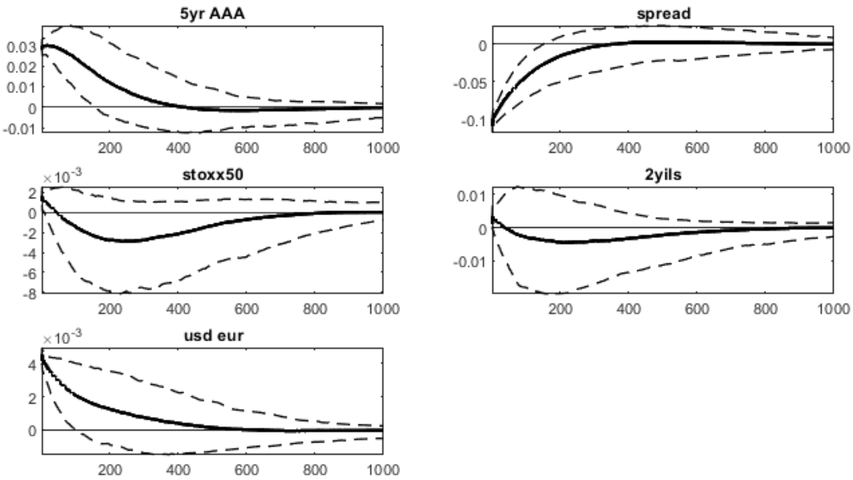

Figure 24: Estimated impulse responses to a spread shock. Dotted lines depict 90% bootstrap confidence intervals.

.2 Including the risk premium on Spanish bonds

In this section we repeat the whole analysis by exploiting also the yield of Spanish sovereign bonds to build the peripheral countries risk premium. This check is needed to make sure that by looking at Italy only, we don't incur into effects specific to the Italian sovereign bond market. This exercise shows that results don't change to this extension.

When looking at HF movements of the sovereign spreads around ECB press conferences, we see that variations in the spread IT-OIS and the spread ES-OIS are very strongly correlated. More precisely, the correlation between HF variations in the risk premium of the two countries at 10-year maturity is 0.96. This extremely high correlation suggests that the factor decomposition analysis performed in section 4 is still valid when including Spanish rates, so we don't repeat this stage of the empirical analysis.

As for the daily proxy-SVAR and the monthly LP-IV, we repeat the analysis by using, instead of the spread IT-OIS at 10-year maturity, the average between this spread and the spread ES-OIS at 10-year maturity. Figures 25 and 26 shows the obtained impulse response functions, at daily and monthly frequency. We can see that there is no tangible difference with the baseline estimations, when only the risk premium on Italian bonds is considered.

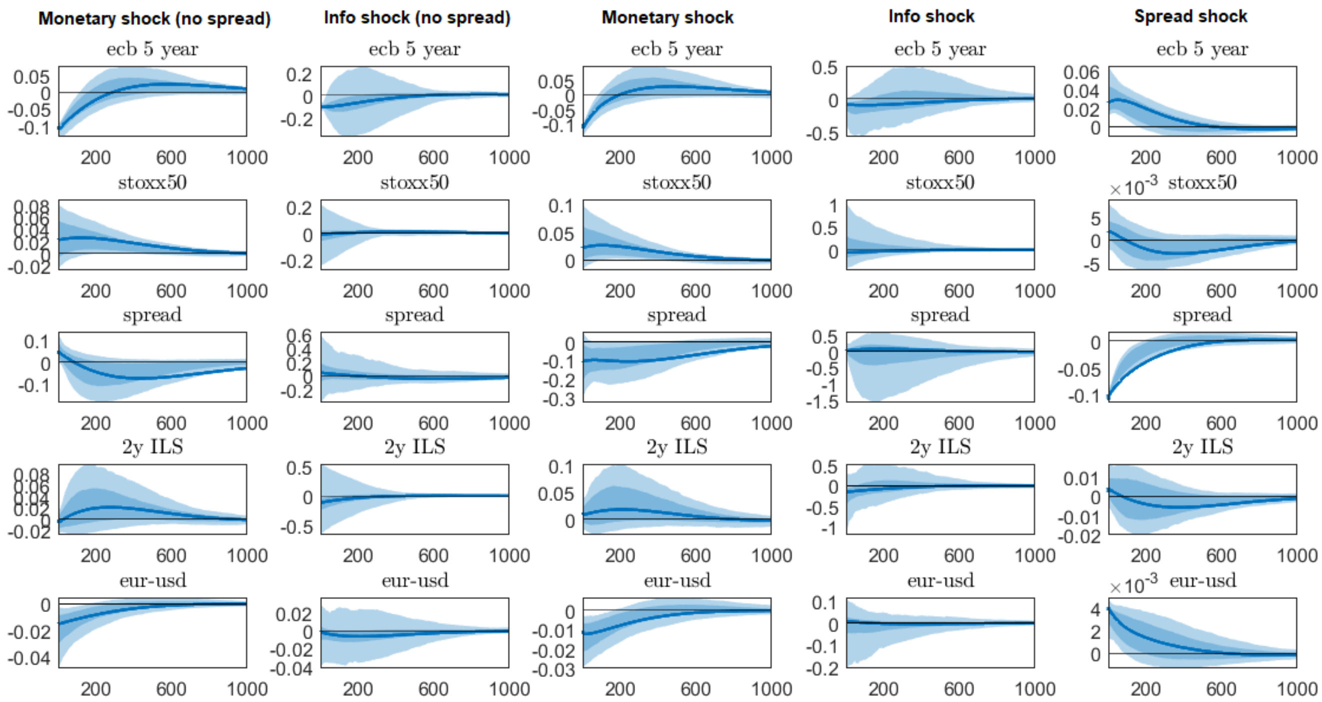

Figure 25: Estimated impulse responses to estimated shocks at daily frequency, using the average of Italian and Spanish spreads. Shaded areas depict 90% bootstrap confidence intervals, darker areas 68% confidence intervals.

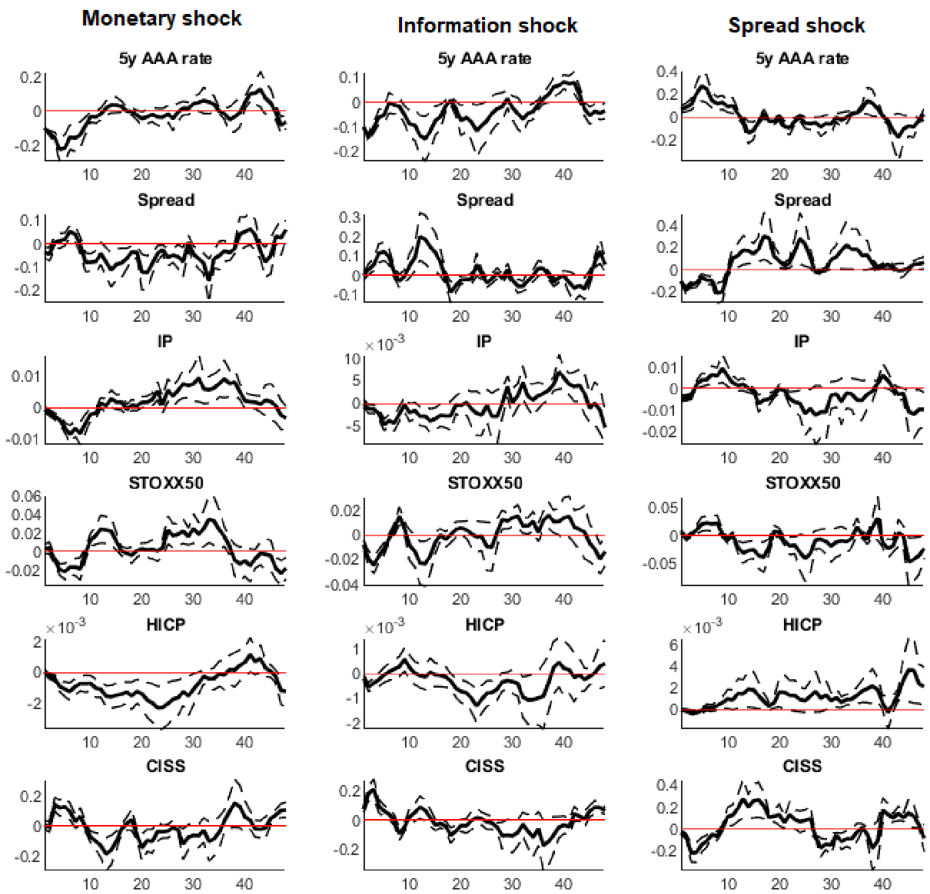

Figure 26: Estimated impulse responses to estimated shocks at monthly frequency, using the average of Italian and Spanish spreads. Dotted lines depict 95% robust confidence intervals.

.3 Model uncertainty

In Section 4 we employed sign+other restrictions to extract factors to be used as proxies for the three shocks. This procedure entails a model-selection stage which needs further discussion. Equations (3.5) and (3.6) in section 4 shows the factor decomposition that we aim to obtain. In practice, there are infinite possible ways to decompose the vector δ_t into three orthogonal factors. In other words, there are infinite possible models that explain the considered HF variations in asset prices using a three-factors setup. Among these infinite possible we select only those satisfying the imposed sign+other restrictions and use the Median Target method to select a single model and obtain the proxies for the three shocks, as explained throughout the paper.
In the discussion above we ignored the issue of model uncertainty, that is: how likely are our sign restrictions to hold among the randomly generated models? How different are the models among which we could choose? How robust are our results to different model-selection procedures?
Starting from the first question, the 1000 randomly generated Λ^* satisfying our restrictions are obtained after having generated 81408 models, i.e. 1.2 % of the generated models satisfy our restrictions.
Regarding the second question, Figure 27 plots the distribution of the single elements of Λ over the 1000 models satisfying the restrictions imposed. Green vertical dashed lines show the values picked by the Median Target method, that is the model we selected. Red lines show instead the model we would select if we were maximizing instead of minimizing the distance from median values. In other words these values represent the worst possible model, from the Median Target perspective. This figure gives us an idea about the uncertainty around our estimates. Most of the coefficient display a nice symmetric distribution around the values selected by the Median Target method. Only few coefficients display instead a more irregular distribution.

Finally, we want to test how our results are robust to other model selection procedures. In Figures 28, 29, 30 we therefore compute the impulse response functions from the daily proxy-SVAR from five different models. To each of the 1000 models generated above a value corresponding to the distance from the Λ^* containing the median values is associated. We therefore obtain a distribution of this distance along the 1000 models. From this distribution we select 5 values, which corresponds to five different models: the minimum (which is the baseline, i.e. the one chosen by the Median Target method), the maximum and the 25^{th}, 50^{th}, 75^{th} percentiles. The impulse responses depicted show the results from the five different models: red lines show the baseline and black lines show the worst models according the Median Target rule. Grey lines show the results from the three percentiles (darker grey lines correspond to higher percentiles).

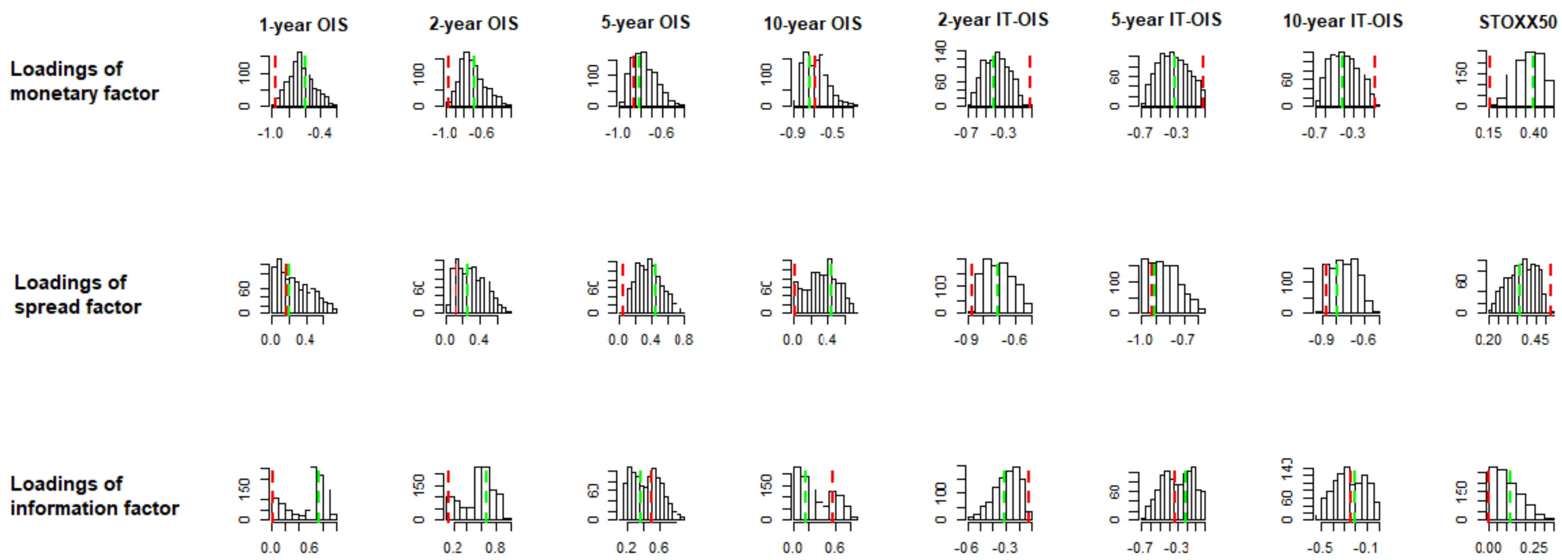

Figure 27: Distribution of the elements of Λ^* over the 1000 generated models satisfying the imposed restrictions. Green and red vertical dashed lines show respectively the best and worst models selected by the Median Target method.

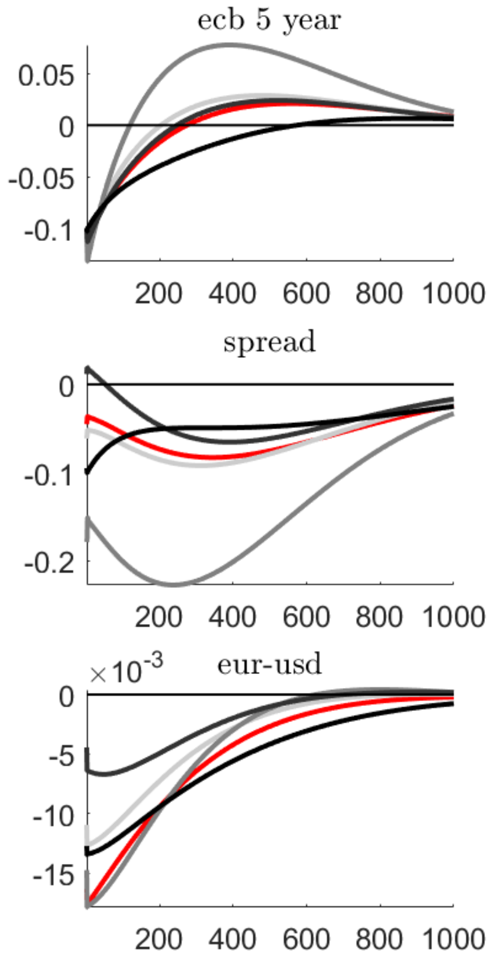

Figure 28: Estimated impulse response functions to a monetary shock, estimated using five different models to extract factors. The red lines depict the baseline estimated using the median target method. Grey to black lines show impulse responses from other models, where darker figures correspond to models further from the median target.

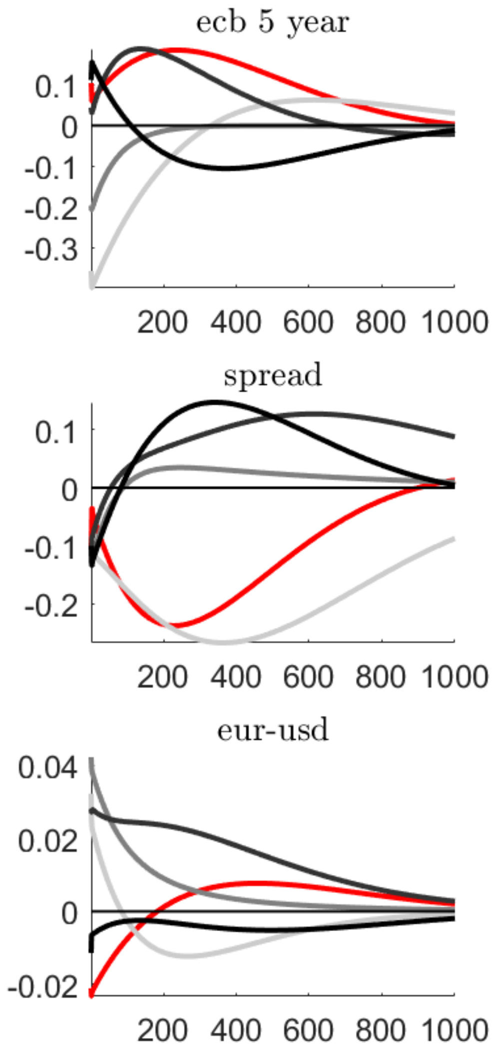

Figure 29: Estimated impulse response functions to a spread shock, estimated using five different models to extract factors. The red lines depict the baseline estimated using the median target method. Grey to black lines show impulse responses from other models, where darker figures correspond to models further from the median target.

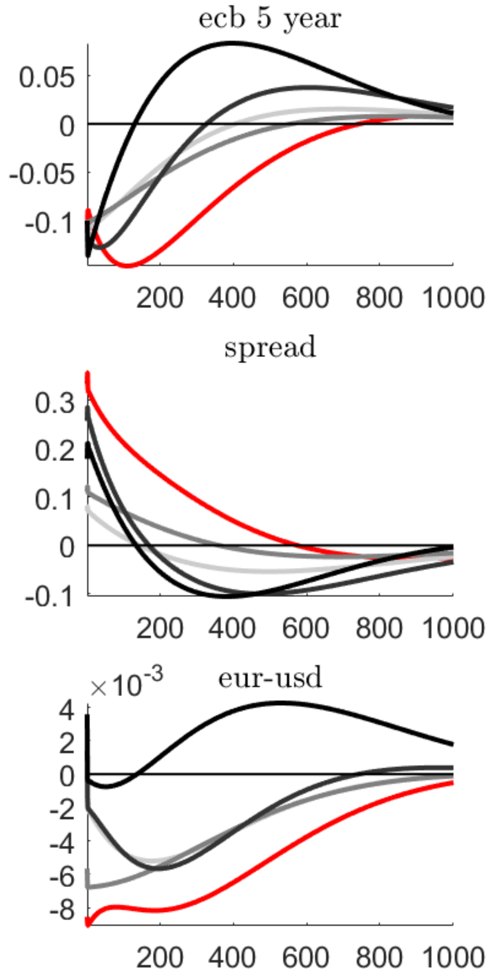

Figure 30: Estimated impulse response functions to a information shock, estimated using five different models to extract factors. The red lines depict the baseline estimated using the median target method. Grey to black lines show impulse responses from other models, where darker figures correspond to models further from the median target.

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