**Monetary Policy and Herd Behavior: International Evidence**

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***Abstract***

This paper is motivated by the recent discussion on the need of market supervisors, regulators, and policy makers, to take into account the behavioral elements of market participant attitudes and psychological and cognitive biases when taking policy decisions. We contribute to the discussion by studying, for the first time, the relationship between conventional and unconventional central bank monetary policy and herd behavior in equity markets, and argue that the transmission channel, through which monetary policy may affect herd behavior, is economic expectations and investor sentiment. We combine a range of research methodologies to measure monetary policy, herd behavior, and their possible relation, and our results indicate that conventional and unconventional Fed monetary policy explains a significant percentage of US equity market herd behavior variance, while ECB monetary policy explains a lower percentage of Eurozone herding variance. Impulse Response Functions indicate that Fed's conventional expansionary policy and non-standard policy reduces the levels of herding in the US equity market, while conventional ECB expansionary policy induces higher levels of herding in Spain and Italy. We also detect spill-over effects from Fed monetary policy to EU market herd behavior.

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"…..*by slightly increasing the price of leverage at an early stage of a developing boom, the central bank could break herding behaviour when the development of a bubble depends on investors observing other investors purchasing the bubble-prone asset*"[1]
Lucas Papademos
Vice President of the ECB (2009)

*"There is a well-developed empirical literature on herding among fund managers in their portfolio allocations, but, as far as I know, this work has not looked at how such herding responds to changes in the monetary policy environment. So, this avenue seems like a potentially promising one to pursue"*[2]
Jeremy C Stein
Member of the Board of Governors of the Fed (2014)

## 1. Introduction

This paper examines, for the first time, the relationship between conventional and unconventional central bank monetary policy and herd behaviour in equity markets. Although many studies examine either the effect of monetary policy on asset prices or herd behaviour in asset markets, no study examines their potential link. We use a range of research methodologies, such as the Qual VAR model of Dueker (2005) to capture the monetary policy stance of the Fed and the ECB, and a structural Factor-Augmented Vector AutoRegression model (see Bernanke, Boivin, and Eliasz, 2005; and Boivin, Giannoni, and Mihov, 2009) combined with 855 macro and 75 financial variables (a total of 930 variables) for the EU sample markets and 110 variables for the US market, to empirically examine whether central bank monetary policy has an impact on equity investor herd behaviour and, if so, whether it results to higher or lower levels of herding.

[1] Lucas Papademos, Vice President of the ECB, "Monetary policy and the 'Great Crisis: Lessons and challenges", Speech at the 37th Economics Conference "Beyond the Crisis: Economic Policy in a New Macroeconomic Environment" organized by the Österreichische Nationalbank, Vienna, 14, 2009.
[2] Comments on "Market Tantrums and Monetary Policy", Speech by Mr Jeremy C Stein, Member of the Board of Governors of the Federal Reserve System, at the 2014 Monetary Policy Forum, New York City, 28 February 2014, available at: https://www.bis.org/review/r140303a.htm

The paper is motivated, and contributes to, the recent discussion on the need of market supervisors, regulators, and policy makers, to take into account the behavioral elements of market participant attitudes and psychological and cognitive biases, when taking policy decisions. For example, in a recent Consultation Paper, the European Securities and Markets Authority (ESMA) recognizes that investors, or at least a significant number of them, may be subject to behavioural biases and heuristics and that their financial decisions might lead to sub-optimal outcomes.[3] The consultation paper is addressed to authorities and firms subject to MiFID II, and the guidelines seek to implement enhanced provisions to ensure investor protection, such as updating the investor suitability assessment questionnaires to take into account clients' behavioural biases.[4] Another example is a recent IMF paper (Khan, 2018) which argues that regulators and market supervisors should incorporate behavioral expertise and complement regular supervision with behavioral supervision and apply behavioral knowledge to policy development and financial regulation (p.30).[5] Khan argues that monetary policy is also the topic of behavioral research and discusses, among others, the case of the central bank of the Netherlands (DNB) which is using a team of psychologists and sociologists to assist regular supervisors in day-to-day supervision. In addition, Papademos (2009)[6] suggested that monetary policy may be an effective tool for the prevention of build-up of imbalances and "irrational exuberance" periods in asset markets.

In financial markets, herd behavior is an important behaviour element (Hwang and Salmon, 2009) and refers to the process where market participants imitate each other's actions, base

[3] Consultation Paper ESMA 13 July 2017 | 35-43-748, p.9.

[4] More specifically, according to the Consultation Paper, if the way questions for the suitability assessment are formulated does not consider cognitive and behavioural biases, the questionnaire may result to be unreliable (p.9-12). Examples of investor biases that should be assessed may include (page 10, footnote 10) representativeness, overconfidence and over-optimism, conservatism, availability bias, frame dependence and anchoring, mental accounting, regret aversion, loss aversion.

[5] Khan, A., (2018). A Behavioral Approach to Financial Supervision, Regulation, and Central Banking., International Monetary Fund Working Papers, WP/18/178.

[6] See footnote 1.

their financial decisions upon the actions of other participants, trade in the same direction, or exhibit an investment behaviour that converges to the consensus/average (see, Nofsinger and Sias, 1999; Avery and Zemsky, 1998; Welch, 2000; De Bondt and Forbes, 1999; Hirshleifer, and Teoh, 2003; Hwang and Salmon, 2004; among others). Devenow and Welch (1996) argue that herd behaviour requires some sort of a coordination mechanism or a significant signal (e.g. a significant price movement, observing the investments of colleagues).[7] Monetary policy actions may potentially play this role and send strong signals that may coordinate similar investor behaviour through at least two channels. Firstly, conventional and unconventional monetary policy announcements, through their informational content, can affect economic expectations and investor sentiment which, in turn, can lead investors to react simultaneously and in the same direction. The European Central Bank[8] recognizes that the expectations transmission channel has gained importance during the recent period, while recent studies find that unconventional monetary policy has an impact on investor sentiment (Lutz, 2015; Galariotis et al. 2018; among others). For example, increased levels of central bank credibility may have a significant effect on price changes by shaping market participants expectations. Another potential channel through which central bank policies may induce herd behaviour is via the risk measurement/management models that are commonly employed for regulatory requirements, which may lead to similar investment decisions. For example, Kremer and Nautz (2013b) point out that the use of VaR models may have as a consequence common sell activity, since these models may "…..*often force banks to close positions in volatile periods*" (p.1678). Kremer and Nautz use data from Germany and show that institutional investor herding has a destabilizing effect on prices and that it is partly due to similar models of risk used by institutional investors.

[7] p.604.

[8] The Monetary Policy of the ECB, 2011, p.61; http://www.ecb.europa.eu

This coordinated behavior of investors and cross-market herd behavior can increase volatility and threaten market stability (Tsionas, 2013) and, in addition, herd behaviour has been linked to fads and bubbles (Devenow and Welch, 1996; Nofsinger and Sias, 1999; Gleason et al., 2004; among others). Thus, major central banks have strong incentives to pay attention to potential herd behaviour induced by their actions with the incentive here being twofold: while, on one hand, investor herding may eradicate the desired impact of a certain policy action, intensify financial instability and market volatility during a crisis period[9] and create the need for further policy actions, on the other hand, monetary policy can also be employed to prevent the development of price bubbles.

Consider, for instance, the case where the central bank aims at stabilizing asset prices and tackling price volatility; the informational content of its actions may simultaneously induce unintentional herd behaviour that could potentially destabilize prices and affect the operational and informational efficiency of asset markets. Investor reaction to public information may lead to unintentional herding (Bikhchandani and Sharma, 2001) and one way that this could occur is in situations where central bank communication and news announcements are subject to subjective or different interpretations by market participants and, as a result, may increase market uncertainty and volatility. Gaballo (2016) discusses this issue and argues that in cases where communication is not specific the main source of information about future events is the market, which in turn, increases uncertainty. The updating of information interpretation based on market reaction leads to market participants unintendedly reacting to noisy or exogenous price movements; a collective behaviour that

[9] For example, in the midst of the EU financial crisis, Olli Rehn, the then European Union Economic and Monetary Affairs Commissioner, while discussing the Irish financial aid-package (2011) suggested that herd behaviour may be partly responsible for market instability. See Bloomberg article: Neuger, J., and Kennedy, S., www.bloombeg.com/news/2010-11-29/ireland-s-eu-financial-rescue-fails-to-stem-contagion-as-spain-bonds-drop.html. Note also that Galariotis, Rong, and Spyrou (2015) find that US equity investors herd during various crisis periods mainly on fundamental macro information releases.

may intensify price noisiness. Gaballo discusses the surprise announcement on May 22, 2013, that the Fed might narrow the scope of its QE policy and the subsequent release of the minutes of the FOMC meeting, which contained more specific information about the diverse opinions of the members on economic outlook and monetary policy. Gaballo points out that the result was a disagreement about the specific informational content of the communication and, in the period that followed, there was increased market turmoil. Note here that the release of fundamental information does necessarily lead to less market confusion and reduced uncertainty. Amador and Weill (2010) examine public information releases on productivity and monetary shocks and find, in cases of endogenous information structures, that information releases may result to increased uncertainty, compared to no information releases at all. In addition, the release of public information may result to several Pareto-ranked equilibria, intensifying uncertainty and reduced welfare. Amador and Weill show that, when market participants learn from market prices, a public information release may result to increased uncertainty, and argue that this inefficiency can be eliminated by sufficiently precise information releases.

Although the empirical evidence is mixed, many authors argue that herding can destabilize prices. Kremer and Nautz (2013) find that unintentional institutional investor herding may destabilize prices in the short-term, Choi and Sias (2009) report that institutional investor herd behaviour may drive market prices away from fundamental values, Xin, Shengmin, and Zheng (2018) find that mutual fund herding intensifies equity price crashes, Cai, et al (2018) report that while the actions of buy herds affect prices permanently, the actions of sell herds distort prices significantly but temporarily and point out that herding in the asset management industry may be an important channel through which amplified risk can be a threat to financial stability.

With regard to the recent financial crises in the US and the EU,  the complexity, magnitude, and intensity of the crises led major central banks to adopt several non-standard (unconventional) monetary policy tools in order to deal with market volatility, since standard policy tools were ineffective[10] (see, among others, Fawley and Neely, 2013; Gambacorta, Hofman, and Peersman, 2014). These policies had significant international spill-over effects on both advanced and emerging economies and in various asset markets. For example, Mohanty (2014) notes that during monetary policy easing by major central banks the correlation between asset prices and interest rates increased internationally; Fratzscher, Lo Duca, and Straub (2016) find that ECB policies had a positive effect on advanced and emerging stock markets and confidence; Tillmann, (2016) finds that quantitative easing policies have a significant role in explaining emerging market capital inflows, stock prices, and exchange rates (see also Neely, 2015; Chen et al, 2016; among others). These results complement previous findings that monetary policy has an impact on asset returns and affect investor sentiment or risk aversion (see, among others, Bernanke and Kuttner, 2005; Kurov, 2010; Bekaert, Hoerova, and Duca, 2013).

As argued above, whether monetary policy affects herd behaviour in asset markets is an issue that has been neglected by the relevant literature. This paper aims to address this gap and examine the extend of the contribution of conventional and unconventional monetary policy measures adopted by the Fed and the ECB to equity market investor herd behavior in the US and major EU markets. More specifically, we examine the impact of monetary policy on herding for the US and the nine Eurozone countries that had adopted the Euro before the financial crisis, i.e. Austria, Belgium, Finland, France, Germany, Netherlands, Spain, Italy,

[10] Official policy rates approached their zero lower bound in 2008: the Federal funds rate in December 16 was at the 0.00 - 0.25 range, while the ECB fixed rate (deposit facility, main refinancing operations) was at 0.25 in April 2009.

and Portugal, for the period May 2007 to December 2016.[11] We exclude Ireland, Luxemburg, and Greece from the sample, since for these markets we do not have stock price data available to calculate the herding measures, after the application of the relevant filters (see below for a discussion). Thus, based on the above discussion, this paper aims to shed light on the following issues: (i) examine whether there is a monetary policy effect on herd behavior in financial markets, (ii) test for potential monetary policy effect asymmetries on herd behavior among different countries, (iii) examine asymmetric effects on herd behavior between the two central banks (ECB and Fed), and (iv) evaluate whether US monetary policy actions have an effect on EU financial market herd behavior.

We combine a range of research methodologies to measure monetary policy, herd behavior, and their possible relation. For example, in order to measure the unconventional monetary policy stance of Fed and ECB we first construct a binary variable based on important monetary policy announcements. We then employ the Qual VAR model of Dueker (2005) and macroeconomic information from our sample countries to transform this variable to a continuous latent variable that captures central bank propensity to non-standard monetary policy. In a second stage, this latent variable enters a structural Factor-Augmented Vector AutoRegression (FAVAR) model combined with 855 macro and 75 financial variables (a total of 930 variables) for the EU sample markets and 110 variables for the US market (such as industrial production, unemployment, producer and consumer price indexes, short and long term interest rates, economic sentiment indicators, etc.) in order to examine its impact on herd behaviour. To test the robustness of our results and evaluate the ability of our variable to capture the effect of non-standard monetary policy, we also employ the Shadow Federal Funds Rate (see Wu and Xia, 2016) and the European Central Bank Shadow rate (see Wu and

[11] The rest of the Eurozone countries joined much later and well within our sample period, e.g. Cyprus joined in 2008, Estonia in 2011, Latvia in 2014, Lithuania in 2015, Malta in 2008, Slovakia in 2007, Slovenia in 2009.

Xia, 2017). Wu and Xia provide an approximation for a term structure model that can be utilized to synopsize the macroeconomic impact of non-standard monetary policy.[12]

Following the continuously extending evidence on the importance of large data set implementation in macroeconomic modelling, we adopt a FAVAR model which has many advantages over more traditional approaches since it utilizes an extensive set of informational variables and combines factor analysis with VAR methodologies. For instance, Boivin and Giannone, (2008a) argue that large data set usage helps pinning down the effects of monetary policy shocks, a crucial issue when the time series dimension is relatively short. In addition, it can produce structural Impulse Response Function (IRFs) and deal with the omitted variables problem that is common in standard VAR analysis. It has been used in many previous studies in order to examine the transmission of monetary policy shocks or related issues (Stock and Watson, 2005; Favero, Marcellino, and Neglia, 2005; Belviso and Milani, 2006; Boivin and Giannoni, 2008b; Lutz, 2015; Gabriel and Lutz, 2015; Abbate, et al., 2016). For example, McCallum and Smets (2007) employ this methodology to examine the impact of monetary policy shocks on real wages and employment in the euro area as a whole, while Eickmeier (2009) uses the model to examine co-movement and heterogeneity in the Eurozone area.

In contrast to many previous studies that use data for one single country, we approach the dimension issue differently and employ the same data set across nine EU countries and then identify the common components from a large cross section of national series and regional/global series (see also, Belke and Osowski, 2019; Galariotis et al. 2018). This approach is also motivated by the results of Georgiadis (2015) who shows that, compared to bilateral VAR models, multi-country modelling with methodologies such as the FAVAR and

[12] See Federal Reserve Bank of Atlanta at https://www.frbatlanta.org/cqer/research/shadow_rate.aspx?panel=1.

GVAR is more appropriate for modelling regional and global shocks as well as spill-over effects across countries.

To measure herd behaviour, we employ the comprehensive herd behaviour[13] measure of Hwang and Salmon (2009). An important advantage of this non-parametric methodology, which is based on the cross-sectional variation of systematic risk (beta-herding), is that it takes into account the dynamic features of herd behavior and treats herding as a time-varying rather than a static process. Hwang and Salmon argue that behavioral biases, such as herding toward the consensus, may affect investors perception of the standard asset pricing equilibrium and, consequently, estimated betas will deviate from the traditional risk-return relationship. Thus, a herding measure, based on beta deviation from equilibrium, can be constructed. Our sample consists of all listed stocks (major securities and primary quotes) for the NYSE, Vienna Stock Exchange, Euronext Brussels, Helsinki Stock Exchange, Euronext Paris, Frankfurt Stock Exchange, Euronext Amsterdam, Madrid-SIBE, Milan Stock Exchange, and Euronext Lisbon. We exclude financials (Industry Classification Benchmark Code: 8000) and foreign companies and stocks with negative or missing values.

Our results suggest that about 10% of the US herd behavior variance is explained by conventional Fed monetary policy, while non-standard policy explains about 15%; when we replace our unconventional monetary policy variable with the shadow Fed funds rate this increases to 24.4%. ECB conventional policy explains about 5% - 10% of herd behavior variance in Eurozone countries, while non-standard monetary policy explains a higher percentage of herding variance for Portugal, Germany, Finland, France, and the Netherlands. We also detect a spill-over effect of Fed policy: conventional Fed policy seems to have a

[13] For recent reviews on herding, testing methodologies, and empirical results see, among others, Kallinterakis and Gregoriou (2017), and Spyrou (2013).

significant impact on herd behavior volatility for Spain (it explains about 15.2% of herd behavior variance), while unconventional Fed policy has an impact on herding volatility for Portugal (21.7%) and the Netherlands (15.9%). Impulse Response Functions (IRFs) indicate that the conventional expansionary policy and non-standard policy adopted by the Fed reduces the levels of herding in the US equity market. Conventional ECB expansionary policy induces higher levels of herding in Spain and Italy, while shocks to non-standard ECB policy reduce herd behavior in the majority of the Eurozone markets.

As argued above, a main transmission channel for this effect could be the expectations transmission channel; for example, increased levels of central bank credibility may have a significant effect on price changes by shaping market participants expectations. This is also consistent with previous findings that both conventional and unconventional monetary policy measures by the Fed tend to increase sentiment in the US (Lutz, 2015). In other words, since evidence indicates that monetary policy uses the confidence and expectations channel that has an impact on investor sentiment, and at the same time herd behavior is often closely related and affected by sentiment, the channel through which policymakers could affect herd behavior in financial markets could be through confidence and investor sentiment. More specifically, there is a documented link between central bank monetary policy actions and information communication and market expectations and sentiment (see, among others, Galariotis, Makrichoriti, and Spyrou, 2018; Lutz, 2015). For example, in a recent study, Schmeling and Wagner (2019) find that even the tone in central bank communication affects market participant expectations about future interest rates. More specifically, Schmeling and Wagner study the statements of ECB press conferences and show that another important factor that may affect asset prices, via a risk-based channel, is the tone of the communication of central banks. This result is robust even after controlling for policy actions, fundamentals, and other features of communication. They show that when the tone in a communication is positive, there are increases in stock prices and decreases in volatility risk premia and spreads. Furthermore, Altavilla and Giannone (2017), who analyse professional forecaster assessments following non-standard policy announcements by the Fed, argue that their findings indicate that these measures had an effective and persistent impact on market participant expectations. As discussed above, central banks recognize the importance of this expectations transmission channel for their monetary policy (see also, Fratzscher, Lo Duca, and Straub, 2014).

At the same time many studies document the effect of investor expectations and sentiment on asset prices (Neal and Wheatley, 1998; Baker and Wurgler, 2006; among others). Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) discuss formal models on how investor sentiment can affect asset prices and the behavior of investors. Furthermore, market expectations and sentiment can lead to correlated investor behavior. For instance, Lakonishok, Shleifer, and Vishny (1992) point out investors may herd not only because they all face similar information about fundamentals but also because they face similar non-rational changes in individual investor sentiment, while Kremer and Nautz (2013) argue that intentional herding, i.e. the imitation of the behavior of other investors without regard to own prior beliefs, is more sentiment-driven. Moreover, Schmeling (2009), who examines 18 equity markets from industrialized countries, finds that the impact of sentiment on returns is higher for countries that are more culturally predisposed to herd-like investment behavior. Our results have implications for the way central banks communicate policy decisions since communication has a role to play in shaping expectations (for a discussion see Blinder et al, 2008) and may affect market participant heuristics-based decision making by sending strong signals that may increase or decrease the coordination of similar investor behaviour. The rest of the paper is organised as follows: section 2 discusses the data and the testing methodologies, section 3 presents the results, whilst section 4 concludes the paper.

## 2. Methodology and Data

### 2.1 Non-standard Monetary Policy: A Qual VAR procedure

In order to measure the impact of unconventional policy measures on investor herding we first construct a variable that captures the effect of these policies on economic activity. To do so we use significant Fed and ECB announcements related to non-standard monetary policy to construct a binary variable that takes the value of one during a month where Fed and ECB announced and important policy, and zero otherwise. These announcements cover the period between 2008 and 2016 and are identified from central bank press releases, Falagiarda, McQuade, and Tirpák (2015), Fratzscher et al. (2014), and Fratzscher et al. (2013). The announcements are presented in Appendix A for US unconventional policy and Appendix B for Eurozone unconventional policy.

We next use the Qual VAR model of Dueker (2005) to transform this binary variable to a continuous latent variable (see also, Galariotis, Makrichoriti, and Spyrou, 2018). The Qual VAR model is linked to the single-equation dynamic ordered probit model (Eichengreen, Watson, and Grossman 1985; Dueker, 1999) and allows the derivation of the latent variable following the estimation of the model with Markov Chain Monte Carlo (MCMC) procedures. This way we are able to employ non-standard policy announcements as an endogenous factor in a VAR system. In this setting, all variables comprise the same VAR system, and the only variable required to yield multi-step forecasts is the dependent variable's own history (see also, Meinusch and Tillmann, 2016; Assenmacher-Wesche and Dueker, 2010; Tillmann, 2015; Bordo, Dueker, Wheelock, 2008; Amstad, Assenmacher-Wesche, and Dueker, 2008).

To describe the model more formally, consider that $y^*$ is a latent variable that is an autoregressive process of order $\rho$ depending on constant $\delta$, a set of explanatory variables $X_{t-P}$ (lagged), and its own lagged values, as in equation (1) below. In (1) $\varphi$ and $\beta$ are vectors of coefficient and $e_t$ is the random error term from a standard normal distribution;

$$y_t^* = \delta + \sum_{l=1}^{\rho} \varphi_l y_{t-l}^* \sum_{l=1}^{\rho} \beta_l X_{t-l} + e_t, \qquad e_t \sim N(0,1). \tag{1}$$

In (1), $t$ is the time index, $y_t$ is a binary variable takes the value unity when a non-standard policy announcement occurs in period $t$ and zero otherwise. The variable $y_t$ takes the form:

$$y_t = \begin{cases} 0 & if\ y_t^* \leq 0 \\ 1 & if\ y_t^* \geq 0 \end{cases} \tag{2}$$

The second component of the model is a VAR ($\rho$) process that captures the dynamics of $k$ regressors:

$$Y_t = \mu + \sum_{l=1}^{\rho} \Phi^l\, Y_{t-l} + \nu_t, \qquad \nu_t \sim N(0, \Sigma) \tag{3}$$

In (3) $Y_t = (X_t, y_t^*)'$ is a $k$ ×1 vector, while $k - 1$ time series of observations (we use macroeconomic data) constitute $X_t$, and $y_t^*$ complements a vector of the latent variable. $\mu$ is a $k$ ×1 vector of constants while $\nu_t$ is the $k$ ×1 error vector and Σ is the covariance matrix of errors. The VAR coefficients are:

$$\Phi^{l} = \begin{bmatrix} \Phi_{XX}^{(l)} & \Phi_{Xy^*}^{(l)} \\ \Phi_{y^*X}^{(l)} & \Phi_{y^*y^*}^{(l)} \end{bmatrix} \tag{4}$$

The complete system is derived from the linear relation among the latent variable and the regressors and is estimated with MCMC techniques and Gibbs Sampling (see Dueker, 2005; Assenmacher-Wesche and Dueker, 2010). Thus, we can sample from the conditional distribution to generate posterior samples by sweeping through each variable, or block of variables, and at the same time keep the rest of the variables fixed at current values. This procedure permits the joint estimation of the coefficients Φ, and Σ, the latent variable $y_t^*$, and the covariance matrix of residuals. The mean and variance of the states (the latent variable) is obtained with Kalman Smoothing, and an iterative algorithm generates the draws, while OLS coefficients estimates and initial values (given the binary data) are employed to obtain the latent variable, $y_t^*$ (drawn from the truncated Normal for each period and based on the first and the second moment).

The final step involves estimating the VAR model, employing the sampled time series of the latent variable and the OLS estimates of Φ and Σ (denoted, respectively, as $\hat{\Phi}$ and $\hat{\Sigma}$). The OLS covariance is defined from this information in conjunction with the assumed Jeffrey's prior, a draw with $T - k$ degrees of freedom for Σ from the inverted Wishart distribution:

$$\Sigma \sim IW\left\{((T\hat{\Sigma})^{-1}, T - k\right\} \tag{5}$$

In (5), $T$ is the number of observations, while $k$ is the number of explanatory variables $((T\hat{\Sigma})^{-1})$. Since the variance of the latent variable ($y_t^*$) is unity, we equally adjust the appropriate element in $\Sigma$ and normalize the other elements in the relevant column. OLS estimates mean is then added to a draw following a multivariate Normal distribution, (with the Kronecker product as the covariance matrix), and draws for Φ, given Σ, are obtained from the draw for Σ and $(\mathrm{Y}'\mathrm{Y})^{-1}$:

$$\Phi \sim N\left\{\widehat{\Phi}, \Sigma \otimes (Y'Y)^{-1}\right\} \tag{6}$$

We run 10,000 iterations for the Gibbs sampling and discard the first 5,000 iterations in order to allow for convergence to the posterior distribution (Dueker, 2005). The draws of coefficients that do not satisfy stationarity are rejected and then resampled and from the resulting sample we obtain the latent variable and the VAR coefficients. In the Qual VAR system, the binary index is entered as $y_t\{0, 1\}$ and along with the rest of the variables in the $X_t$ vector is used for the derivation of central bank latent tendency to unconventional monetary policy, $y_t^*$ (y*). The model is estimated in first differences and for the recursive ordering we follow Christiano, Eichenbaum, and Evans (1999).

For the lag length, we use three lags as more appropriate for shorter samples, since criteria for the selection of the lag structure are not defined for binary data (Meinusch and Tillmann, 2016; Tillmann, 2016). The choice of three lags in the Qual VAR model, allows, on the one hand, for well-behaved residuals by including enough lags and, on the other hand, the reduction of the dimensionality of the model and reduction of the instability of the MCMC estimation. We believe that three lags are sufficient since our analysis includes detrended growth rates and logarithmic differences (Chen et al. 2017); note, however, that the results remain qualitatively similar when using one or two lags.

The variables that we include in this model capture the business climate, economic expectations, and stock market conditions in the US and the Eurozone sample countries.[14] We follow Lutz (2015) and use industrial production excluding Construction (IP), the Harmonised Index of Consumer Prices (HIPC), stock market returns and the Economic Sentiment Indicator (ESI) for all the sample countries. When adding in the system the unemployment rate (UE) and Trade Balance (TB) the results remain qualitatively the same (see also, Galariotis. Makrichoriti, and Spyrou, 2018). For the US we use industrial production excluding Construction (IP), the Consumer Price Index (CPI), stock market returns and the Michigan Consumer Sentiment Index (MCSI). We employ monthly data on sentiment indicators, financial variables, and macroeconomic aggregates. All data cover the period between May 2007 and December 2016, are obtained from Thomson Reuters Eikon and Bloomberg. Figures 1 to 3 present the resulting continuous variable that captures central bank tendency to unconventional monetary policy for each sample country (dash line); the announcements are reflected with the shaded areas.

[INSERT FIGURE 1 ABOUT HERE]

[INSERT FIGURE 2 ABOUT HERE]

[INSERT FIGURE 3 ABOUT HERE]

Note that we may expect differences between conventional and nonconventional policies in terms of herd behavior due to the different nature of these policies. For instance, unconventional policies are usually implemented in crises periods when conventional policies have exhausted their use. In a recent study with eurozone countries, Kucharčuková, Claeys,

[14] Note that there are some differences in the number of variables included in our analysis between the EU and US FAVAR dataset, due to differences in the availability of the data. Moreover, since we use a balanced panel for the EU, we had to deal with the availability of variables across countries and match each country-specific dataset with the US dataset.

and Vašíček (2016) find that with non-standard measures, compared to conventional measures, prices react quickly, but other variables, such as output, react softly. Apart from this, monetary policy transmission mechanism asymmetries among different countries has been evidenced by several previous studies (Barigozzi Conti and Luciani, 2014; Clausen and Hayo, 2006; Ehrmann, 1998; Chen, 2007; Napolitano, 2006; among others).

More specifically, with unconventional policy we mean the policies used during the recent financial crises. During the financial crisis in the US (2007-2009) conventional policy measures, such as setting a target for interbank money market rates and then through open market operations modifying the supply of money by the central bank became ineffective in affecting money market liquidity, since main policy rates reached their lower bound. In order to restore liquidity conditions and tackle market volatility central banks resorted to non-conventional monetary policies which differs from conventional policies mainly because with these policies central banks attempt to affect prices and market conditions by actively managing their balance sheet. For instance, with the Enhanced Credit Support (ECS) the ECB mainly extended the maturity of liquidity provisions in Longer-Term Refinancing Operations, the LTROs (Supplementary Long-Term Refinancing Operations (SLTROs), and "Very" Long Term Refinancing Operations (VLTROs)). Also, it proceeded with direct purchases from secondary markets of government securities with the Securities Markets Programme (SMP), and then with the Outright Monetary Transactions (OMTs), i.e. purchases of government securities issued by countries under a European Stability Mechanism (ESM) adjustment programme. The Fed resorted to Quantitative Easing (QE): its balance sheet before the crisis contained about 700-800 billion $ of Treasury notes; by June 2010 it contained approximately 2.1 trillion $ in Treasury notes, mortgage-backed securities, and bank debt.

## 2.2. Measuring Herd Behavior

Herd behaviour, may be intentional, i.e. market participants intentionally disregard their own private information and follow the herd (e.g. assuming that previous traders possess superior information), or spurious (unintentional), i.e. market participants take similar decisions because they face the same information set (Bikhchandani and Sharma, 2001). Hwang and Salmon (2009) find that herd behavior occurs in both bear and bull markets and that during periods of unanticipated shocks and crises herd behavior disappears.

Empirical evidence indicates that institutional investors have the tendency to follow each other's trades not only in the US but also in international asset markets (see, Sias, 2004; Choi and Sias, 2009; Holmes, Kallinterakis, and Ferreira, 2013; Kremer and Nautz, 2013; among others). For example, Choi and Skiba (2015) examine 41 countries and find that institutional herd behaviour is more pronounced in markets that exhibit high level of information transparency;[15] while Chen (2013) reports evidence of significant herd behaviour in a sample of 69 countries.[16] This behaviour does not necessarily lead to superior performance; Koch (2017) finds that it is leader mutual funds (i.e. funds whose trades lead the trades of other funds) that exhibit superior performance, while Wei, Wermers, and Yao (2015) report superior performance for contrarian approaches, i.e. funds that trade against the herd; these results are suggesting the possession of superior private information.

[15] The authors argue that this is consistent with the notion that herd behavior may be driven by fundamental information. Also note that, Brown, Wei, and Wermers (2014) show that changes in analyst recommendations have an impact on mutual fund herding especially following negative information and mainly for fund managers with the higher career concerns.

[16] Galariotis, Krokida, and Spyrou (2016) find macro information induced herd behaviour in EU sovereign bond markets during the EU crisis, while Cai, et al (2018) find a much higher level of institutional herding in the corporate bond market compared to equity markets.

In order to measure the level of herding activity we follow the methodology introduced by Hwang and Salmon (2009). An important feature of their herding measure is that it can capture investor herding as a time-varying phenomenon. Their approach is based on the rationale that investors suppress their beliefs regarding equilibrium which is subsequently reflected on individual stock betas that converge (beta herding). More specifically, the following equation (7) presents the relationship between the beta in asset pricing equilibrium ($\beta_{imt}$) and the biased beta ($\beta_{imt}^{b}$) (see, Hwang and Salmon, 2004):

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1) \qquad (7)$$

In (7), $r_{mt}$ and $r_{it}$ are the market return and the excess returns of asset $i$ at time $t$, respectively, and $E_t(.)$ is the expectation operator conditional on the information set at time $t$. The mispricing due to cross-sectional bias is reflected in the superscript $b$, and the level of herding in betas due to the mispricing is $h_{mt}$. It follows that, (*i*) when $h_{mt}$ is equal to 0, prices are in equilibrium and there is no herd behavior, (*ii*) when $h_{mt}$ is between zero and unity ($0<h_{mt}<1$) there is evidence of herd behavior towards the consensus, (*iii*) when $h_{mt}$ is negative ($h_{mt}<0$) we have adverse herding, and (*iv*) when $h_{mt}$ equals one ($h_{mt}=1$) perfect herd behavior is suggested, i.e. asset prices move towards the consensus (the market portfolio).

Based on the above, beta deviation from equilibrium values serves as a framework for the construction of a measure that gauges herding activity in equity markets. Thus, Hwang and Salmon (2009) suggest that the distortion in betas consists of three components, herding, market sentiment and individual sentiment. Specifically, the bias in betas is expressed as follows:

$$\beta_{imt}^s = 1 + \frac{1}{1+s_{mt}}[(1 - h_{mt})(\beta_{imt} - 1) + \omega_{it}] \qquad (8)$$

In (8), $\beta_{imt}^{s}$ is the systematic risk which is biased due to sentiment, $s_{mt}$ represents the level of market optimism or pessimism and $\omega_{it}$ is the idiosyncratic sentiment. Note that only in very few extreme situations where, $s_{mt} = h_{mt} = \omega_{it} = 0$ and $h_{mt} = -s_{mt}$, $\beta_{imt}^{s}$ corresponds to the equilibrium beta (for details see, Hwang and Salmon, 2009). Alternatively, betas would enclose a sentimental bias to a certain degree. Hence, there are two main forces that contribute to the distortion in betas (either individually or combined), i.e. biased expectations with respect to market sentiment concerning future returns and/or biased estimations depending on the market consensus while disregarding the systematic risk.

The initial beta herding measure suggested by Hwang and Salmon (2009) is:

$$H_{mt} = \frac{1}{N}\sum_{i=1}^{N_t}\left(\hat{\beta}_{imt}^{s} - 1\right)^2 \tag{9}$$

In (9), $\hat{\beta}_{imt}^{s}$ is the estimated biased beta when cross sectional herd behavior takes place and $N_t$ is the number of stocks. Equation (9) can be rewritten as:

$$H_{mt} = \frac{1}{N_t}\sum_{i=1}^{N_t}(\beta_{imt}^{s} - 1)^2 + \frac{1}{N_t}\sum_{i=1}^{N_t}\eta_{im}^2 \tag{10}$$

In (10) $\eta_{im}^2$ is the estimation error. Since cross sectional average estimation errors may bias $H_{mt}$, a standardized measure of beta herding is introduced in order to sufficiently capture herding effects (for more details see Hwang and Salmon, 2009):

$$H_m^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\widehat{\beta}_{im}^{s} - 1}{\widehat{\sigma}_{\widehat{\beta}_i}}\right)^2 \tag{11}$$

In (11), $\hat{\sigma}_{\hat{\beta}_i}$ is the standard error of $\hat{\beta}_{im}^{s}$ and $H_m^*$ is computed as the cross-sectional variance of the *t*-statistics of the estimated coefficients on the market portfolio. One important issue in the implementation of the herding measure in (11) is the choice of the appropriate asset pricing model. In this paper, the four-factor asset pricing model of Carhart (1997) is employed, i.e. betas are adjusted, in addition to the market portfolio, for market capitalization, book to market values, and momentum (see also Fama and French, 1993). To proxy for the euro area risk-free rate we employ the 3-month German Treasury bill (Bubill) rate. The data are obtained on a monthly basis from Bloomberg.

For the herding measure we follow Hwang and Salmon (2009) and employ a rolling sample of 36 observations (monthly) with a constant step of one month; we use the initial 36 monthly observations to obtain OLS beta estimates and *t*-statistics using Newey-West standard errors for each stock. More specifically, we use 36 monthly observations as follows: assume we start with February 2003 to January 2006, to obtain the beta and *t*-stat for January 2006. Next, we roll everything by one month, i.e. we use March 2003 to February 2006 to estimate the beta and *t*-stat for February 2006, and so on. We employ statistical trimming on the herding measure where we omit the 1% top and bottom standardized beta estimates, in order to mitigate the effect of outlier values (Hwang and Salmon, 2013), and consider the Carhart (1997) model since it is a widely accepted asset pricing model (Hwang and Salmon, 2009). In addition, since empirical betas may exhibit limitations (liquidity, microstructure issues, thin trading)[17], we impose a number of criteria on sample stocks (for a more detailed discussion, see Hwang and Salmon, 2009). More specifically, for a stock to be included in the sample it must have available at least 60 past observations, its stock price must be above 1€ (i.e. we

[17] For example, Andronikidi and Kallinterakis (2010) show that thin trading severely affects beta herding estimates.

exclude ‘penny’ stocks), its turnover should be above the bottom 1%, its return volatility based on the past 60 observations (60 months) should not be in the top and bottom 1% of the sample (alternative cut-off points produce qualitatively similar results).[18]

We employ the universe of stocks for each market. This means we include dead/suspended stocks but only keep major securities and primary quotes for all stock exchanges examined, i.e. the NYSE, Vienna Stock Exchange, Euronext Brussels, Helsinki Stock Exchange, Euronext Paris, Frankfurt Stock Exchange, Euronext Amsterdam, Madrid-SIBE, Milan Stock Exchange, and Euronext Lisbon. As discussed above, we apply several filters on this initial universe of stocks as in Hwang and Salmon (2009). For example, we exclude financial firms (Industry Classification Benchmark Code: 8000), foreign companies and stocks with negative stock prices, market to book ratio and/or missing values. We exclude NASDAQ stocks because of the differences in reported trading volumes and in line with the literature (see for example, Henry and Koski, 2017) in order to control for variation in microstructure across exchanges. However, we do include NASDAQ index in the FAVAR estimation to gauge the state of the equity market in US. We provide indicative descriptive statistics for the number of firms used in the herding measure for each country in Table D1 in APPENDIX D. That is, we present averages of the number of stocks included and the market capitalization and the number of shares traded (volume) included in the final sample for each equity market examined. For example, for Germany the average number of stocks included for the herding measure are 342, with an average firm market capitalization $1746,7 million.

Figures 4 to 6 present the resulting herding measures for each sample country for the period between December 2005 and December 2016. The intuition here is that lower values of the

[18] For the sample markets, we obtain our monthly time series for each stock from Thomson Reuters Eikon. The following datatypes are used for each stock: equity price (P), total return (RI), market value (MV), number of shares (NOSH), trading volume (VO) and common equity (CEQ).

herding measure imply higher levels of herding activity. In other words, lower values imply smaller deviations from the consensus (i.e. high levels of herding) while higher values suggest large deviations from the consensus (i.e. low levels of herding). Note that herd behavior is not similar within Eurozone markets. For instance, in some markets there are significant fluctuations in herding levels (e.g. Austria, Germany) while in others herd behavior levels are more stable overtime with few peaks (e.g. France). In Germany the herding measure spikes in 2010-2011 and then again in 2016. These two spikes coincide with the beginning of the EU financial crisis with the fiscal problems in Greece and the bail-out agreements for Greece (May 2010), Ireland (November 2010), and Portugal (May 2011), and the result of the Brexit referendum (June 2016), respectively. Note also that between 2008 and 2012 in some markets (e.g. Italy, Spain, Portugal) we observe higher levels of herding compared to before and after this period, while in other markets (e.g. Finland) we observe lower levels of herding. For the US it is notable that herd behavior was more prevalent for the period leading to the financial crisis (2006 -2008) rather than during (2008-2009) or afterwards, consistent with the findings of Hwang and Salmon (2009); in addition, for the US market (Figure 6) we observe much lower levels of herd behavior from 2010 onwards.

[INSERT FIGURE 4 ABOUT HERE]

[INSERT FIGURE 5 ABOUT HERE]

[INSERT FIGURE 6 ABOUT HERE]

### 2.3. The Effect of Monetary Policy on Herding: A FAVAR Approach

In order to examine the effect of monetary policy on herding we employ a structural Factor-Augmented Vector AutoRegression (FAVAR) model. The idea is that we include in the model the latent variable that we derived from the Qual VAR estimation, which captures the propensity of ECB and Fed for non-standard (unconventional) monetary policy. We estimate the FAVAR model with a two-step principal component analysis (see, Bernanke Boivin, and Eliasz, 2005; Boivin et al., 2009). Initially, we employ a large set of variables and Principal Component Analysis (PCA) to derive a set of factors that describe the dynamics of financial markets. More specifically, for the US FAVAR model we use 110 variables while for the EU FAVAR model we use 930 variables for the sample markets such as industrial production indexes, unemployment, producer and consumer price indexes, short and long-term interest rates, capacity utilization rate, money supply, GDP, unit labour cost, main stock price indexes, economic sentiment indicators, imports and exports. We also use world variables (oil price, S&P 500 Composite Index, VIX-CBOE volatility index, ECB Commodity price index) and aggregate euro-area variables (EUROSTOXX 50, Yen to EU exchange rate, EU to UK exchange rate, EU to USD exchange rate, VSTOXX, etc). Some time series are quarterly and have been disaggregated into monthly with cubic spline interpolation (see, among others, Abbate, et.al. 2016; Lescaroux and Mignon, 2009). The variables (except rates) are in log levels and if required differenced to achieve stationarity. The herding measures constructed are included in the FAVAR model together with macroeconomic and financial variables discussed above; the nine EU country-specific herding measures enter the EU FAVAR model while the US herding measure enters the US FAVAR model.

Also, all variables employed to estimate the factors are standardised (zero mean, unit variance) to deal with the impair factor extraction issue that arises due to the different time series scales. For a list of the variables employed in the EU FAVAR model see Appendix C. These variables cover national accounts, prices, income and consumption, the labour market, monetary aggregates, interest rates, financial markets (i.e. bond, stock and credit markets) and business conditions and the foreign exchange market. The dataset is augmented with EU aggregates and world aggregates. For the US FAVAR model we update the dataset from Boivin et al (2009) and Stock and Watson, (2004).[19] We employ an extensive and balanced panel-dataset across EU countries and the US in order to increase the significance of the inferences made and to enable comparisons.

In Appendix D we present indicative descriptive statistics for sample variables. Note that the total equity market capitalisation of the Eurozone markets in the third quarter of 2019 is approximately 7.3 trillion million Euro (see Table D1, Panel A, in Appendix D, for more details) while the sample markets examined in the paper have a combined equity market capitalisation of 6.9 trillion Euro (Table D1, Panel A); that is, they represent approximately 94% of total Eurozone market capitalisation. The market cap of the New York Stock Exchange (NYSE) by mid-2019 was approximately US$22.9 trillion (with a further US$10.8 trillion for NASDAQ). The three largest Eurozone equity markets in terms of market capitalisation are France with a market cap of approximately 2.1 trillion Euro, Germany (1.7 tr) and the Netherlands (1.1 tr). Spain has the highest average number of listed stocks 1856 (see Table D1, Panel B) although it is the fourth largest market. Portugal is the smallest market with a market cap of approximately 54 billion and has the lowest average number of listed stocks (66). Also, southern Eurozone countries tend to have higher inflation rates, higher unemployment rates, and higher bond yields, compared to Core Eurozone countries (Table D1, Panel C).

[19] Due to lack of data we do not include Baker and Wurgler, 2006; Baker and Wurgler, 2007 Sentiment Index and Net Exchange Between Stock and Bond Mutual Funds.

The second step consists of estimating a VAR model where we also include the latent factors that capture unconventional policy as derived using the Qual VAR approach,[20] the Federal Funds Rate (FFR, US) and the Main Refinancing Operations Rate (MRO, Eurozone) rate in the case where we investigate the conventional monetary policy effect (see also Galariotis, Makrichoriti, and Spyrou, 2018). More formally, suppose that $N \times 1$ is a vector of macro variables $X_t$, and that capital market dynamics are affected by a $K \times 1$ vector of (unobserved) factors ($F_t$). Also, suppose that an observed factor $R_t$ exists such:

$$C_t = \begin{bmatrix} \frac{F_t}{R_t} \end{bmatrix} \tag{12}$$

Using PCA the estimation of the observation equation is:

$$X_t = \Lambda^f F_t + \Lambda^r R_t + e_t \tag{13}$$

In (13) $\Lambda^f$, is the $N \times K$ matrix of factor loadings, $\Lambda^r$ is the $N \times 1$ vector of factor loadings, and $e_t$ is he $N \times 1$ vector of error terms with zero mean. Then, we estimate the following standard VAR with the $C_t$:

$$C_t = \Phi(L)C_{t-1} + u_t \tag{14}$$

In (14) $\Phi(L)$ is the matrix of lag polynomials of finite order. In the next section, we present IRFs and the Forecast Error Variance Decompositions (FEVDs) from the model. We use Cholesky ordering, with monetary policy last in the ordering since we assume that it has an

[20] As the Qual VAR model was estimated for each of the nine countries separately, a principal component analysis (PCA) to the country specific latent propensities was conducted, in order to produce a latent propensity for ECB's unconventional monetary stance for the euro area as a whole, in order to be used in the FAVAR model.

impact on the unobserved factors, $F_t$, with a lag. We report results with a lag length of three, and follow Bernanke, Boivin, and Eliasz (2005) and employ three factors in our model.[21]

## 3. Results

### 3.1. The Effect of Conventional Monetary Policy on Herding

Table 1 presents the contribution of conventional monetary policy to the variance of the common component, i.e. the Forecast Error Variance Decompositions (FEVDs). The FEVDs are obtained via the estimation of a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis, as discussed above. For the US we use the Federal Funds Rate (FFR) to proxy for conventional monetary policy, while for the EU we use the Main Refinancing Operations (MRO) rate. The model is estimated with 3 common factors for the period 2007-2016. The column titled FEVD reports the fraction of the variance of the forecast error explained by the policy shock. $R^2$ refers to the fraction of the variance of the variable explained by the common factors, ($F_t$ and $R_t$).

The results suggest that for the US (Panel A) conventional Fed monetary policy explains an important proportion of the US herding variance (9.6%), the $R^2$ indicates that the variables included in the model explain an important fraction (55.1%) of equity market herding variance for the US. The results in Panel B suggest that for many Eurozone markets standard monetary policy explains about 5% - 10% of herding variance. For example, conventional ECB policy shocks explain 9.1% of the variance in the herding measure for Spain, 7.6% for

[21] Our results remain qualitatively the same after adopting five or more factors and using different lag length, as discussed in the next section. Note that, although Bai and Ng (2002) suggest a criterion for the number of factors, Bernanke, Boivin, and Eliasz (2005) argue that the decision relies on the exploitation of the sensitivity of the results to alternative factor numbers.

Italy, 5.3% for France, 4.6% for the Netherlands (for the rest countries it is quite low. i.e. 0.1% - 1.5%). Note also that the fraction of the herding variance explained by the common macro factors ($F_t$ and $R_t$) is significantly higher mainly for Southern markets and the Netherlands: about 22% to 26% for Italy, Portugal, and France, 41% for Spain, and 62.4% for the Netherlands.

[INSERT TABLE 1 ABOUT HERE]

### 3.2. The Effect of Unconventional Monetary Policy on Herding

Table 2 is arranged in a similar manner as Table 1 and presents the contribution of unconventional monetary policy to the variance of the common component (FEVDs). Non-standard monetary policy is measured, for each market, with the use of a binary variable based on significant Fed and ECB announcements related to non-standard monetary policy and its transformation to a continuous latent variable, denoted as y*, via the implementation of the Qual VAR model of Dueker (2005). Panel A presents the result for the US market: the FEVD suggests that Fed's unconventional monetary policy, as captured by the y* variable, explains a significant fraction of US herd behavior variance (15.3%), while the respective $R^2$ is also important and equal to 55.1%. Panel B presents the results for the Eurozone markets. Compared to the results in Table 1 we observe that non-standard ECB monetary policy explains a higher percentage of herding variance compared to standard policy for Portugal (16.7% compared to 1.5%), for Germany (3.7% compared to 0.7%), for Finland (2.4% compared to 0.4%), and for the Netherlands (5.6% compared to 4.6%). At the same time, it explains a lower percentage for Spain (2.8% compared to 9.1%) and Italy (0.9% compared to 7.6%). The results from the $R^2$ of the model are qualitatively similar to the results in Table 1.

[INSERT TABLE 2 ABOUT HERE]

### 3.3. Spill-Over Effects

This sub-section examines potential spill-over effects of Fed's monetary policy on Eurozone equity market herd behaviour. Although monetary policy spill-over effects on herd behaviour have not been examined before, there is evidence to suggest that Fed monetary policy does affect international markets. For instance, Curcuru and Kamin (2018) find that conventional Fed policies exert greater international spill-overs than unconventional policies (such as QE), Albagli et al (2018) show that US monetary policy spill-overs to long-term yields have increased substantially after the global financial crisis, while Yang and Zhou (2017) report a significant contribution of Fed unconventional policy to international volatility spill-overs. In addition, Schmidt et al (2018) provide evidence on the impact of US and UK monetary policy shocks on domestic credit supply of French and Italian banks; Georgiadis (2015) documents that US monetary policy generates sizable output spill-overs to the rest of the world; Hanisch (2018) shows that US monetary policy has a substantial impact on individual EA economic and financial stability, with financial sector represented by bond, stock and credit markets serving as an active transmission channel. In order to detect potential US monetary policy spill-over effects, we employ the same FAVAR model as above for the Eurozone sample markets, except that instead of using ECB policy we use Fed standard (FFR) and non-standard (y*) monetary policy. The results are presented in Table 3 and are arranged in the same manner as in the previous Tables.

Conventional Fed policy (Panel A) seems to have a significant impact on herd behaviour volatility only for Spain (15.2%); for the rest of the Eurozone markets its impact is relatively low although it appears to be higher for Finland and Portugal and lower for Italy when compared to the impact of ECB's policy. For instance, conventional Fed policy explains about 2.3% for Finland, 4.4% for Italy, 4% for Portugal of the herding variance, while ECB policy explains 0.4%, 7.6% and 1.5%, respectively. The FEVD results for Fed's unconventional monetary policy (Panel B) indicate that y* explains a significant fraction of herd behavior variance for Portugal (21.7%) and the Netherlands (15.9%). For the rest of the markets the contribution varies between 0.01% to 2% (Austria, Belgium, Finland, Spain, Germany), 5.2% for France, and 3.4% for Italy, fractions that are very close to the ones explained by ECB unconventional policy ( 0.1% for Austria, 1% for Belgium, 2.4% for Finland, 2.8% for Spain, 3.7% for Germany, 5.3% for France and 0.9% for Italy). The $R^2$ statistics are qualitatively similar to the ones reported above.

[INSERT TABLE 3 ABOUT HERE]

The results so far indicate that Fed's conventional monetary policy contributes approximately 10% to US equity market herd behaviour variance, while unconventional policy has a more significant impact (about 15%). Conventional ECB monetary policy explains about 5% - 10% of herding variance for many Eurozone markets, while non-standard monetary policy explains a higher percentage of herding variance compared to standard policy for Portugal, Germany, Finland, France, and the Netherlands. We also detect an effect of Fed's policy on Eurozone markets: conventional Fed policy seems to have a significant impact on herd behaviour volatility for Spain (15.2%), while unconventional Fed policy has an impact on herding volatility for Portugal (21.7%) and the Netherlands (15.9%). Note that, the two Southern Eurozone markets (Portugal and Spain) that were most severely affected by the financial crisis seem to be more sensitive to monetary policy shocks, while Netherlands, despite being a small open economy, it has a large financial sector and is one of the countries that experienced a real estate bubble. An interesting observation is that Germany seems to be one of the countries with the smallest effect, in all specifications.

## 4. Robustness tests

One issue that arises at this point is whether our proxy (y*) does indeed capture the impact of unconventional monetary policy on macroeconomic dynamics, asset prices, and expectations. Note that during the financial crisis main rates had reached their zero lower bound and, thus, it is crucial to have a valid proxy for monetary policy during this period. To test the robustness of our results, with regards to the policy proxy we use, we re-estimate the results in Table 2, replacing our y* variable with the Shadow Federal Funds Rate (see Wu and Xia, 2016) for the US and the European Central Bank Shadow rate for the EU (see Wu and Xia, 2017). This rate is estimated using Treasury forward rates up to a 10-year horizon and takes into account the impact of policies such as the Quantitative Easing (QE) policy and other non-standard policy tools in order to determine an accurate measure of the impact of Central Bank policy on economic fundamentals.

Table 4 presents the results of the model when the y* variable is replaced with the Shadow Rates (Wu and Xia, 2016; Wu and Xia, 2017). Note that for the US (Panel A) the results are virtually identical with the results presented in Table 2, indicating that, for the US, our variable captures the main dynamics of Fed's unconventional monetary policy. For instance, when the shadow rate is used, non-standard Fed policy contributes 14.5% to the variance of the herding measure (compared to 15.3% in Table 2), while the $R^2$ is 56.6% (compared to 55.1% in Table 2). For the Eurozone markets (Panel B) there are two notable differences: the contribution of non-standard policy to herd variance in France is much more significant (13.8% from 5.3%) while in Portugal is less significant (1.6% from 16%). This could be due to the fact that we include 9 Eurozone countries in order to construct the latent propensity to ECB unconventional monetary policy, in contrast to the European Central Bank Shadow rate, which covers the whole of the EU.

[INSERT TABLE 4 ABOUT HERE]

Another issue that may affect our results is the number of factors included in the model. To deal with this issue, as a robustness test, we re-estimate our models but this time we employ 5 factors in the FAVAR model (rather than 3) according to the Bai and Ng (2002) factor determination criterion, although Bernanke, Boivin, and Eliasz (2005) argue that the decision relies on the exploitation of the sensitivity of the results to alternative factor numbers. Table 5 presents these robustness tests results as follows: Panel A reproduces the results presented in Table 1 for conventional policy, while panel B reproduces the results presented in Table 2 for unconventional policy. For conventional policy (Panel A) we can see that the results do not change significantly except for the US, for which the proportion of the US herding variance explained falls to 5.8% from 9.6%. For the Eurozone markets the results are more or less similar to the results in Table 2: conventional ECB policy shocks explain approximately 11.7% (from 9.1%) of the variance in the herding measure for Spain, 6.2% (from 5.3%) for France, 5.3% (from 4.6%) for the Netherlands, while for the rest countries the proportion is much lower, i.e. between 0.1% and 3%. The fraction of the herding variance explained by the common factors is (as in Table 2) higher mainly for Southern markets and the Netherlands. The most striking difference between the 3 and 5 factor FAVARs is the result for the impact of non-standard Fed policy on equity market behaviour herding for the US (Panel B): the

FEVD suggests that Fed’s unconventional monetary policy, as captured by the y* variable, explains 24.4% of US herd behavior variance (compared to 15.3% in Table 2), which is a notable increase. For ECB non-standard policy, the 5-factor model does not produce any significant changes, compared to the results in Table 2. As a final robustness test we re-estimate with the 5-factor FAVAR the results presented in Table 3 (Panel B) and Table 4 and arrive at qualitatively similar findings, with minor exceptions; when we replace y* with the shadow Fed fund rate and use a 5-factor FAVAR, the effect for the US is slightly reduced while for Spain it is increased to about 14%. (these results are not reported here, available upon request).

[INSERT TABLE 5 ABOUT HERE]

In other words, the results of the robustness tests are in line with our original results, with the notable exception of the US market where the explained variance of the herding measure by Fed non-standard policy increases to 24.4%. Overall, the results presented in this section seem to indicate that (i) monetary policy has an impact on equity market herd behaviour, (ii) non-standard policy has a much more significant impact compared to standard policy, especially for the US and Southern European markets, (iii) there exists evidence of US monetary policy spill-over effects with important impact on herding behaviour in Spain, Portugal and the Netherlands[22], iv) a significant fraction of the variance in herding is explained by macro factors.

[22] Note that the Netherlands is an internationalized market, with a huge foreign investors' component in its capitalization. More specifically, ownership of companies held by domestic institutional investors in Netherlands in 2007 is less than 10% while ownership held by foreign investors appears to be more than 90% (OECD, The Role of Institutional Investors in Promoting Good Corporate Governance, 2011); as a result, it would be expected the Netherlands to be more vulnerable to global shocks such as the one of the US monetary policy. Indeed, when we test for spill-over effects with y* variable used in order to capture the contribution of US unconventional monetary policy to the variance of the common component for the Netherlands, that contribution is around 15.6%, one of the highest in our sample (Table 3).

## 5. Impulse Response Functions (IRFs)

The findings discussed in the previous section indicate that monetary policy has an impact on equity market herd behaviour; for instance, monetary policy seems to contribute about 15% to herd behaviour variance in the US, although its magnitude varies among markets. This may have been expected, since shocks in monetary policy often convey significant information for market participants. An important question for policy makers, however, is whether shifts in monetary policy tend to increase or decrease herd behaviour. For instance, herd behaviour, as a response to an important policy announcement, may offset the potential effect of the announcement on expectations and asset prices, i.e. on relevant transmission channels. This section presents the Impulse Response Functions (IRFs) that are obtained from the various FAVAR models, to examine the effect of monetary policy on the level of herding.

For the IRFs we follow Christiano, Eichenbaum, and Evans (1999) recursive ordering procedure. More specifically, we use a Cholesky decomposition based on the following ordering of variables for the model: IP, HICP/CPI, MROr/FFR, Stock_Ret,, ESI/MCSI, HM. This ordering was followed by Galariotis et al (2018) as well. The monetary policy shocks are identified using a Cholesky identification scheme in the FAVAR model as well, under the assumption that the monetary policy variable comes last in the ordering, indicating that it affects the unobserved factors, Ft, with only one lag. Nevertheless, we define two categories of variables: “slow-moving” and “fast-moving” according to Bernanke et al. (2005). A “slow-moving” variable is one that is largely predetermined as of the current period, while a “fast-moving” variable – think of an asset price – is highly sensitive to contemporaneous economic news or shocks. We considered alternative orderings, like the one in Bloom (2009) by listing stocks first in the ordering and IP after the monetary rate, but the change in ordering does not affect our analysis and conclusions.

Figure 7 presents the response (IRFs) of our Herding Measure to shocks in conventional monetary policy. Recall, from section 2, that lower values of the herding measure imply higher levels of herding; i.e. lower values of the herding measure imply smaller deviations from the consensus (high levels of herding) while higher values of the herding measure suggest large deviations from the consensus (low levels of herding). From Figure 7 note that the response for Spain and Italy is positive, i.e. a contractionary policy tends to increase the level of the herding measure, while for the US we observe a negative response of the herding measure. The implication is that, the expansionary policy followed by the ECB tends to increase the levels of herd behaviour in the Spanish and Italian equity markets, while the expansionary policy adopted by the Fed tends to decrease the levels of herd behaviour in the US equity market.

Figure 8, presents the response (IRFs) of our US (Eurozone markets) herding measure to shocks in Fed (ECB) unconventional monetary policy as measured by the y* variable: on average, we see a positive response, i.e. shocks to non-standard policy result to lower levels of herding for most sample markets. Figure 9 presents the herding measures responses after a positive shock on the shadow rates: for both France and Italy, the response is positive indicating that the levels of herding increase after an expansionary policy adoption, while in the US the levels of herd behaviour decrease. Overall, the IRF results indicate that conventional and unconventional Fed policies resulted to reduced levels of US equity investor herd behaviour.

[INSERT FIGURE 7 ABOUT HERE]

[INSERT FIGURE 8 ABOUT HERE]

[INSERT FIGURE 9 ABOUT HERE]

Figures 10 and 11, present the IRFs for the spill-over effects. Figure 10 presents the response of Eurozone markets to Fed conventional policy shocks, i.e. the spill-over effect to Eurozone markets. Note that for Spain the response is positive indicating an increase in herding levels after an expansionary policy adoption from the Fed. Figure 11 presents the response of Eurozone markets to Fed unconventional policy shocks, i.e. the spill-over effect of the y* variable to Eurozone markets. Here the response is positive for Portugal, indicating a reduction of herd behaviour levels following a shock in non-standard Fed policy, while the response is negative for the Netherlands underlining an increase in herd behaviour in the respective market. We obtain a similar result when we use the shadow Fed funds rate to proxy for non-standard Fed policy (not reported here, available upon request).

[INSERT FIGURE 10 ABOUT HERE]

[INSERT FIGURE 11 ABOUT HERE]

Overall, the results seem to indicate that conventional expansionary policy and non-standard policy by the Fed reduces the levels of herding in the US equity market; conventional ECB expansionary policy seems to induce higher levels of herding in Spain and Italy, while shocks to non-standard ECB policy seem to reduce herd behavior in the majority of the Eurozone markets. Conventional Fed policy, however, seems to increase herd behavior in Spain, while the unconventional monetary policy stance adopted by the Fed increased the herding levels in the Netherlands and caused a decrease in herding behavior in Portugal. Note that our results cannot be due to factors such as differences in gross domestic investment growth rates: the annual % growth in gross capital formation for the sample countries (see Figure D1, in Appendix D) follows a very similar trend in the sample countries, except for the Netherlands for the 2014-2016 period. In other words, there are no notable differences in the trend for the gross domestic investment growth rate between the sample countries.

## 6. Conclusion

Whether monetary policy has an impact on herd behaviour in asset markets is an issue that has been neglected in the relevant literature. This paper examines the extent of the contribution of monetary policy measures adopted by the Fed and the ECB to equity market investor herd behavior in the US and major EU markets. We argue that monetary policy may affect herd behavior through its impact on economic expectations and investor sentiment. We combine a range of research methodologies to measure monetary policy, herd behavior, and their possible relation. For example, we first construct a binary variable based on important monetary policy announcements and then employ the Qual VAR model of Dueker (2005) and macroeconomic information from our sample countries to transform this variable to a continuous latent variable that captures central bank propensity to non-standard monetary policy. In a second stage, this latent variable enters a structural FAVAR model in order to examine its impact on herd behaviour across countries. To measure herding, we employ the measure of Hwang and Salmon (2009), that considers herding as market wide phenomenon that evolves over time. The sample consists of all listed stocks for the NYSE, Vienna Stock Exchange, Euronext Brussels, Helsinki Stock Exchange, Euronext Paris, Frankfurt Stock Exchange, Euronext Amsterdam, Madrid-SIBE, Milan Stock Exchange, and Euronext Lisbon. Overall, the results indicate that conventional expansionary policy and non-standard policy by the Fed reduces the levels of herding in the US equity market; conventional ECB expansionary policy seems to induce higher levels of herding in Spain and Italy, while shocks to non-standard ECB policy seem to reduce herd behavior in the majority of the Eurozone markets. Conventional Fed policy, however, seems to increase herd behavior in Spain, while the unconventional monetary policy stance adopted by the Fed increased the herding levels in the Netherlands and caused a decrease in herding behavior in Portugal.

On balance, we find that monetary policy seems to have a greater impact over market herding in the US compared to Eurozone markets. The differences in the results between the two central banks and across countries can be due to several reasons. Firstly, note that central banks communicate their policy decisions in different ways. For instance, empirical evidence suggests that markets react stronger to communication form the Head of a central bank such as the Fed, while to ECB communications which is characterized by a more collegial approach, markets react more evenly to Governing Council member statements (see, among others, Ehrmann and Fratzscher 2007a; Ehrmann and Fratzscher 2007b). Kohn and Sack (2004) present evidence that FOMC statements are significant market movers, while Rosa (2008) examines the unexpected components of announcements by the FOMC and the ECB and finds a weaker market reaction to unexpected ECB communication compared to the Fed. Secondly, the two institutions faced different challenges: whilst the Fed had to deal initially with a subprime loan banking crisis (2007-2009), the ECB had to deal with a (multiple) sovereign debt crisis (2010-2013), which followed immediately after the respond to the global financial crisis. The ECB had to provide liquidity and generally consider issues for seventeen (17) different countries (and bond markets), rather than just deal with one sovereign security. Another difference is that the ECB, with the LTROs and the SMP measures, aimed at a ‘credit easing’ approach, i.e. an approach aiming at also minimizing its own risk, in contrast to the Fed whose Quantitative Easing policies indicated a will to undertake credit risk (see for a discussion, Gros, Alcidi, and Giovanni, 2012). Thirdly, compared to the Fed, the ECB has only one primary objective (price stability), a narrower role as a lender of last resort, and did not use to publish the minutes of the monetary policy meeting (in this sense, it may be argued that Fed policies have been more transparent). Finally, one has to keep in mind that at some point the ECB had to also consider the survival of the single European currency and had to send the appropriate signals to the market: "*Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough*".[23] The survival of the US currency was never an issue for the Fed during the global financial crisis.

The differences in the results at the country level could be due to the different financial phases the Eurozone countries were facing for most of the sample period and, as a result, a specific monetary policy measure may have had a different effect in each country. Recall that in 2010, Greece was dealing with its worst fiscal crisis in many decades and had to request an EU/IMF bailout package, while within the same year a similar package was negotiated for Ireland, and in the following year (2011) for Portugal. Yield spreads rose significantly not only for the affected countries but also for other Southern European countries; it soon became apparent that Italy and Spain were faced with serious problems in their banking systems. While many Peripheral Eurozone countries were facing either fiscal problems or banking system difficulties, many Core Eurozone countries were much better prepared to deal with this crisis and could offer "flight to quality" options for investors. This shows in Financial Account trends (see Table A2 in the Appendix) which are in deficit for Spain, Italy, France,

[23] Speech by Mario Draghi, President of the ECB, at the Global Investment Conference in London, 26 July 2012.

and, Portugal for most of the sample period, while for Core countries (such as Germany and the Netherlands) are in significant surpluses.

Another reason for the different results could be the cultural characteristics. Many studies find that cultural differences may explain different financial market behavior through their impact on financial decision making. For instance, recent studies indicate that investor sentiment may have a strong impact on asset returns in countries that are more prone to herd or overreaction (Schmeling, 2009). In another study Chui, Titman, and Wei (2010) adopt Hofstede's (1984) individualism index and find that it has a positive correlation with momentum strategy profitability, while, Chang and Lin (2015) examine the relationship between national culture and investor decision making behavioral pitfalls and find that herd behavior may occur in Confucian and less sophisticated stock markets, since they place an emphasis on public morality and majority behavior.

Overall, an important implication of our results is that market supervisors, regulators, and policy makers ought to take into account potential limitations of rational models when designing programmes and taking policy decisions. They should also consider the behavioral elements of market participant attitudes and psychological and cognitive biases. For instance, Hwang and Salmon (2009) find that beta herding is more significant not when markets are in turmoil but rather when markets are in a smooth (falling or rising) state. Their evidence indicates that during a financial crisis herding weakens (as we also find in this paper) and attribute this to the tendency of investors to focus on fundamentals during the crisis, rather than herd. The implication is that, if policy makers intend to influence herd behavior, the intervention should take place early, i.e. when markets are still in a smooth state, rather than during a volatile period or during a bubble period. This, however, may not always be feasible since, decision makers in central banks may not be free of behavioral biases such as loss aversion, which could lead to lags or postponements in altering a policy stance (see Masciandaro and Romelli, 2019; among others).

Another example of taking into account potential limitations of rational models are the behavioral aspects of the risk management procedures established by the central bank of the Netherlands (NB) and discussed in Khan (2018) which, among others, aim at recognizing behavioral risks early. In addition, central banks should also consider behavioral issues when communicating views and policies that aim at shaping expectations; as discussed elsewhere in the paper, evidence indicates that even the tone in central bank communication affects expectations (Schmeling and Wagner, 2019). Finally, note that behavioral elements have been incorporated to models related to central bank policies. For instance, Hommes, Massaro, and Weber (2019) propose a model of expectation formation with behavioral elements according to which, in addition to the reaction to inflation, central bank reaction to the gap in output can lower volatility in inflation; while other models employ certain heuristics to forecast inflation which may do a superior job in economy stabilization than monetary policy rules (Brazier, Harrison, King, and Yates, 2006).

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# APPENDIX A
## Fed Announcements on Unconventional Policy

| | |
|---|---|
| 25/11/2008 | Fed Announces Purchases of MBS and Agency Bonds |
| 16/12/2008 | FOMC Meeting: FFTR decreased to 0–0.25% |
| 28/1/2009 | FOMC Meeting, Large Scale Asset Purchase (LSAP) announcement |
| 18/3/2009 | FOMC Meeting, LSAP |
| 10/8/2010 | FOMC Meeting, LSAP |
| 27/8/2010 | Bernanke Speech at Jackson Hole |
| 21/9/2010 | FOMC Meeting, LSAP |
| 15/10/2010 | Bernanke Speech at Boston Fed |
| 3/11/2010 | FOMC Meeting, LSAP |
| 26/8/2011 | Bernanke Speech at Jackson Hole |
| 21/9/2011 | FOMC Meeting, LSAP |
| 20/6/2012 | FOMC Meeting |
| 13/9/2012 | FOMC Meeting, LSAP |
| 22/5/2013 | Bernanke Testimony, Tapering Announcement |
| 19/6/2013 | FOMC Meeting, Tapering |
| 18/12/2013 | FOMC Meeting, Tapering |
| 29/1/2014 | FOMC Meeting, Tapering |
| 11/2/2014 | Yellen Testimony |

*Source*: Fratzscher et al. (2013); Falagiarda, et al., M. (2015).

## APPENDIX B
## ECB Announcements on Unconventional Policy

| | |
|---|---|
| 28/3/2008 | 6 month SLTROs |
| 4/9/2008 | Roll over of the outstanding 6 month SLTROs |
| 15/10/2008 | 6 month SLTROs and other measures |
| 7/5/2009 | 12 month SLTROs and other measures |
| | (including covered bond purchases) |
| 4/6/2009 | Details for the purchase programme of |
| 10/5/2010 | SMP and other measures |
| 30/6/2010 | Completion of covered bond purchases |
| 4/8/2011 | SLTROs and other measures |
| 7/8/2011 | SMP reactivation |
| 6/10/2011 | 12 month SLTROs and covered bond |
| 8/12/2011 | 36 month VLTROs and other measures |
| 26/7/2012 | M. Draghi's Speech "Whatever it takes" |
| 6/9/2012 | Details for the OMT |
| 21/2/2013 | Details on securities holdings acquired under the SMP |
| 2/5/2013 | Details of refinancing operations |
| 22/11/2013 | ECB suspends early repayments of the 3-year LTROs |
| 3/6/2014 | Further details of the targeted longer-term refinancing operations |
| 29/6/2014 | Legal act relating to targeted longer-term refinancing operations |
| 17/11/2014 | Unanimous in its commitment to using additional unconventional instruments (M. Draghi, speech at the EP) |
| 18/9/2014 | The ECB allots €82.6 billion in first targeted longer-term refinancing operation |
| 30/10/2014 | ECB appoints executing asset managers for the ABS Purchase Programme |
| 4/12/2014 | "Evidently we are convinced that a QE programme which could include sovereign bonds falls within our mandate." (M. Draghi press conference) |
| 22/1/2015 | ECB announces expanded asset purchase programme (FT Front Page) |
| 18/6/2015 | ECB Governing Council takes note of ruling on OMT |
| 23/9/2015 | Eurosystem adjusts purchase process in ABS programme |
| 10/3/2016 | The monthly purchases under the asset purchase programme will be expanded to €80 billion. |
| 2/6/2016 | The Eurosystem will start making purchases under its corporate sector purchase programme (CSPP). |
| 8/12/2016 | APP from €80 to billion to €60 billion |

*Sources*: ECB Press Releases (available at: https://www.ecb.europa.eu/); Falagiarda, et al., M. (2015); Fratzscher et al. (2014); Fratzscher et al. (2013).

# APPENDIX C
# Variables employed in the EU FAVAR Model

| |
|---|
| Herding Measures |
| Long-term interest rates, Short-term interest rates |
| Effective exchange rates |
| ECB Commodity Price index; Brent |
| Economic sentiment indicator |
| Current level of capacity utilization (%) |
| GDP and main components (output, expenditure and income) |
| Production expectations over the next 3 months |
| Households; non-profit institutions serving households |
| Disposable income, gross |
| Compensation of employees; Property income |
| M1, M3 |
| **Production in industry** |
| Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; construction; intermediate goods; capital goods; consumer goods; durable consumer goods; non-durable consumer goods; Mining and quarrying; manufacturing; Manufacture of food products; beverages and tobacco products |
| **Consumption** |
| Households; non-profit institutions serving households; Final consumption expenditure of households; Final consumption expenditure; Individual consumption expenditure |
| **Unemployment** |
| Percentage of active population, Total; Less than 25 years; From 25 to 74 years; Unemployment rates by sex, age and citizenship (%), Total; From 15 to 74 years; From 20 to 64 years; From 25 to 49 years; From 40 to 64 years; From 15 to 24 years; Employment rates by sex, age and educational attainment level (%); Average number of usual weekly hours of work in main job, by sex, professional status, full-time/part-time and occupation (hours) |
| **Imports & Exports** |
| Consumer goods; Consumer goods (excluding transport equipment); Intermediate goods; Capital goods; Total |
| **Labour cost index by NACE** |
| Industry and construction; Wages and salaries (total); Labour costs other than wages and salaries; Labour cost for LCI (compensation of employees plus taxes minus subsidies); Transportation and storage; Accommodation and food service activities; Financial and insurance activities; real estate activities; professional, scientific and technical activities; administrative and support service activities |
| **HICP** |
| Housing, water, electricity, gas and other fuels; Domestic services and household services; Health; Cultural services; Accommodation services; Insurance; Industrial goods; Food and non-alcoholic beverages; Non-durable household goods; Transport; Communications; Education; Energy |
| **Equity Market Indexes** |
| DAX, ATX, BEL20, CAC, IBEX, FTSE-MIB, PSI20, AEX, HEX, S&P 500 COMPOSITE, NYSE COMPOSITE, DOW JONES INDUSTRIALS, NASDAQ COMPOSITE, NASDAQ 100, CBOE S&P 100 Volatility Index, EUROSTOXX, VSTOXX |

# APPENDIX D

## Table D1

| Panel A: Market Capitalisation | | | |
|---|---|---|---|
| Eurozone Countries Included in the Sample | | Eurozone Countries Not Included in the Sample | |
| **Market** | **MV** | **Market** | **MV** |
| Austria | 119.74 | Cyprus | 2.992 |
| Belgium | 344.124 | Estonia | 2.787 |
| Finland | 254.60 | Greece | 36.52 |
| France | 2140.09 | Ireland | 220.71 |
| Germany | 1722.937 | Lithuania | 3.57 |
| Netherlands | 1103.87 | Luxembourg | 105.06 |
| Italy | 507.26 | Latvia | 0.793 |
| Spain | 656.05 | Malta | 6.39 |
| Portugal | 53.83 | Slovenia | 6.71 |
| **Total** | **6902.5** | Slovakia | 5.02 |
| | | **Total** | **390.5** |

| Panel B: Average Number of Firms Listed in Sample Countries | | | |
|---|---|---|---|
| | **Average** | **Min** | **Max** |
| Austria | 86 | 62 | 112 |
| Belgium | 191 | 111 | 290 |
| Finland | 92 | 48 | 158 |
| France | 642 | 218 | 1185 |
| Germany | 590 | 408 | 761 |
| Netherlands | 214 | 98 | 392 |
| Italy | 230 | 132 | 311 |
| Spain | 1856 | 519 | 3623 |
| Portugal | 66 | 23 | 158 |

| Panel C: Macroeconomic Indicators | | | | |
|---|---|---|---|---|
| | **Inflation (INF)** | **Unemployment (UN)** | **Δ Industrial Production (IND)** | **Bond Yield (Y)** |
| Austria | 1.73 | 4.91 | 0.09 | 3.58 |
| Belgium | 1.87 | 7.98 | 0.17 | 2.69 |
| Finland | 1.72 | 8.74 | 0.13 | 3.51 |
| France | 1.47 | 9.52 | 0.10 | 3.73 |
| Germany | 1.39 | 8.85 | 0.10 | 3.30 |
| Netherlands | 1.91 | 5.12 | 0.15 | 3.49 |
| Italy | 1.91 | 9.36 | 0.12 | 4.29 |
| Spain | 2.17 | 15.85 | 0.17 | 4.27 |
| Portugal | 2.06 | 9.62 | -0.02 | 5.09 |

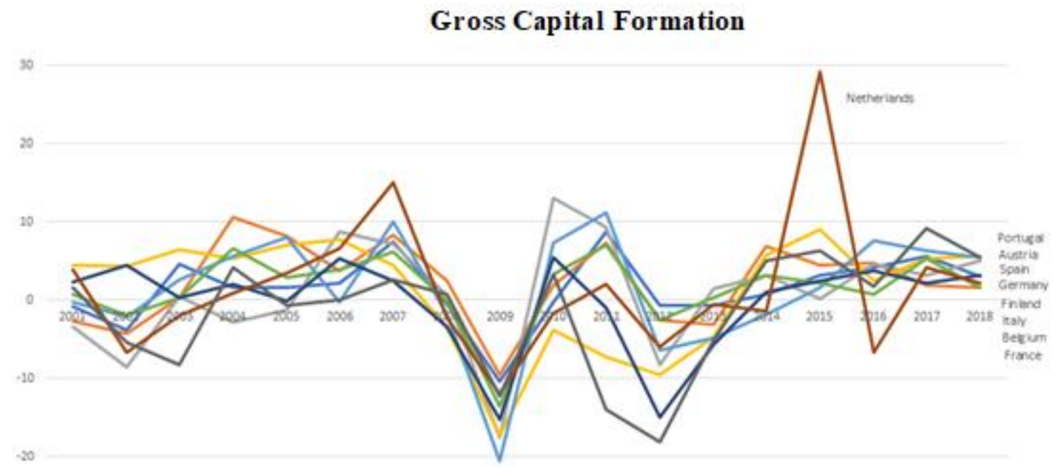
*Notes to Table D1*
**Panel A:** Market Value (Market Capitalization in billions of Euro) for the sample Eurozone Stock Markets (Q03, 2019; *Source:* Eurostat, Euro Area Statistics. Available at: https://www.euro-area-statistics.org). **Panel B:** Average Number of Firms Listed are between 1975 and 2018; source: World Bank. **Panel C:** descriptive statistics of macro variables. For each country, Inflation (INF) is proxied with the rate of change of Harmonized Consumer Price Index (HICP All-items), Industrial Production (IND) is proxied with the rate of change in producer prices in industry (NACE_R2, Industry; except construction, sewerage, waste management and remediation activities), Unemployment (UN) with the seasonally adjusted rate (percentage) of active population, and sovereign bond yields are redemption yields on long term (10-years) government (or benchmark) bonds. Data are monthly, in %, and cover the period between April 1997 and December 2016.

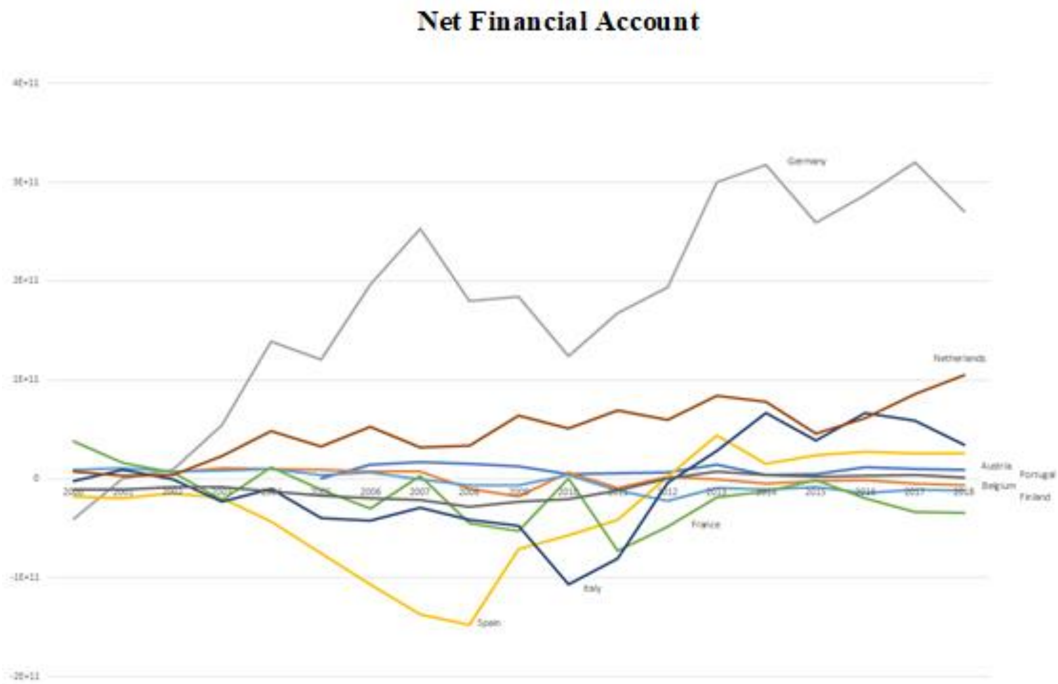
**Table D2**
**Constructing the Herding Measures: Descriptive statistics**

| Equity Market | Number of stocks included for the herding measure | Median Firm Market Capitalization (in $ mln.) | Average Firm Market Capitalization (in $ mln.) | Median Number of Shares Traded (volume) (in $ thousands | Average Number of Shares Traded (volume) (in $ thousands) |
|---|---|---|---|---|---|
| **Austria** | 53 | 371.44 | 912.59 | 308.54 | 2014.60 |
| **Belgium** | 62 | 293.11 | 1208.56 | 174.65 | 1801.36 |
| **Finland** | 41 | 420.72 | 1044.58 | 1279.11 | 5625.54 |
| **France** | 449 | 176.82 | 2299.87 | 108.13 | 4666.39 |
| **Germany** | 342 | 154.73 | 1746.71 | 31.14 | 231.58 |
| **Italy** | 81 | 291.16 | 1787.52 | 985.35 | 28884.96 |
| **Portugal** | 15 | 671.16 | 2253.87 | 4303.61 | 21256.89 |
| **Spain** | 46 | 1200.15 | 5305.76 | 3491.54 | 38585.88 |
| **US** | 1430 | 1498.59 | 6131.94 | 7418.74 | 24410.33 |

*Notes to Table D2*
Descriptive statistics for the Herding Measures.

**Figure D1**
**Gross Capital Formation**




**Gross Capital Formation.** *Source*: World Bank national accounts data, and OECD National Accounts data files. (annual % growth). According to the World Bank (see, https://data.worldbank.org/indicator/) "Gross capital formation consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements; plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings".

**Net Financial Account.** *Source*: International Monetary Fund, Balance of Payments Statistics Yearbook and data files. According to the World Bank (see, https://data.worldbank.org/indicator) "The net financial account shows net acquisition and disposal of financial assets and liabilities. It measures how net lending to or borrowing from non-residents is financed and is conceptually equal to the sum of the balances on the current and capital accounts".

## Table 1
## Contribution of Conventional Monetary Policy to the Variance of Herd Behavior

| Herding Measure (HM) | Forecast Error Variance Decomposition (FEVD) | $R^2$ |
|---|---|---|
| **Panel A<br>US (Fed, Federal Funds Rate, FFR)** | | |
| **US** | 0.096 | 0.551 |
| **Panel B<br>Eurozone (ECB, Main Refinancing Operations, MRO)** | | |
| **Austria** | 0.001 | 0.013 |
| **Belgium** | 0.002 | 0.078 |
| **Finland** | 0.004 | 0.098 |
| **France** | 0.053 | 0.231 |
| **Germany** | 0.007 | 0.179 |
| **Italy** | 0.076 | 0.219 |
| **Portugal** | 0.015 | 0.262 |
| **Spain** | 0.091 | 0.410 |
| **Netherlands** | 0.046 | 0.624 |

*Notes to Table 1*

The Table presents the contribution of convectional monetary policy to the variance of the common component, i.e. the Forecast Error Variance Decompositions (FEVDs). The FEVDs are obtained via the estimation of a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis (Bernanke Boivin, and Eliasz, 2005; Boivin et al., 2009). Initially, a large set of variables and Principal Component Analysis (PCA) is employed to derive a set of factors that describe the dynamics of financial markets. More specifically, 110 and 930 variables are used for the sample market of the US and the EU, respectively, such as industrial production, unemployment, producer and consumer prices, short and long-term interest rates, capacity utilization rates, money supply, GDP, unit labour cost, main stock price indexes, economic sentiment indicators, and imports and exports. We also use global variables (oil price, S&P 500 Composite Index, VIX-CBOE volatility index, ECB Commodity price index) and aggregate euro-area variables (EUROSTOXX 50, Yen to EU exchange rate, EU to UK exchange rate, EU to USD exchange rate, VSTOXX, etc). Some time series are quarterly and have been disaggregated into monthly with cubic spline interpolation (see, among others, Abbate, et.al. 2016; Lescaroux and Mignon, 2009). The variables (except rates) are in log levels and if required differenced to achieve stationarity. All variables employed to estimate the factors were standardised (zero mean, unit variance) to deal with the impair factor extraction issue that arises due to the different time series scales. For the US we use the Federal Funds Rate (FFR) to proxy for conventional monetary policy, while for the EU we use the Main Refinancing Operations (MRO) rate. The model is estimated with 3 common factors and 3 lags for the period 2007-2016. The column titled FEVD, reports the fraction of the variance of the forecast error, explained by the policy shock. $R^2$ refers to the fraction of the variance of the variable explained by the common factors, ($F_t$ and $R_t$).

**Table 2**
**Contribution of Unconventional Monetary Policy to the Variance of Herd Behavior**

| Herding Measure (HM) | Forecast Error Variance Decomposition (FEVD) | $R^2$ |
|---|---|---|
| **Panel A US (policy proxied by y*)** | | |
| **US** | 0.153 | 0.551 |
| **Panel B Eurozone (policy proxied by y*)** | | |
| **Austria** | 0.001 | 0.013 |
| **Belgium** | 0.010 | 0.063 |
| **Finland** | 0.024 | 0.091 |
| **France** | 0.053 | 0.124 |
| **Germany** | 0.037 | 0.184 |
| **Italy** | 0.009 | 0.172 |
| **Portugal** | 0.167 | 0.271 |
| **Spain** | 0.028 | 0.298 |
| **Netherlands** | 0.056 | 0.627 |

*Notes to Table 2*
The Table presents the contribution of unconvectional monetary policy to the variance of the common component, i.e. the Forecast Error Variance Decompositions (FEVDs). The FEVDs are obtained via the estimation of a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis (Bernanke Boivin, and Eliasz, 2005; Boivin et al., 2009). Initially, a large set of variables and Principal Component Analysis (PCA) is employed to derive a set of factors that describe the dynamics of financial markets. More specifically, 110 and 930 variables are used for the sample market of the US and the EU, respectively, such as industrial production, unemployment, producer and consumer prices, short and long term interest rates, capacity utilization rates, money supply, GDP, unit labour cost, main stock price indexes, economic sentiment indicators, and imports and exports. We also use global variables (oil price, S&P 500 Composite Index, VIX-CBOE volatility index, ECB Commodity price index) and aggregate euro-area variables (EUROSTOXX 50, Yen to EU exchange rate, EU to UK exchange rate, EU to USD exchange rate, VSTOXX, etc). Some time series are quarterly and have been disaggregated into monthly with cubic spline interpolation (see, among others, Abbate, et.al. 2016; Lescaroux and Mignon, 2009). The variables (except rates) are in log levels and if required differenced to achieve stationarity. All variables employed to estimate the factors were standardised (zero mean, unit variance) to deal with the impair factor extraction issue that arises due to the different time series scales. To proxy for unconventional monetary policy, we use significant Fed and ECB announcements related to non-standard monetary policy to construct a binary variable and then use the Qual VAR model of Dueker (2005) to transform this binary variable to a continuous latent variable (denoted as y*). The Qual VAR model is linked to the single-equation dynamic ordered probit model (Eichengreen, Watson, and Grossman 1985; Dueker, 1999) and allows the derivation of the latent variable following the estimation of the model with Markov Chain Monte Carlo (MCMC) procedures. The model is estimated with 3 common factors and 3 lags for the period 2007-2016. The column titled FEVD, reports the fraction of the variance of the forecast error, explained by the policy shock. $R^2$ refers to the fraction of the variance of the variable explained by the common factors, ($F_t$ and $R_t$).

## Table 3
## Spill-Over Effects

| Herding Measure (HM) | Forecast Error Variance Decomposition (FEVD) | $R^2$ |
|---|---|---|
| **Panel A US Conventional Monetary Policy** | | |
| **Austria** | 0.001 | 0.015 |
| **Belgium** | 0.007 | 0.062 |
| **Finland** | 0.023 | 0.099 |
| **France** | 0.018 | 0.125 |
| **Germany** | 0.004 | 0.180 |
| **Italy** | 0.044 | 0.170 |
| **Portugal** | 0.040 | 0.259 |
| **Spain** | 0.152 | 0.309 |
| **Netherlands** | 0.009 | 0.651 |
| **Panel B US Unconventional Monetary Policy (y*)** | | |
| **Austria** | 0.001 | 0.012 |
| **Belgium** | 0.012 | 0.065 |
| **Finland** | 0.009 | 0.088 |
| **France** | 0.052 | 0.116 |
| **Germany** | 0.019 | 0.179 |
| **Italy** | 0.034 | 0.180 |
| **Portugal** | 0.217 | 0.294 |
| **Spain** | 0.007 | 0.296 |
| **Netherlands** | 0.159 | 0.647 |

*Notes to Table 3*

The Table presents the contribution of US conventional (Federal Funds Rate, FFR) and unconventional (y*) monetary policy to the variance of the common component, i.e. the Forecast Error Variance Decompositions (FEVDs). To create the y* we use significant Fed announcements related to non-standard monetary policy to construct a binary variable and then use the Qual VAR model of Dueker (2005) to transform this binary variable to a continuous latent variable. The FEVDs are obtained via the estimation of a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis (Bernanke Boivin, and Eliasz, 2005; Boivin et al., 2009). Initially, a large set of variables and Principal Component Analysis (PCA) is employed to derive a set of factors that describe the dynamics of financial markets. More specifically, 930 variables are used for the sample markets such as industrial production, unemployment, producer and consumer prices, short and long term interest rates, capacity utilization rates, money supply, GDP, unit labour cost, main stock price indexes, economic sentiment indicators, and imports and exports. We also use global variables (oil price, S&P 500 Composite Index, VIX-CBOE volatility index, ECB Commodity price index) and aggregate euro-area variables (EUROSTOXX 50, Yen to EU exchange rate, EU to UK exchange rate, EU to USD exchange rate, VSTOXX, etc). Some time series are quarterly and have been disaggregated into monthly with cubic spline interpolation (see, among others, Abbate, et.al. 2016; Lescaroux and Mignon, 2009). The variables (except rates) are in log levels and if required differenced to achieve stationarity. All variables employed to estimate the factors were standardised (zero mean, unit variance) to deal with the impair factor extraction issue that arises due to the different time series scales. The model is estimated with 3 common factors and 3 lags for the period 2007-2016. The column titled FEVD, reports the fraction of the variance of the forecast error, explained by the policy shock. $R^2$ refers to the fraction of the variance of the variable explained by the common factors, ($F_t$ and $R_t$).

# Table 4
## Robustness Test – Shadow Fed Funds Rate

| Herding Measure (HM) | Forecast Error Variance Decomposition (FEVD) | $R^2$ |
|---|---|---|
| **Panel A**<br>**US (Policy proxied by Shadow Rate; Wu and Xia, 2016)** | | |
| **US** | 0.145 | 0.566 |
| **Panel B**<br>**Eurozone (Policy proxied by Shadow Rate; Wu and Xia, 2017)** | | |
| **Austria** | 0.027 | 0.050 |
| **Belgium** | 0.009 | 0.072 |
| **Finland** | 0.009 | 0.107 |
| **France** | 0.138 | 0.314 |
| **Germany** | 0.006 | 0.179 |
| **Italy** | 0.092 | 0.245 |
| **Portugal** | 0.016 | 0.248 |
| **Spain** | 0.038 | 0.314 |
| **Netherlands** | 0.007 | 0.627 |

*Notes to Table 4*
The Table presents the contribution of unconvectional monetary policy to the variance of the common component, i.e. the Forecast Error Variance Decompositions (FEVDs). The FEVDs are obtained via the estimation of a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis (Bernanke Boivin, and Eliasz, 2005; Boivin et al., 2009). Initially, a large set of variables and Principal Component Analysis (PCA) is employed to derive a set of factors that describe the dynamics of financial markets. More specifically, 110 and 930 variables are used for the sample market of the US and the EU, respectively, such as industrial production, unemployment, producer and consumer prices, short and long term interest rates, capacity utilization rates, money supply, GDP, unit labour cost, main stock price indexes, economic sentiment indicators, and imports and exports. We also use global variables (oil price, S&P 500 Composite Index, VIX-CBOE volatility index, ECB Commodity price index) and aggregate euro-area variables (EUROSTOXX 50, Yen to EU exchange rate, EU to UK exchange rate, EU to USD exchange rate, VSTOXX, etc). Some time series are quarterly and have been disaggregated into monthly with cubic spline interpolation (see, among others, Abbate, et.al. 2016; Lescaroux and Mignon, 2009). The variables (except rates) are in log levels and if required differenced to achieve stationarity. All variables employed to estimate the factors were standardised (zero mean, unit variance) to deal with the impair factor extraction issue that arises due to the different time series scales. To proxy for unconventional monetary policy we use the Shadow Rate (see Wu and Xia, 2016; Wu and Xia, 2017). The model is estimated with 3 common factors and 3 lags for the period 2007-2016. The column titled FEVD, reports the fraction of the variance of the forecast error, explained by the policy shock. $R^2$ refers to the fraction of the variance of the variable explained by the common factors, ($F_t$ and $R_t$).

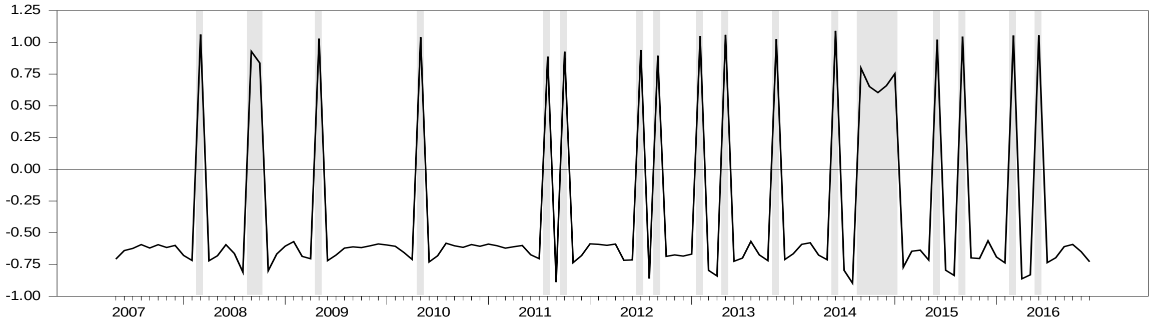
## Table 5
## Robustness Test – 5 FAVAR Factors

| Herding Measure (HM) | Forecast Error Variance Decomposition (FEVD) | $R^2$ |
|---|---|---|
| **Panel A Conventional Policy (See Table 1)** | | |
| **US** | 0.058 | 0.638 |
| **Austria** | 0.001 | 0.019 |
| **Belgium** | 0.005 | 0.079 |
| **Finland** | 0.012 | 0.194 |
| **France** | 0.062 | 0.261 |
| **Germany** | 0.010 | 0.196 |
| **Italy** | 0.033 | 0.288 |
| **Portugal** | 0.026 | 0.265 |
| **Spain** | 0.117 | 0.473 |
| **Netherlands** | 0.053 | 0.648 |
| **Panel B Unconventional Policy (See Table 2)** | | |
| **US** | 0.244 | 0.660 |
| **Austria** | 0.002 | 0.018 |
| **Belgium** | 0.010 | 0.064 |
| **Finland** | 0.021 | 0.178 |
| **France** | 0.076 | 0.209 |
| **Germany** | 0.030 | 0.200 |
| **Italy** | 0.026 | 0.285 |
| **Portugal** | 0.146 | 0.276 |
| **Spain** | 0.052 | 0.381 |
| **Netherlands** | 0.068 | 0.647 |

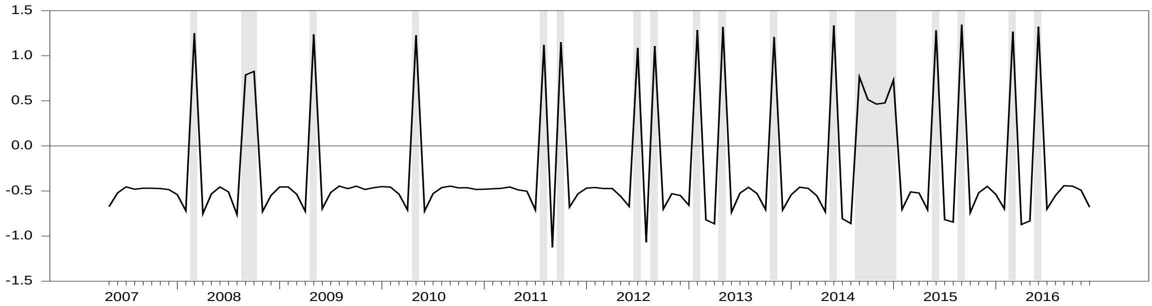
*Notes to Table 5*
The Table presents robustness test results. Panel A reproduces the results presented to Table 1 and panel B the results presented in Table 2. The difference here is that the factors employed in the FAVAR model here are 5 (rather than 3), according to the Bai and Ng (2002) factor determination criterion. The FEVDs are obtained via the estimation of a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis (Bernanke Boivin, and Eliasz, 2005; Boivin et al., 2009). Initially, a large set of variables and Principal Component Analysis (PCA) is employed to derive a set of factors that describe the dynamics of financial markets. More specifically, 110 and 930 variables are used for the sample market of the US and the EU, respectively, such as industrial production, unemployment, producer and consumer prices, short and long-term interest rates, capacity utilization rates, money supply, GDP, unit labour cost, main stock price indexes, economic sentiment indicators, and imports and exports. We also use global variables (oil price, S&P 500 Composite Index, VIX-CBOE volatility index, ECB Commodity price index) and aggregate euro-area variables (EUROSTOXX 50, Yen to EU exchange rate, EU to UK exchange rate, EU to USD exchange rate, VSTOXX, etc). Some time series are quarterly and have been disaggregated into monthly with cubic spline interpolation (see, among others, Abbate, et.al. 2016; Lescaroux and Mignon, 2009). The variables (except rates) are in log levels and if required differenced to achieve stationarity. All variables employed to estimate the factors were standardised (zero mean, unit variance) to deal with the impair factor extraction issue that arises due to the different time series scales. For the US we use the Federal Funds Rate (FFR) to proxy for conventional monetary policy, while for the EU we use the Main Refinancing Operations (MRO) rate. The model is estimated for the period 2007-2016. The column titled FEVD, reports the fraction of the variance of the forecast error, explained by the policy shock. $R^2$ refers to the fraction of the variance of the variable explained by the common factors, ($F_t$ and $R_t$).

## Figure 1
## ECB announcements (shaded) and latent propensity for ECB unconventional monetary measures (dash line)
## Austria, Belgium, France, Netherlands

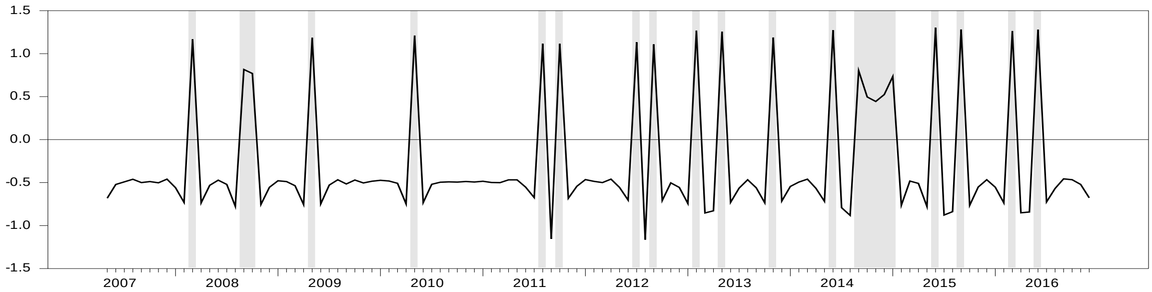
### Austria



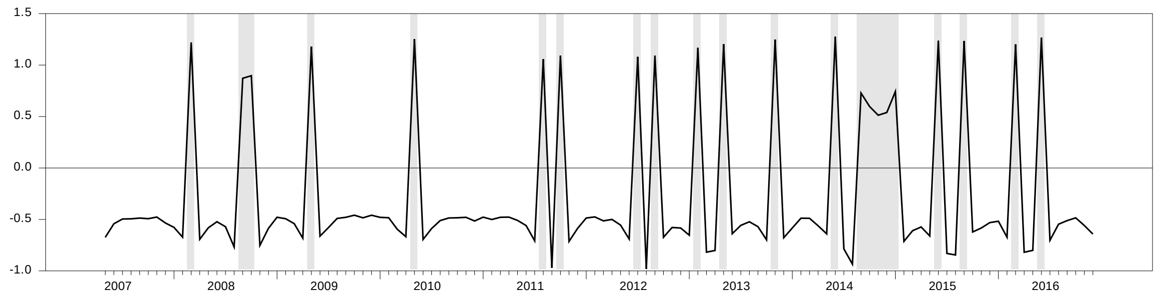

### Belgium




### France




### Netherlands

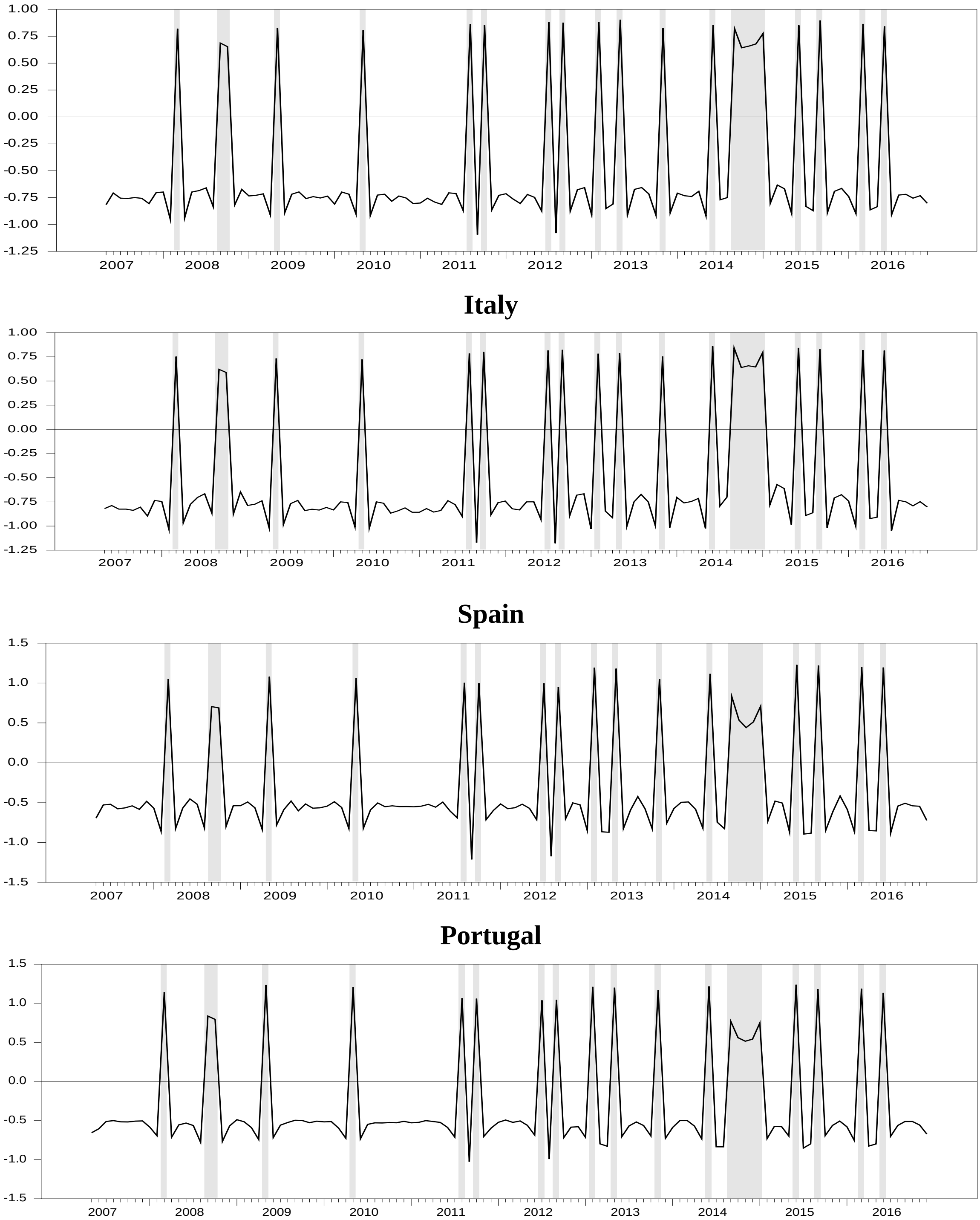



*Notes to Figure 1*

ECB announcements (shaded) and latent propensity for ECB unconventional monetary measures estimated in the Qual VAR model.

**Figure 2**
**ECB announcements (shaded) and latent propensity for ECB unconventional monetary measures (dash line)**
**Finland, Italy, Spain, Portugal**

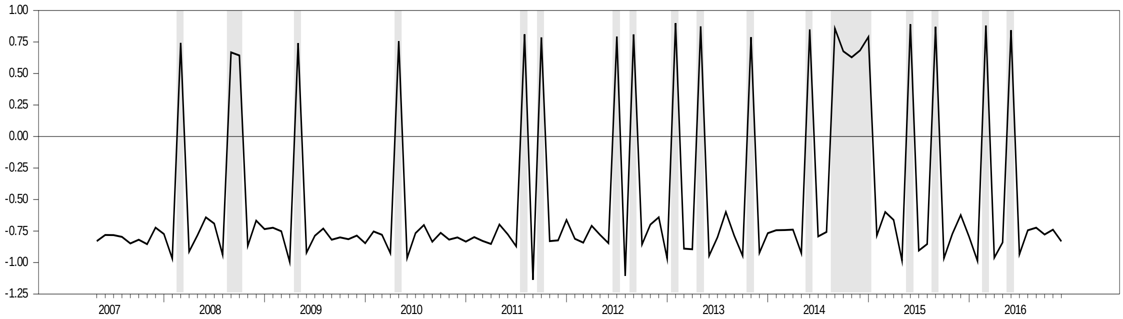
**Finland**



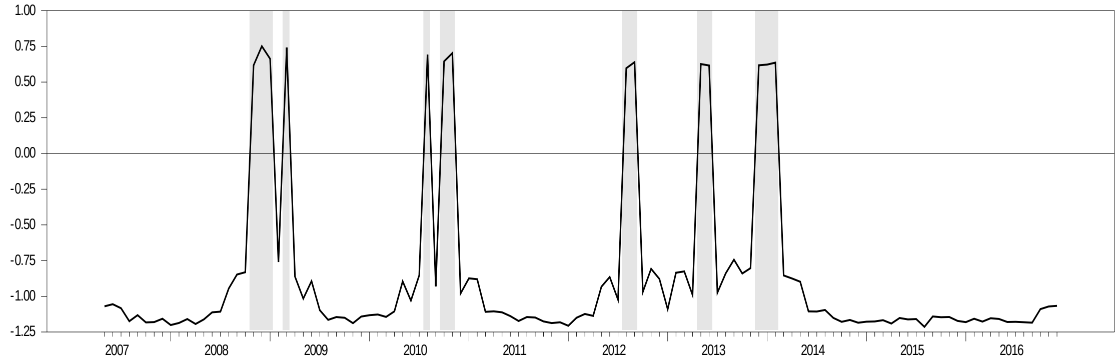

*Notes to Figure 2*
ECB announcements (shaded) and latent propensity for ECB unconventional monetary measures estimated in the Qual VAR model.

**Figure 3**
**ECB (Fed) announcements (shaded) and latent propensity for ECB (Fed) unconventional monetary measures (dash line)**
**Germany (US)**

**Germany**

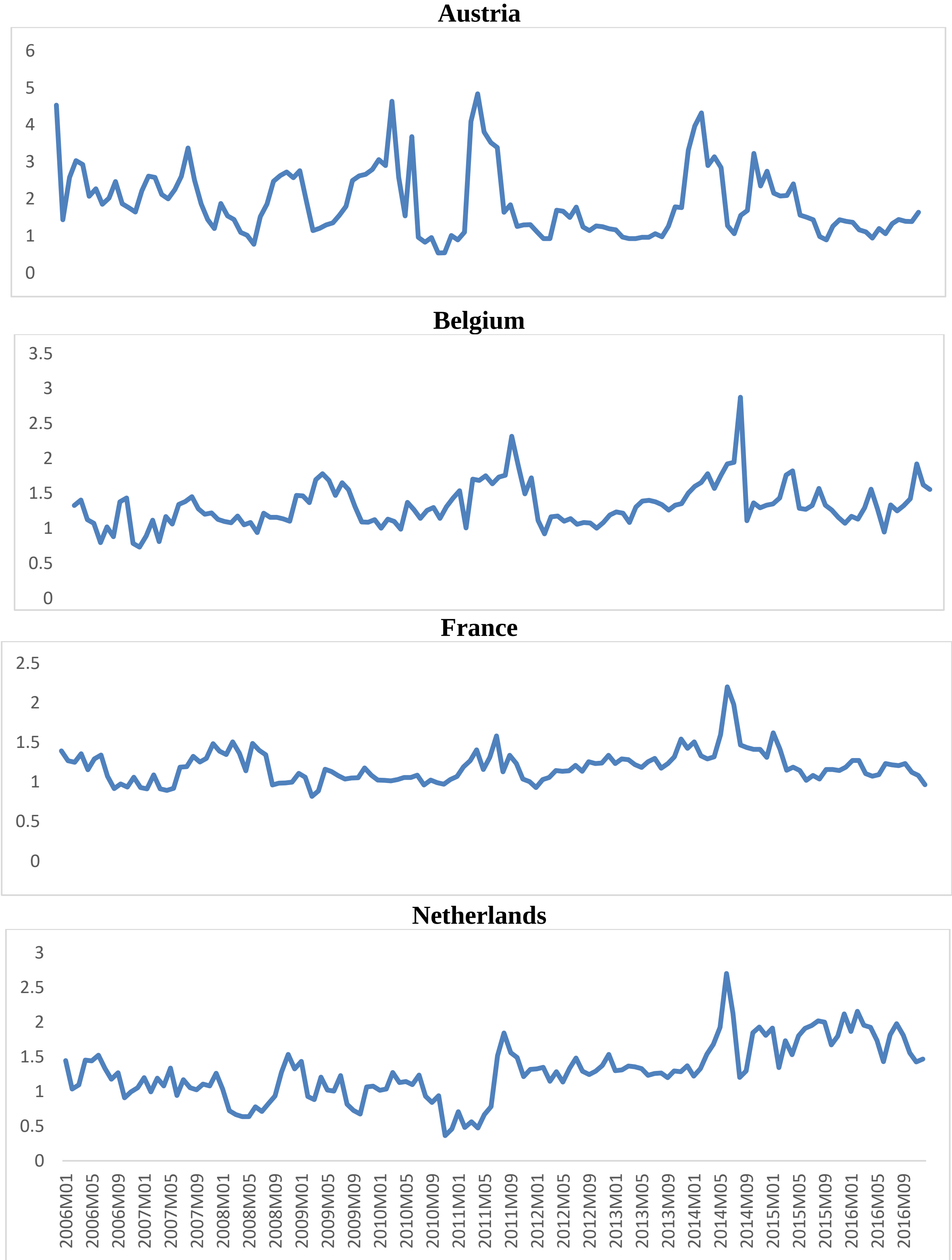



**US**




*Notes to Figure 3*
ECB announcements (shaded) and latent propensity for ECB unconventional monetary measures estimated in the Qual VAR model for Germany. Fed announcements (shaded) and latent propensity for Fed unconventional monetary measures estimated in the Qual VAR model for the US.

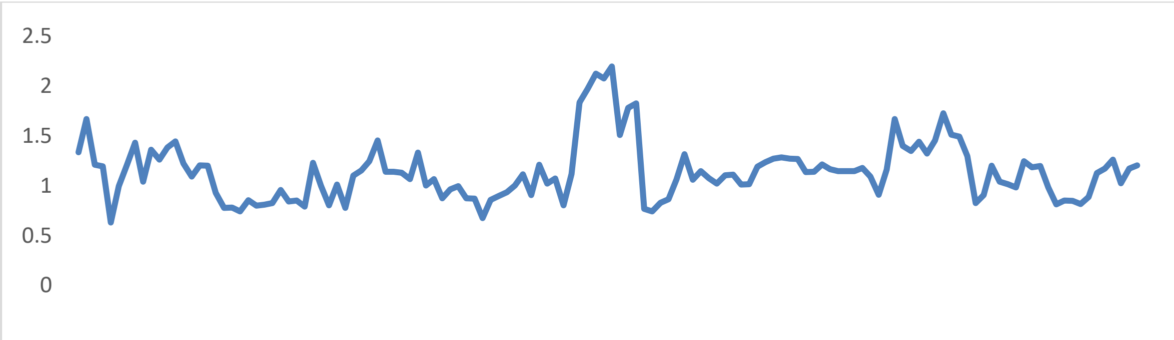
**Figure 4**
**Herding Measure for Austria, Belgium, France, Netherlands**



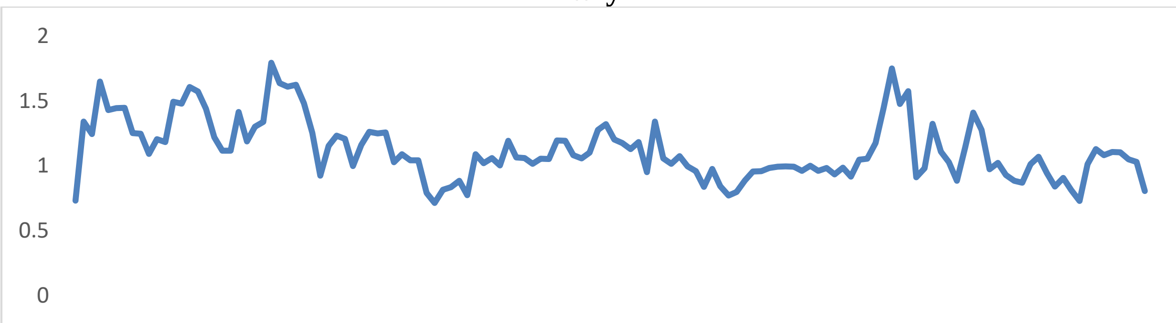

*Notes to Figure 4*
The Herding Measure for the sample markets is estimated as in Hwang and Salmon (2009).

## Figure 5
## Herding Measure for Finland, Italy, Spain, Portugal

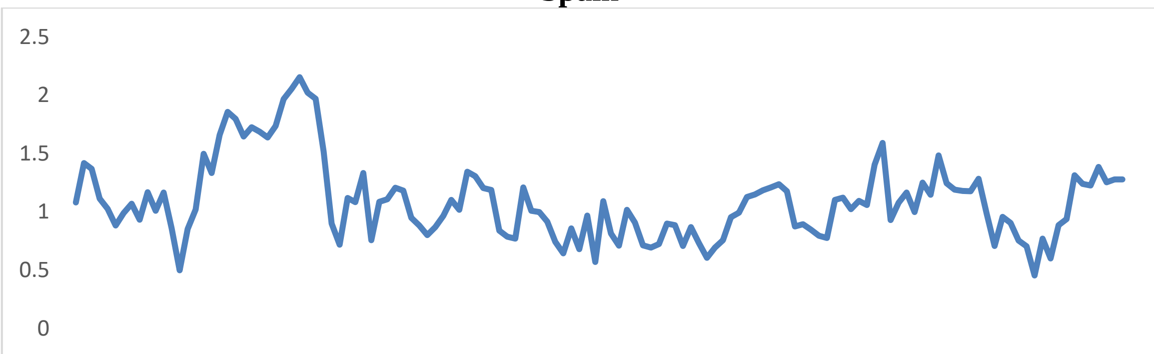
**Finland**



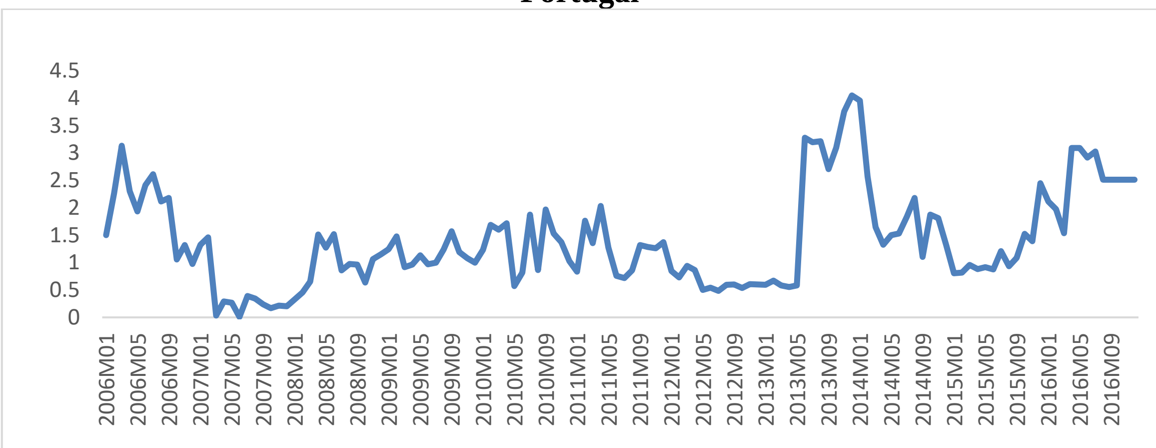

**Italy**




**Spain**

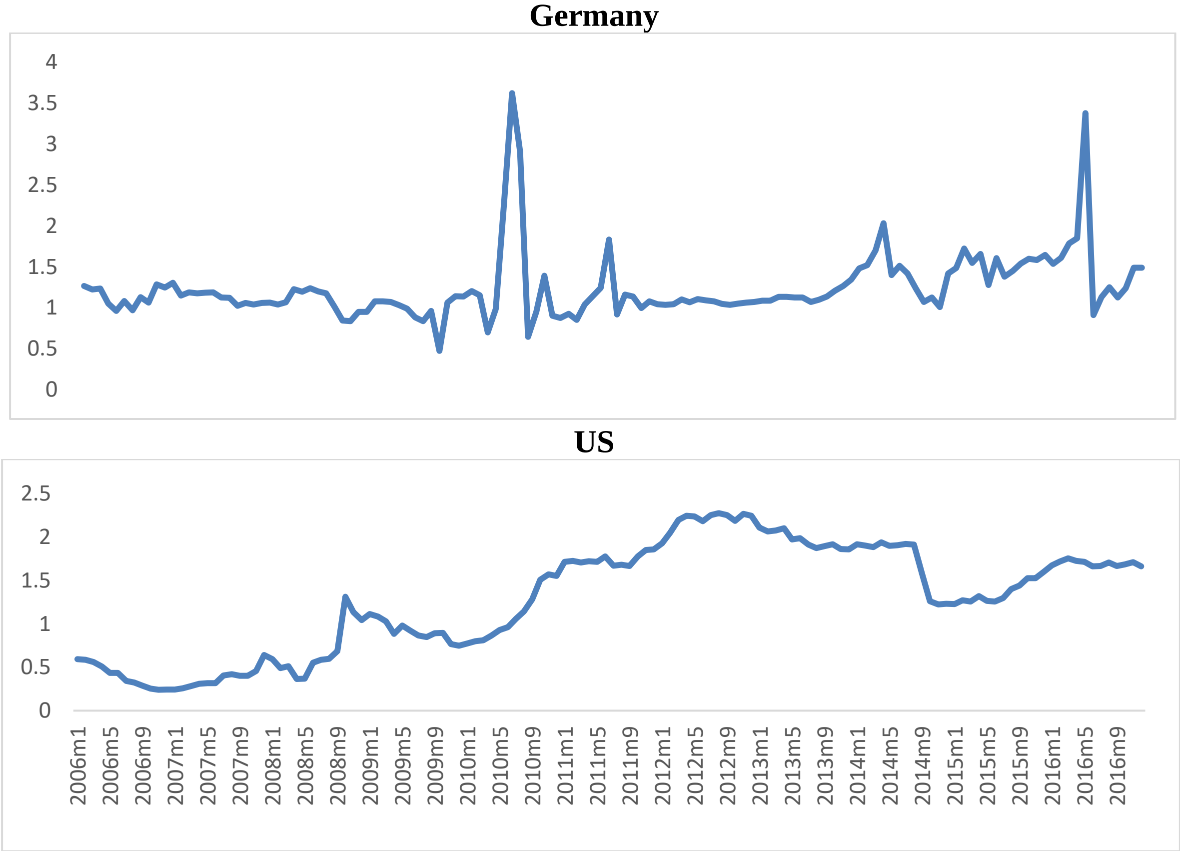



**Portugal**



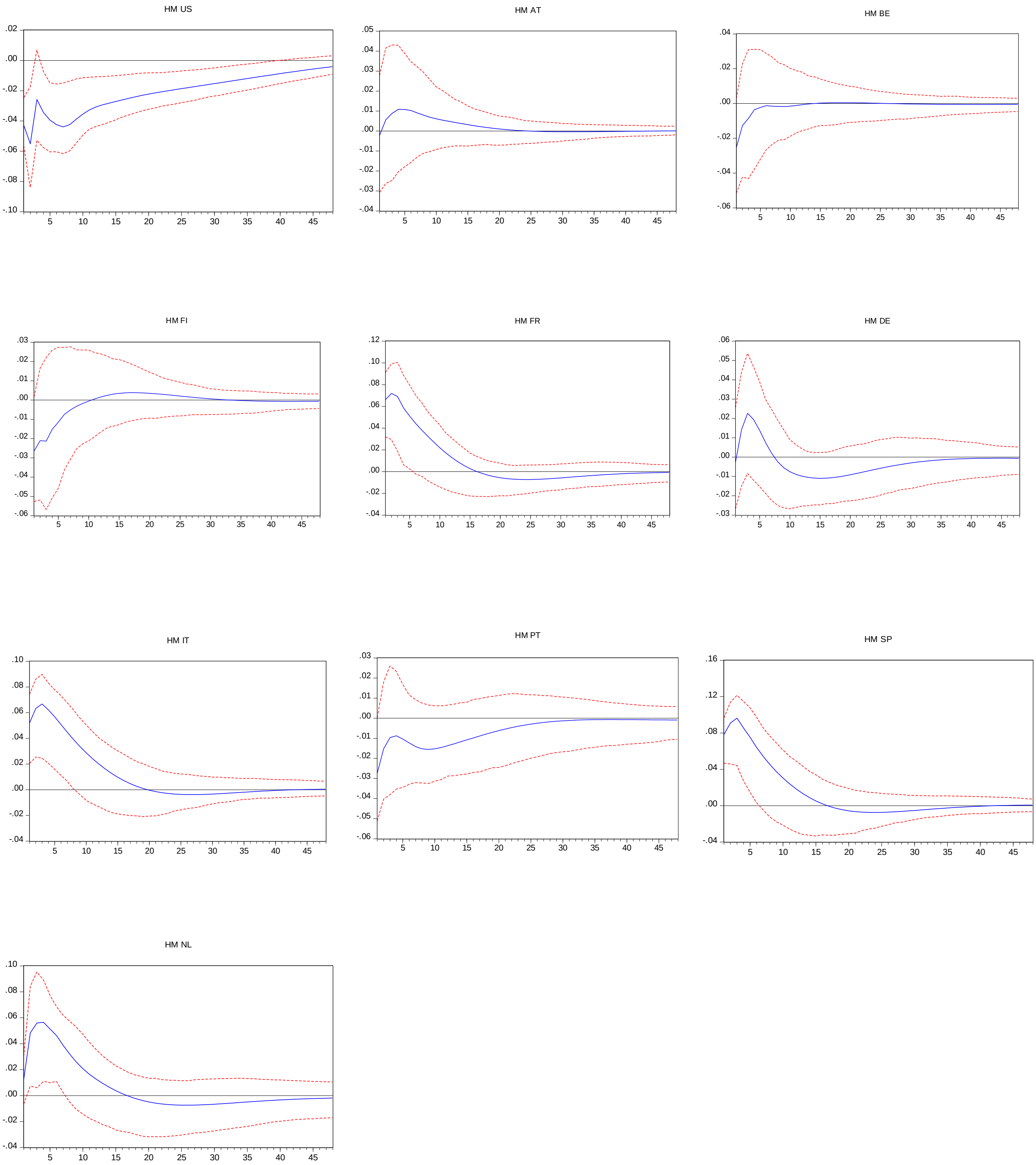

*Notes to Figure 5*
The Herding Measure for the sample markets is estimated as in Hwang and Salmon (2009).

**Figure 6**
**Herding Measure for Germany and US**



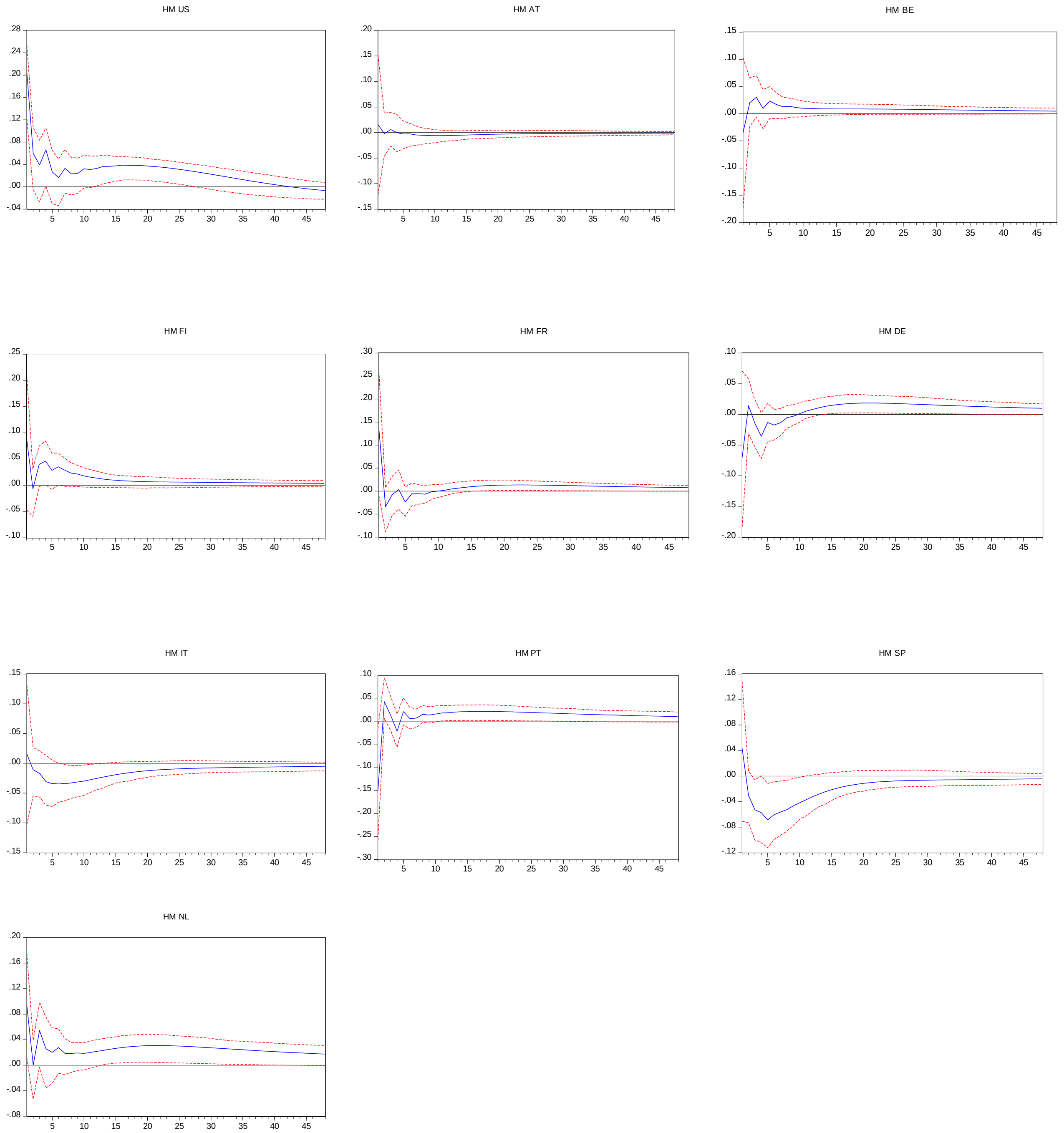

*Notes to Figure 6*
The Herding Measure for the sample markets is estimated as in Hwang and Salmon (2009).

## Figure 7
## IRFs of Herding Measure to shocks in Conventional Monetary Policy (FFR/MRO rate)



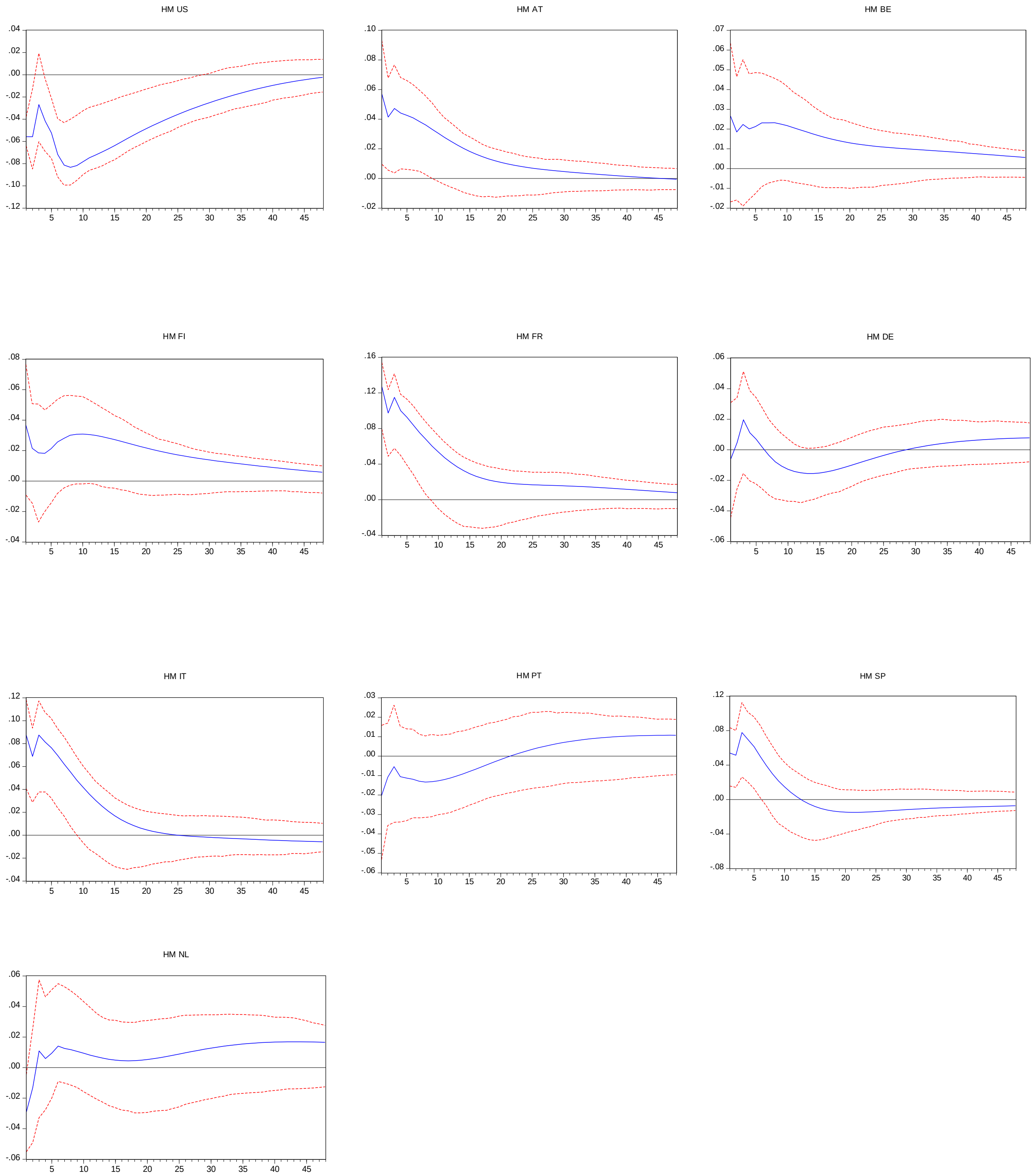

*Notes to Figure 7*
Impulse Responses generated from FAVAR with three factors and FFR/MRO rate estimated by Principal Components with Two-Step Bootstrap.

# Figure 8
# IRFs of Herding Measure to shocks in Unconventional Monetary Policy (y*)



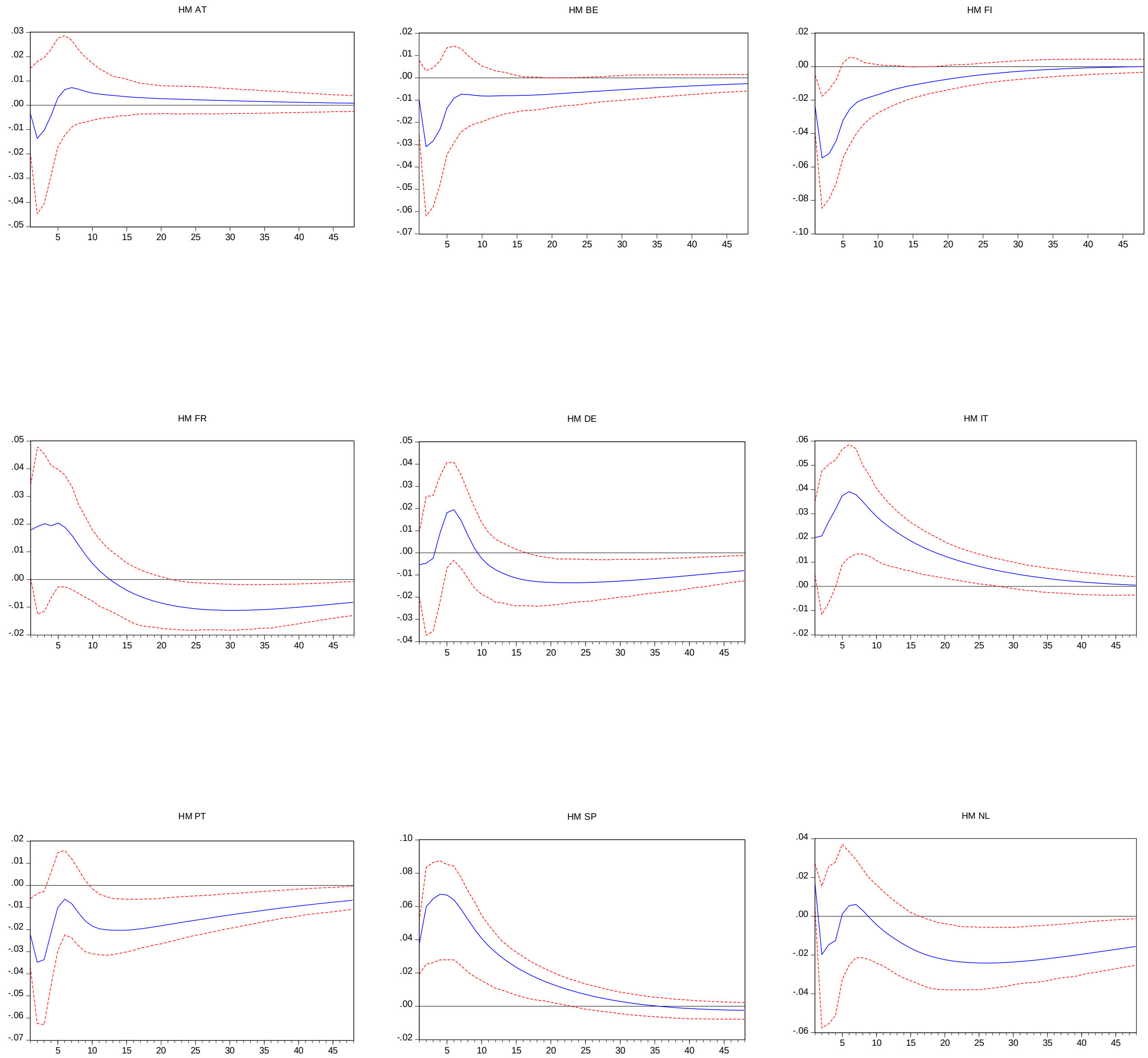

*Notes to Figure 8*
Impulse Responses generated from FAVAR with three factors and y* estimated by Principal Components with Two-Step Bootstrap.

## Figure 9
## IRFs of Herding Measure to shocks in the Shadow Rates
## (Wu and Xia, 2016; Wu and Xia, 2017)



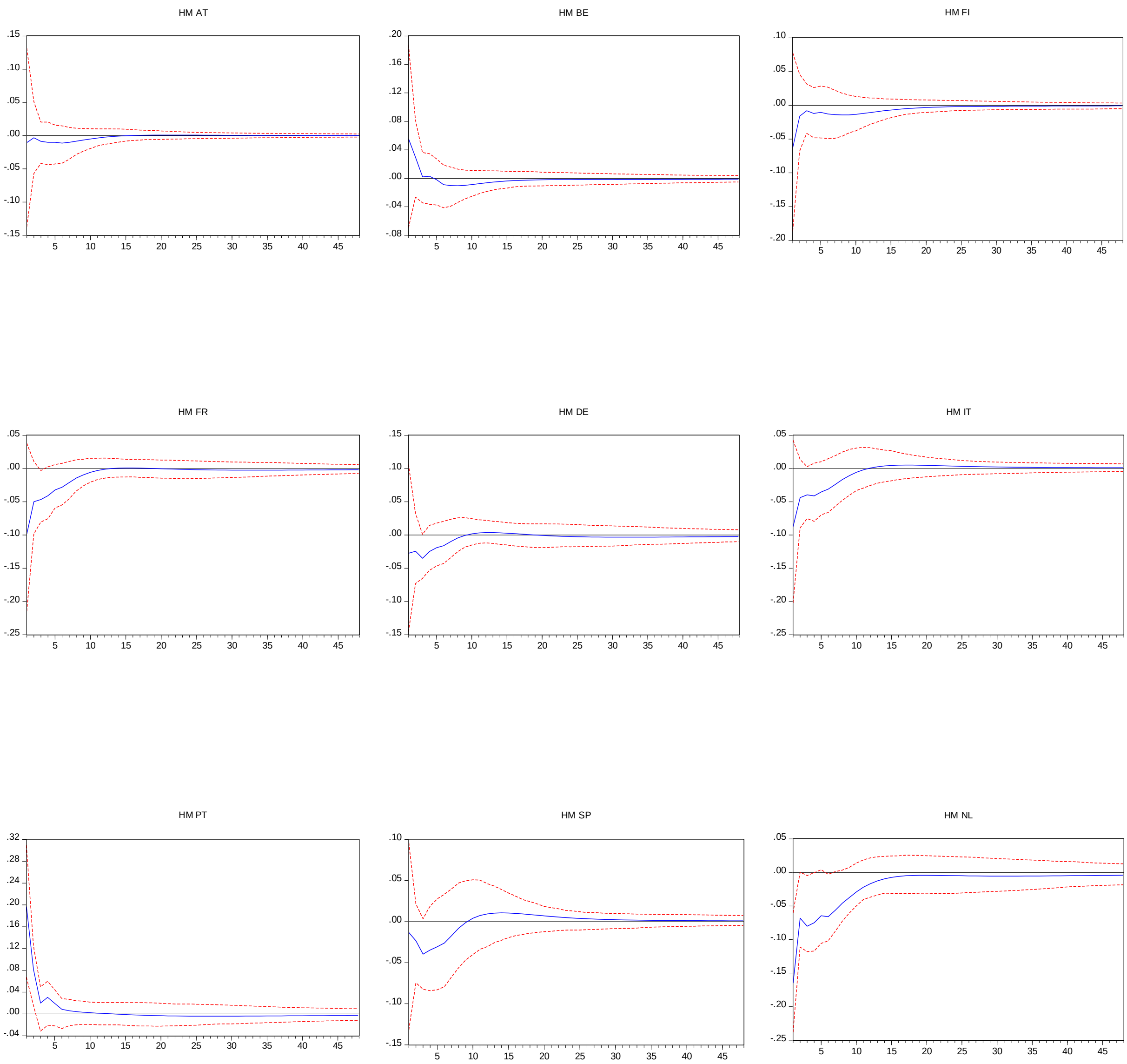

*Notes to Figure 9*
Impulse Responses generated from FAVAR with three factors and Shadow rates estimated by Principal Components with Two-Step Bootstrap.

## Figure 10
## IRFs: Fed Conventional Policy Spill-over Effect to Eurozone Markets




*Notes to Figure 10*
Impulse Responses generated from FAVAR with three Factors and FFR rate estimated by Principal Components with Two-Step Bootstrap.

# Figure 11
# IRFs: Fed Unconventional Policy (y*) Spill-over Effect to Eurozone Markets




*Notes to Figure 11*
Impulse Responses generated from FAVAR with three Factors and US y* estimated by Principal Components with Two-Step Bootstrap.