When Policy Surprises Spain: Volatility and Predictability of Monetary shocks around Policy Announcements

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Abstract

The European Central Bank has a particular manner of realising news about future monetary paths: First the Council of Governors reveals which are the new paths, and 30 minutes later they explain why the decision was taken. I exploit a novel data base from [Altavilla et al., 2019] that tracks asset prices around these two different monetary events to investigate how Spanish bonds react to monetary news. First, Spanish bonds have volatility clusters on the explanation window (Press Conference), thus the variance of the shocks is forecastable. Second, I find that it is possible to predict shocks from the explanation of the news, based on observed shocks that took place at the first announcement. The reaction of Spanish assets during the explanation time is linked to the reaction of other assets during the Press release, hence it is possible to build a dynamic regression that estimates the reaction of a a yield to a shock, based on previous shocks from a different window.

1 Introduction

Over the last decades central banks around the world have been moving toward transparency. They release more (valuable) information, and spread views about the economic outlook. This is, in fact, good news for both markets and banks (see [Woodford, 2005]). However, the communication strategy has never been as important as it is nowadays, in developed economies, from the 2008 Financial Crisis up to date.
The current monetary landscape is populated by unconventional policy tools that serve central banks to stabilise the economy at the effective lower bound. Many papers discuss those new tools, their effectiveness, and to what extent are reliable to achieve policy targets. [Bernanke and Reinhart, 2004] makes an early assessment of how banks may face low short term interest rates, when only few countries were effectively constrained. [Joyce et al., 2012] measures the effect of Quantitative Easing and reviews theoretical literature, and [Bernanke, 2020] revisits the initial question posed in 2004, concluding that Quantitative Easing, Forward Guidance and communication strategies have worked pretty well helping policy makers to stabilise the economy and pursue inflation targets.

This paper does not pretend to extend the literature on unconventional monetary policy, either to measure its effectiveness. Instead, I exploit a feature in the communication strategy of the *European Central Bank* that allows me to link the movement of many different assets and yields right on the announcement window. Concretely, I am able to 1) match the reaction of assets across various countries and maturities, 2) decompose the total reaction to news released into two, one linked to the pure policy change, and the other feeded by the explanation of why the policy was taken.
This paper makes a comprehensive assessment of the response of Spanish financial assets to policy announcements. By mean of the recently released *Euro Area Monetary Policy Event-Study Database*, presented in [Altavilla et al., 2019], I track movements, co-movements, and volatility, in response to policy actions and explanations, for the period 2002-2020.

As an overview of contents, the paper is organized as follows: 2) Second section defines the data and discuss the identification strategy that I follow to capture the dynamics of news over asset prices. 3) Third part develops the econometric procedures needed to isolate effects. There I discuss identification problems and explain the mathematical reasoning behind news releases. It has three subsections: The first one visually discuss the data, throw descriptive statistics and argue about the volatility. Second subsections estimates G/ARCH models, while the third estimates the dynamic regression to make forecast. 4) Fourth sections is left for comments, results and further research, as well as weaknesses of the paper.

2 Data and Identification

2.1 Data

I work out the novel database built by [Altavilla et al., 2019], which is intended to serve as the base source of information to study causal monetary phenomenons in the Euro Area. The database contains detailed temporal information of the movement of many financial variables, assets and yields, on the basis of the ECB's Governing Council meetings. Available information starts on the early 2000's. The data is reported on irregular time spans, which match the monetary announcements of the ECB. Yet the uneven distribution of observations does not pose an interpretation problem because policy makers meet on regular basis. Along the 20 years covered by the sample, the Council meets once a month at the same time, 13:30 Central Europe Time. Moreover, mismatches on the regularity of the meetings are addressed on the Online Appendix provided by the authors. Variables of interest do not suffer from this miss alignment on the time series because they are not stock variables. As an example, GDP cannot be measured on an irregular basis because it is real variable that captures the stock of something that takes time to be produced. However short-term rates and IOS's indexes automatically adjust so do not reflect any stock of nothing that requires certain production time. Another point worth to mention is that I look at very specific market reactions to policy news, so by definition of the research question I pay attention to highly flexible variables that react to news, hence the timing convention of the time series is not a problem.

2.2 Identification of Events

The *Euro Area Monetary Policy Database* is meant to be used for Event Study designs, concretely, it reports market reactions to policy announcements. Its design relies on the fact that news are revealed in a two-step conference at the ECB.

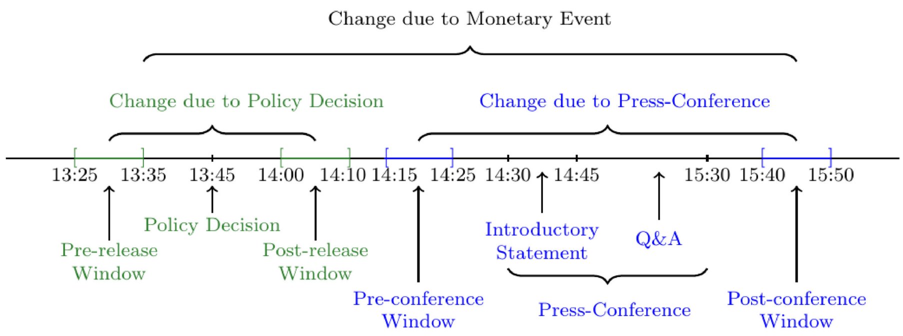

Figure 1: Timing Convention of a typical ECB's meeting

Figure 1 shows how news are revealed. There are two brackets to which the market reacts differently. Over the press conference window, between 13:25 and 14:00, the Council unmasks the new paths for monetary variable and targets, without further information. Changes on this span are the result of the Policy Decision itself. After a break, there is a press conference in which entitled members explain the why of the policy. The conference reveals news about the estate of the economy, and journalists ask questions to officials. Asset prices on this interval have more informed reactions because the market already knows the policy, in addition to the arguments that support it. The window structure of the conference allows to isolate the effect of central bank communication on the assets' return. Precisely, it is possible to estimate the relative difference in effects that produces informed and uninformed policy decisions. Figure 1 shows the time span between news communication and their respective supporting arguments. So far, I am able to observe how much asset prices deviate due to policy announcements, and to what extent the policy conference offsets this initial deviation.

3 Methods

3.1 Descriptive statistics

Figure 2 plots two effects: red line represent deviations during the Press Release, while the blue line is deviations that take place over the Press Conference. Deviations due to the conference are much larger than the ones with respect to the Press Release. This holds true for the selection of treasury bills I have chosen, however, it holds for German, French and Italian assets too, as well as for exchange rate with respect to the (USA) Dollar. The stock market Euro Stockxx 50 has reactions of similar magnitude, there is no diffrence between the Conference and the Release.

The distribution of volatility has shifted over the last two decades. Between 2002-2008, shorter-termed assets are more volatile and hardly affected by the press Release. From 2008 onward, specially during the 2012 Debt Crisis, both variables become more volatile. French and Italian bonds follows close related

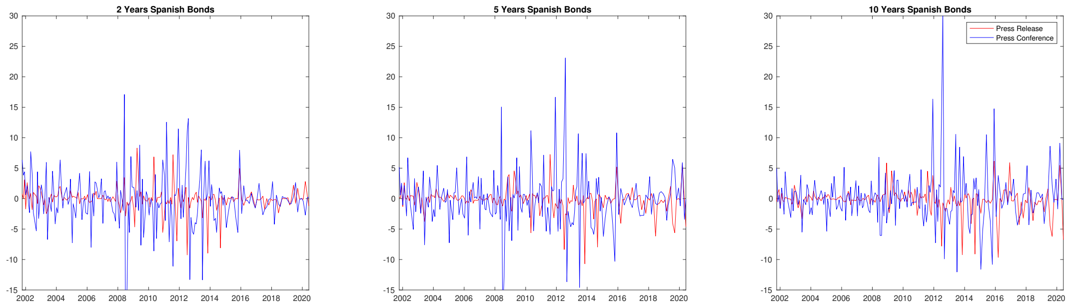

Figure 2: Median deviation of the relevant variable during the Monetary Event (13:25-15:50)

patterns on the distribution of volatility across years. Germany experienced its volatile period during 2004-2008.

At a first glance, Figure 2 displays the miss match among market reactions. Assets move twice in a very short period of time. The red movement occurs due to the fact the the policy is about to change, hence it reflects pure expectations about how the market accommodate the new policy path. But recall that movements on the red line are formed by the economic agents, inducing what the monetary authority is really thinking about. Alternatively, the blue line exhibits how assets change due to the explanation that the Governing Council gives on the press conference. Thus, blue movements are informed movements that already know what will be the path for monetary policy, and why the ECB takes such decision. The difference between the blue line and the red line is what I call the miss match forming expectations. The sum of the two is the total monetary reaction.

Reaction to news are, by definition, shocks, hence it is not possible to estimate a model to predict the mean based on past observations. Notice that we observe the percentage (median) change suffered by assets over the announcement window. Consider that r_t captures the price of a given asset at time t, and let τ be exactly the moment in which asset's price changes. During a short-enough period of time, seconds or minutes at most, price may evolve as

$$r_t = r_{t-1} + \varepsilon_t$$

News are released between 13:45 - 14:00, and explanations are given around 14:30 - 15:30, thus assuming τ is the relevant moment in time, what we observe in the data-set is

$$r_\tau - r_{\tau-1} = \varepsilon_\tau$$

This theoretical presentation holds true for all the observations in the data. Among the three properties that define weak stationarity[1]: $\mathbf{E}(r_t) = \mu$, $\mathbf{E}(r_t^2) = \sigma_u^2$ and $COV(r_t, r_{t-h}) = 0$ the first and the last are always matched. The second moment, on the other hand, does not remain constant.

Figure 3 shows both autocorrelation and partial auto-correlation for 2 Years Spanish Bonds. Apart from the lag at 0, which of course is 1 for both cases because is the function with respect to itself, pretty much all lags lie within the confidence bands. The absence of significant correlation with any lag warns about

[1]I use the notion of weak stationarity, or second order stationarity because the notion involving the full joint distribution for any subset and any period is too restrictive for this type of analysis.

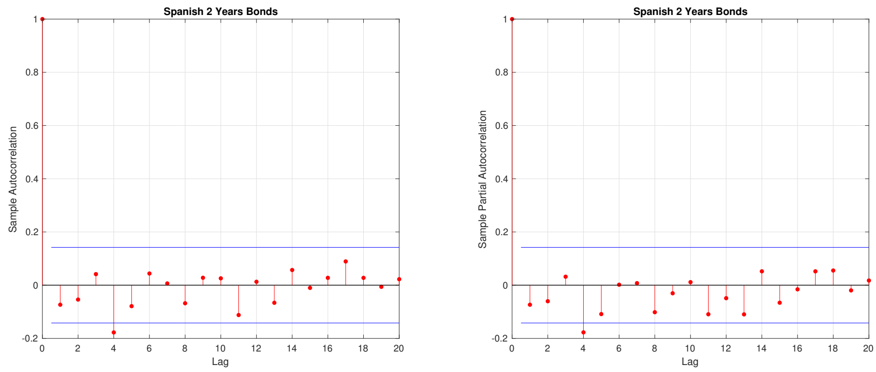

Figure 3: Autocorrelation and Partial Autocorrelation functions for Spanish Bonds with a maturity of two years.

mean-stationarity. On the other hand, notwithstanding most series have constant mean across period and windows, their volatility changes a lot. These shifts in variance are patent by two measures: 1) Time varying variance reflects that news provoke reactions of different magnitude during different period of time, and these periods are somehow clustered, 2) Window-Variance, that shows how market reactions to the press conference are of different magnitude than to the press release, being the former the window with larger magnitude and volatility. I use a non-parametric approach to argue visually how variance changes through the two mentioned channels, for the three most relevant Spanish bonds. The Kernel Density Function approximates the distribution of observations without further parametric assumptions. Two Kernel densities together allows for an easy interpretation of the distribution. For example, Figure 4 depicts the distribution of an asset, comparing the press conference and the press release. For all assets the response during the press release is centered around the mean. Conversely, the press conference have less kurtosis, and is more volatile. This picture remains true for other countries' bonds. Overall, the debt market reacts in a similar fashion for all countries. Variations during the first statement are less volatile and of lower magnitude than reactions to the press conference.

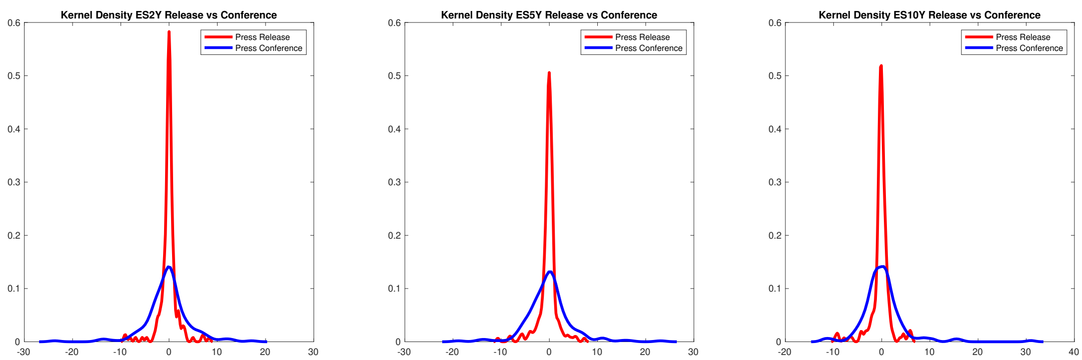

Figure 4: Kernel Density estimation of the distribution of observations for Spanish Bonds with 2, 5 and 10 years of maturity. The red line is the distribution of changes over the Press Release, while the blue line is for the Press Conference.

Differences in volatility for different communication windows claim that economic agents extract distinct information from each announcement. Large monetary shocks are almost exclusively expected upon the Press Conference. Huge shocks over the press conference, quantitatively speaking those at the tail of the distribution, are more expected to be negative for the 2-Years bond, whereas positive on the 10-Years market. Surprises to the 5-Years bond are roughly equally distributed, in terms of density, along both tails. Conversely, the variation of shocks have changed across years conditional on a given window. Figure 5 shows the estimated density up to 2008, and post 2008. The red line stands for the post 2008 period, its tails are longer and are less centered around the mean. The financial crisis is, without doubt, the threshold for the increase in volatility for the set of countries that were more affected by the financial adjustments. For instance, Spanish and Italian bonds fluctuate notably during news releases, departing from 2008. The peak was arguably reached in 2012, year in which the European Debt Crisis was sizzling.

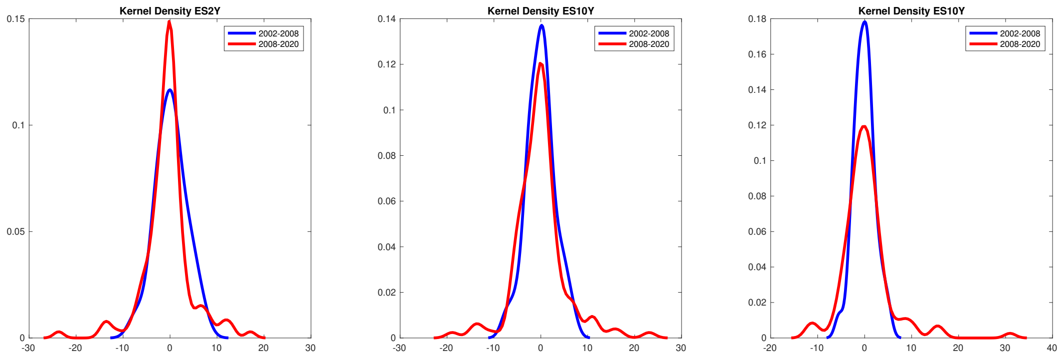

Figure 5: Kernel Density estimation of the distribution of observations pre-2008 and post-2008, for Spanish Bonds with 2, 5 and 10 years of maturity. Only Press Conference Window.

The variance of bonds issued by safer countries such as Germany have a modest increase. Exchange rates and stock indexes follow similar patterns. In contrast, short term interest rate (OIS's) fluctuates but quickly recover.

3.2 Conditional Volatility

Due to the structure of the data standard time series models for the mean are not appropriate in this context. In the previous section I provide a theoretical explanation of why data is close to weak stationarity, at least for the first moment and covariance, and an empirical validation of why all series fail to match the definition completely due to the time varying variance. According to this, I employ a family of models that are capable to match 1) correlation of the square of the residuals, i.e serial correlation in "absolute terms", and 2) time varying variance. See [Mumtaz and Zanetti, 2013] for related literature using a S-VAR for identification, and [Lanne and Lütkepohl, 2008].

The workhorse model that fits these characteristics is the G/ARCH model proposed by [Engle, 1982] and [Bollerslev, 1986]. Contrary to ARIMA models, G/ARCHs allow the square of the residual ε_t^2 to be a function of its own past, so large values of past residuals are followed by periods of less fluctuation. Volatility is not uniformly distributed along the sample, however periods of large volatility, i.e large absolute values of the residual tend to cluster. Models for conditional heterocedasticity grant us to exploit this feature and asses how the volatility of the serie changes in time.

The first step to fit those models is to make sure of the fact that volatility changes. Until here I have provided two visual proofs relying on the plot of the series and the estimated Kernel density. To finally conclude that what we need is a G/ARCH I will run two test and provide an additional visual proof.

Figure 6 confirms the conjecture that even with uncorrelated residuals, there are correlation when they are squared. Apparently, square residuals for two year Spanish bonds follows an ARMA(2,1) during the press conference. Most of the series have similar behaviour. Figure 12 shows the same for the press conference

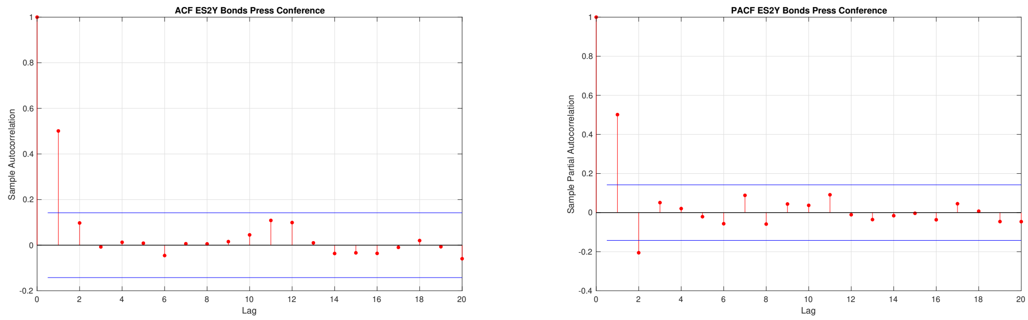

Figure 6: ACF and PACF of the square of Spanish 2 years bonds during the press conference window.

and Press Release window. The residual at the press release is never correlated with its own past. In terms of the estimation procedure, that means there is no point estimating a model for the conditional variance in a time window that has no correlation with its own past. Translated to economics, since the variance of the reaction is not autocorrelated, we can infer that the market does not look at the past to expect new policy announcement. On the other hand, the reaction of the market when new policy paths are explained is, indeed autocorrelated. To test statistically for conditional heterodedasticity I employ the ARCH test, which essentially is a Lagrange multiplier tests to asses the time dependency of the variance. In the absence of ARCH effects: $a_1 = a_2 = ... = 0$ for the specification

$$\varepsilon_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + a_2\varepsilon_{t-2}^2 + ...$$

Table 6 on the appendix presents p-values of the ARCH test on the Press Conference Window. I have chosen up to four lags in order to maintain the models as parsimonious as possible. According to [Hansen and Lunde, 2005], for predictive purposes a GARCH(1,1) is the right choice, hence I do not pretend to go far beyond that paper. As shown in the table, the nine relevant variables have time dependent residuals. Bonds with shorter maturity have stronger time dependency than assets with long's. For instance, 10 years bond for both Spain and German have larger P-value, while their short-term counterparts have smaller ones. Table 3 shows the same but for the whole monetary event. Overall, there are stronger P-values during the press conference than during the monetary event. However, except for ten-years German bond at the whole monetary event, we can conclude based on the ARCH test that there are strong ARCH effects on the series. Next step is to estimate parsimonious model to fit the conditional variance over time. Based on the discussion, I fit the following model to the data

$$\varepsilon_t = v_t \sqrt{h_t}$$

where v_t is a Gaussian process and

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}$$

I estimate two different specifications for each series, GARCH(1,1) and ARCH(1), over the full sample. intead of leaving out some observations to do forecast, I run a Montecarlo Simulation that serves to asses the top and the bottom quantiles, which serves as reference.

	Press Conference		Monetary Event	
	ARCH(1)	GARCH(1,1)	ARCH(1)	GARCH(1,1)
ES2Y	0.52***	0.56***	0.35***	0.35***
		0.03		0
ES5Y	0.42***	0.42***	0.301***	0.301***
		0.02		0
ES10Y	0.41***	0.43***	0.27***	0.11***
		0.13		0.88**

Table 1: Estimation output from G/ARCH.

Table 1 shows the estimation output for Spanish Yields. There are two acknowledge observations, ARCH coefficients are always statistical significant regardless of the variable and the time window, and GARCH effects are insignificant except for the 10 Years bond on the whole monetary window. Figure 7 asses the

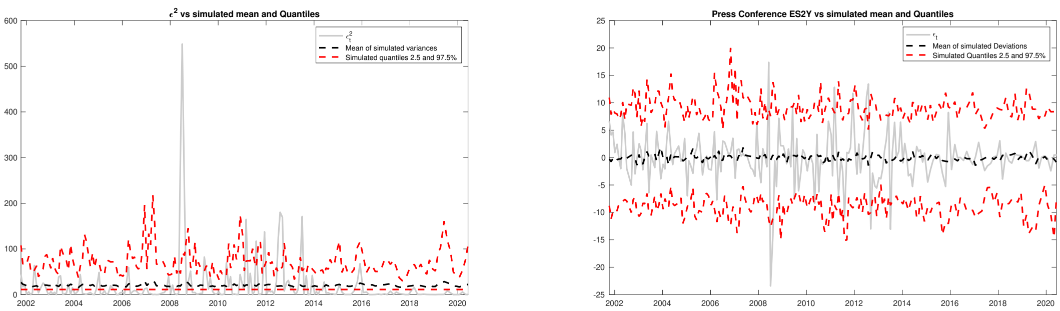

Figure 7: Results based on Montecarlo simulation with 50 iterations. On the left, square of ES2Y during the Press Conference vs simulated moments. On the right, actual series vs simulated moments.

fit of the model trough a simulation experiment. The first picture shows how volatility peaks in 2008 and 2012, coinciding with crisis in which the ECB took a central role.

3.3 Contemporaneous Relationships

This section address the study of contemporaneous relations in the data. Concretely, I link changes in asset prices between the Press Release and the Press Conference. Effects are said to be contemporaneous according to the time label in the data, however, due to the communication structure of the ECB, there is a delay between the Press Release and the Press Conference. I exploit this delay to relate the magnitude of shocks occurring at the press release, with the ones from the Press Conference. At this point two natural questions arise:

1. How is it possible to estimate an *iid* shock?

2. Why don't we exploit its time series properties?

The answer to the second question is essentially the first question, and the other way around. With respect to 1) Yes, it is true that observations are totally unpredictable realizations. Nevertheless, since we observe two shocks during a short time span for each asset, it is possible to map shocks during the Press Release onto shocks during the Press Conference. The paragraph below I provide a discussion of why this is more reasonable than what it sounds *a priori*. The answer to 2) shocks are serially uncorrelated, it is simply no possible to draw on past observations of the sequence to predict future values.

Here I turn back to the discussion of why mapping a random realization from the Press Release onto the Press Conference is reasonable. Consider two relevant variables from the data set, can be the same, the only restriction is that each of them must be from each time-window. Let ε_t and v_t be the sequence from the Press Conference and Press Release respectively. For a given variable, Spanish 2-Year Bonds for instance, it is reasonable to think that reactions during the Press Conference correlates with reactions during the Press Release. Consider the case in which a shock at the Press Conference is a function of the shocks, already visible, from the Press Release. This structure is nice because it allows for 1) Realizations, in all windows are serially uncorrelated shocks and 2) It is possible to predict changes at the Press Conference by looking at changes in the Press Release. Let ε_t be a linear function of v_t and another random component η_t

$$\varepsilon_t = \phi v_{\tau,t} + \eta_t$$

η_t is a standard error term that follows some known distribution and crops up simultaneously with ε_t. The key is the relation between ε and v. The sub index in $v_{\tau,t}$, τ makes explicit that v is generated before t, that is $\tau < t$. Until the moment τ, which is the Press Release, everything is unpredictable. Around 13:30 $v_{\tau,t}$ is observed, hence it is possible to draw some prediction on ε_t. The sequence of expactations proceed as follows:

$$\mathbb{E}_\tau[v_{\tau,t}] = 0$$

$$\mathbb{E}_t[v_{\tau,t}] = v_{\tau,t}$$

$$\mathbb{E}_t[\varepsilon_t] = \phi v_{\tau,t}$$

The subindex of the expectation operator indicates when it is taken. For example, the expected value of v at τ is 0, however at t is known. This specification raises naturally from the fact that we have a data set explicitly designed to identify the two events, the Release and the Conference otherwise it would be impossible to asses anything to the shock happening at the conference window.

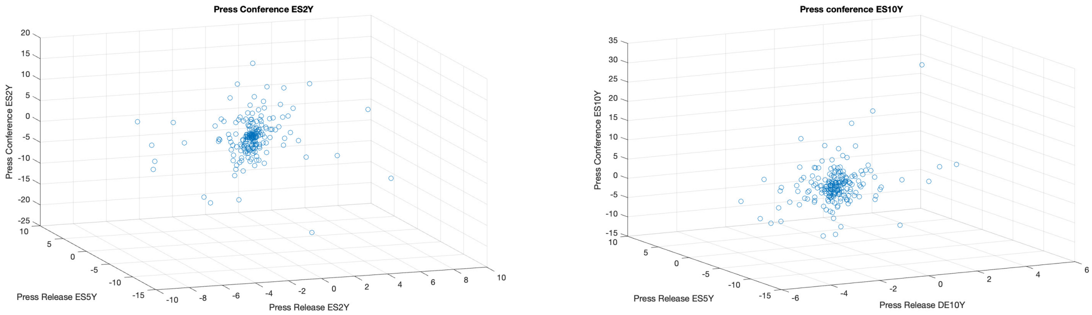

Figure 8: 3-D Scatter plot for the joint relation among 2-years Spanish bonds' reaction on the Press Conference, to reactions at the Press Release. Full sample.

Figure 8 shows the relation between changes during the press release to changes during the press conference. As we see, there is an association between the movements that happens in each window time. Here the figure may look distorted by the scale, however when some outliers are removed the relation is much more clear. The idea is to exploit this dynamic co-movement between the series to asses the effect of shocks during the press conference before hand. I run a Dynamic Regression based on contemporaneous observations. There are no distributed lags because variables are serially un correlated. The only source of identification arises from the two-steps communication strategy of the ECB. Table 2 has the estimation output of the models. Bonds with maturity of 2 and 5 years correlates negatively with themselves during the press conference. For instance, If ES2Y changes 1% its value during the press conference, it has an estimated decrease of -1.17% during the press conference. Same happens for the 2-Years bond but with smaller magnitude. 10-Years Spanish bonds do not correlate with themselves, however they are positively associated with 10-Years German Bonds, and negatively with 5-Years Spanish Bonds.

	ES 2 Year Yield	ES 5 Year Yield	ES 10 Years Yield
ES 2 Years Yield	-0.45***	0.49***	0.26
ES 5 Year Yield	0.18	-1.17***	-0.78***
ES 10 Years Yield	-0.08	0.47	0.17
DE 10 Years Yield	0.043	0.46	0.66***

Table 2: Estimated parameters of the dynamic equation. The first row contains the dependent variable, Spanish yield movements during the Press Conference, and the first column shows the covariates, Spanish bond yields and 10 Years German bonds during the Press Release. Three asterisks means significance over 5%

Notice that the relations that we are drawing here are not direct causality. As a result, it is not possible to asses direct causation, however some shocks can be used empirically to predict others. Even though the causation does not have the same interpretation as in cross-sectional settings, yet useful results can be obtained. The notion of causality in time series analysis is named as **Granger-Causality**. Granger causality requires two premises: 1) The cause happens before the caused and 2) The cause has unique information about the caused. Those series attains both. The first one by construction of the dataset, and the second because both variables co-move, the only different is that one receives the news earlier, therefore reacts earlier. As a consequences, some information of the first movement can be projected onto the second movement that the variable will have during the Press Conference.

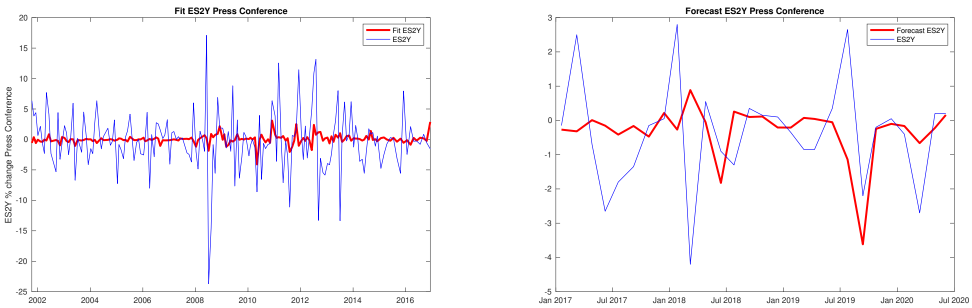

Figure 9: On the left fitted vs actual values. On the right predicted vs actual values. 2 years Spanish bonds.

Figure 9 shows the estimated model fits and forecast the data. The first figure ranges until the end of 2016. The last years has been left out for the forecast. The model fits the data pretty well, however it has problems fitting the volatility of the series. The other cases are shown by Figure 13 at the appendix. Results are pretty similar.

4 Conclusions, Extensions and Weaknesses

Employing the novel database from [Altavilla et al., 2019], this paper investigate some characteristics of the movement of Spanish assets' yields around monetary events. On the context of unconventional monetary policy, news released by the monetary authority are of increasing relevance. Here I shed light on two facts. First, monetary shocks during the Press Conference are much more volatile than they are during the Press Release. A model for conditional volatility of assets' movement may be a good option to study the dynamics of monetary shocks around the announcement window. Second, shocks for news are correlated, and good predictor of shocks for explanations. Using high frequency data, it is possible to observe the first shock, and use it to predict the shock corresponding to the explanation of the policy. However, the increased volatility of the second shock reduces the predictive power. At the end, the best choice to forecast shocks during the press conference is to use both the conditional volatility and Press Release shocks.
The main weakness of the project woul be corrected by an extension. Like the authors do in [Altavilla et al., 2019], instead of using the time series properties, they use factor models to identify how some shocks affects other. This allows them to draw many interesting correlations. However, the applied methods are interesting from the univariate point of view to study monetary shocks via news.

5 Repository for Replication

HERE You will find the Matlab code and data I have used to produce all the results in the paper. Comments of any type are welcomed

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6 APPENDIX

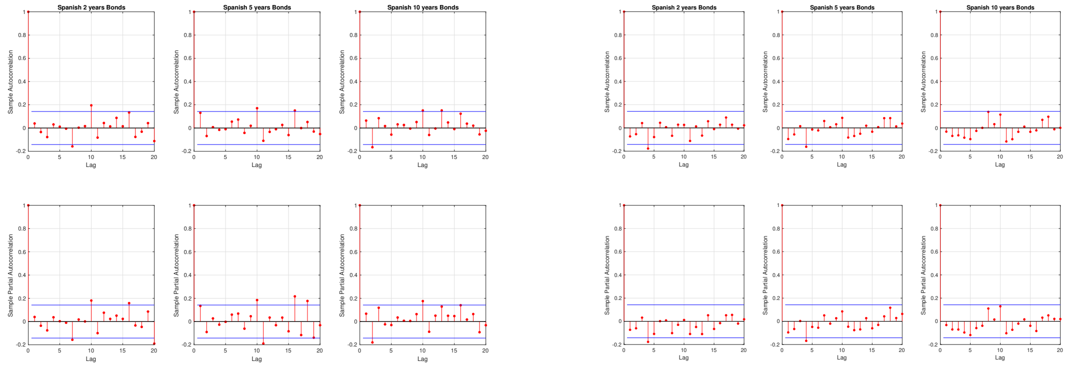

Figure 10: ACF and PACF for Spanish Bonds with maturity 2, 5 and 10 years, during the Press Release, and Press Conference.

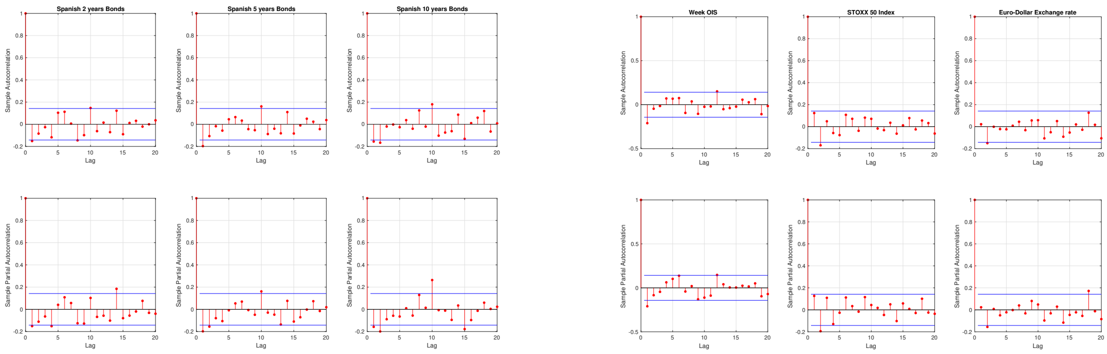

Figure 11: ACF and PACF for Spanish Bond during the whole monetary event, Weekly Overnight Index Swap and Euro-Dollar Exchange Rate during the Press Conference.

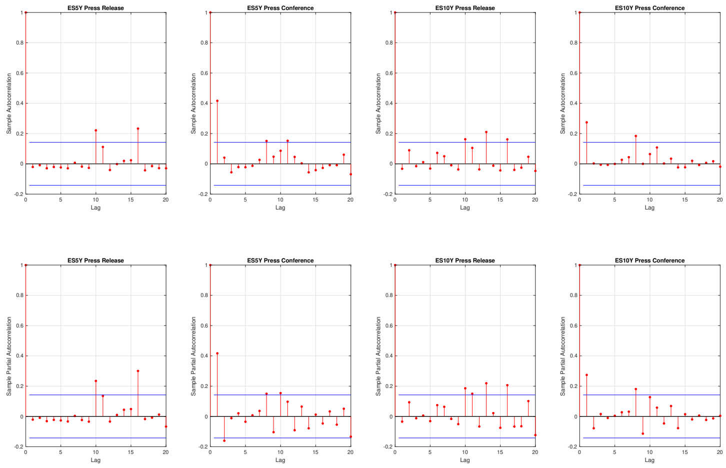

Figure 12: ACF and PACF for spanish bonds 5 and 10 years, during the press release and the press conference window.

	ε^2_{t-1}	ε^2_{t-2}	ε^2_{t-3}	ε^2_{t-4}
ES2Y	1.47437617670221e-12	5.35793631684101e-13	3.04511971194188e-12	1.56598067846403e-11
ES5Y	6.78436840040320e-09	7.06735669986358e-09	3.93905722484433e-08	1.67620923807732e-07
ES10Y	0.000101668585632875	0.000308390675013204	0.00108316019075672	0.00300790551980112
DE2Y	5.91637849822746e-13	3.39162031792739e-12	2.11920481163475e-11	8.25055579412037e-11
DE5Y	8.26230961425978e-09	5.83275959753493e-08	2.30220356889355e-07	9.31862809250283e-07
DE10Y	0.0526072191579182	0.142394690358806	0.201649782004661	0.299771923315749
OIS Week	0.725063997048658	0.395633222451297	0.0434746039622184	0.0104437649016316
STOXX50	0.000168267981416670	0.000606169291875069	0.00209118330625091	0.00457243109602812
EUR-USD	0.00301473394253615	5.83208458426743e-05	4.09032176503787e-05	0.000123824240687576

P-values

	ε^2_{t-1}	ε^2_{t-2}	ε^2_{t-3}	ε^2_{t-4}
ES2Y	6.87847223623805e-10	3.53662099605856e-10	1.30577093582218e-09	2.47849396561861e-09
ES5Y	9.88787388411794e-07	6.26985340423936e-07	2.87797184606031e-06	9.97188483098377e-06
ES10Y	0.0147702605834035	0.0479908183873196	0.107426679850335	0.175043799199683
DE2Y	3.93992616309902e-11	2.26221485988276e-10	1.35415234581160e-09	1.53183765672082e-09
DE5Y	5.25235235304677e-08	3.81849945663149e-07	1.71795327053026e-06	5.00447129558879e-06
DE10Y	0.258473376913030	0.513596705598645	0.649809379609379	0.638545163879600
OIS Week	0.0437426615571376	0.376098729008000	0.530676638399638	0.678894601372140
STOXX50	0.0128705972490801	0.0447101068692187	0.0931141627338806	0.154701611100943
EUR-USD	0.00588866451567272	0.0202603628837827	0.0424104699500285	0.0800473969128096

Table 3: P-values of ARCH test for selected lags and variables over the whole **Monetary Event window**.

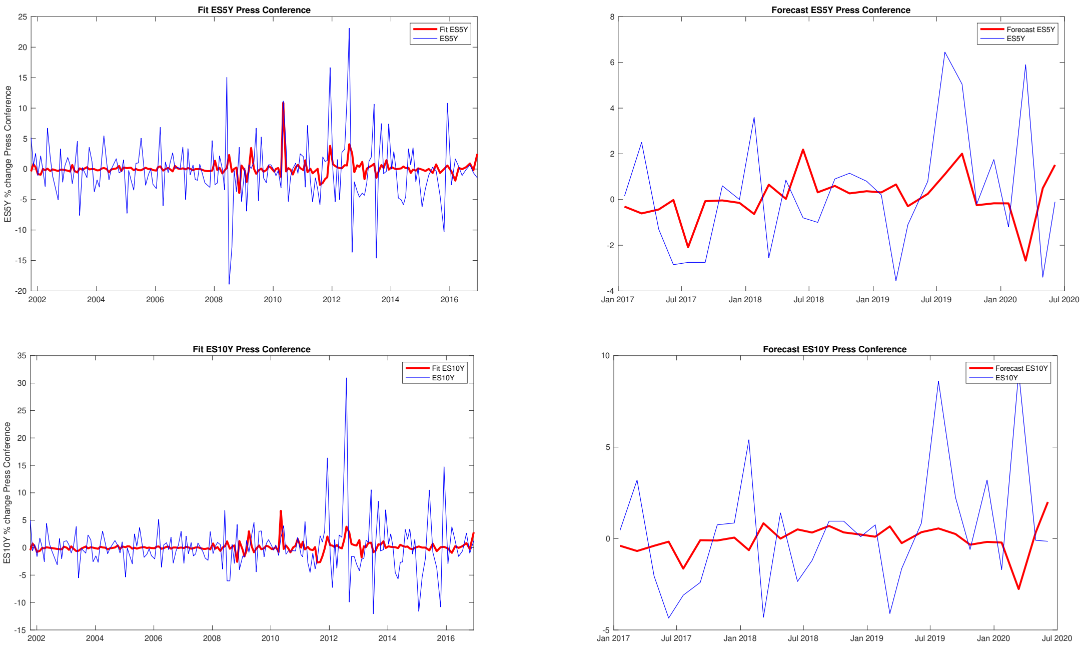

Figure 13: Fitted and Predicted values for ES5Y and ES10Y.