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Endogenous Volatility in the Foreign Exchange Market

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Abstract

We study two sources of heteroscedasticity in high-frequency financial data. The first source is the behavior of market participants. The second source is the flow of information. We estimate the impact of the two sources by means of a Markov switching (MS) structural VAR model. Following the original intuition of Rigobon (2003), we achieve identification for all coefficients by assuming that the structural errors of the MS-SVAR model follow a GARCH-DCC process. Using transaction data of the EUR/USD interdealer market in 2016, we firstly detect three regimes of volatility. Then we show that both sources of volatility matter for the transmission of shocks, and that information is channeled to the market mostly through price variations. This suggests that, on the EUR/USD market, liquidity providers are better informed than liquidity takers, who act mostly as feedback traders. The latter are able to profit from trade because, unlike noise traders, they respond immediately to informative price shocks.

Keywords: heteroscedasticity, asset pricing model, heterogeneous beliefs, foreign exchange market, Markov switching, GARCH,SVAR, high frequency data.

JEL codes: G12, D84, F31, C32, C55

1 Introduction

The efficiency of financial markets is a subject of great controversy among economists. Usually the claim that markets are efficient is associated to the supposed perfect rationality of market participants and to the free availability of information. Thus, if some agents hold private information or if some others are unable to properly elaborate the available public information, markets are doomed to be inefficient and market excess volatility and eventually bubbles ensue. At the same time, a growing stream of literature assumes that market participants might deviate from the paradigm of perfect rationality. In particular, models with heterogeneous agents (HAM) assume that the deviations of the price of assets from their fundamental value arise because the heterogeneous beliefs of market participants are myopic and evolve endogenously (Brock and Hommes, 1998). In parallel, the market microstructure (MM) approach provides powerful insights into the working of financial markets under conditions of asymmetry of information. These conditions seem very important also for the FX market, contrary to what we might assume from the fact that the fundamental value of a currency reflects only public information (Vitale, 2007; Osler, 2009; King *et al.*, 2013). In this paper we incorporate both approaches in a model which explains how the heteroscedasticity of price variations and demand might arise, at least in part, as a consequence of endogenous factors which depend on the decisions of bounded rational market participants. At the same time we argue that volatility also depends on exogenous forces, since the market must adjust to real world events which are highly unpredictable and unevenly distributed over time.

In order to quantify both sources of volatility, we apply an articulated econometric framework to high-frequency spot transaction data provided by the NEX EUR/USD interdealer market platform. The main result of our analysis is that endogenous as well as exogenous factors play a role in determining the volatility of the market. The two sources of volatility tend to correlate so that, when exogenous information arrives, the market reacts more strongly to shocks and this amplifies volatility further. In these situations we observe that demand reacts positively to a positive price shock, while price reacts negatively to a positive demand shock. This result suggests that liquidity providers are better informed than liquidity takers, so that the price posted by the former reflects the relevant information. Accordingly, we might claim that the EUR/USD market is efficient, notwithstanding bounded rationality and asymmetric information. Indeed, in our framework price reflects the available information exactly because liquidity providers are better informed than liquidity takers and do not want to be outplayed by them. The latter are nevertheless able to gain because, acting as feedback traders, they react quickly to price shocks. At the same time, other market participants trade with a loss, since we observe a negative correlation of the structural errors. This result is in line with the established view that noise traders act as market stabilizers on the foreign exchange market (Black, 1986; Evans and Lyons, 2002; King *et al.*, 2013).

The remaining of the paper is organized as follows. In Sec. 2 we present our theoretical model. In Sec. 3 we describe the data set we employ for our empirical analysis. In Sec. 4 we describe our estimation strategy. In Sec. 5 we present the main results of the analysis. Finally, Sec. 6 concludes.

2 The model

Our model incorporates two basic assumptions. The first one, coming from the MM literature, is the dependency of price variations on the contemporaneous net order flow, which is defined as buy-initiated transactions minus sell-initiated transactions over a given period (Evans and Lyons, 2002). The second one, coming from the literature on models with heterogeneous agents (HAM), is the dependency of current demand on price variations (Brock and Hommes, 1998). The first assumption is motivated either by the quoting decisions of market makers in a quote-driven market (Madhavan and Smidt, 1993), or by the effect of market orders on prices in an order-driven market. The second assumption is motivated by the myopic nature of speculators who form their expectation of tomorrow's returns based on the returns observed to date. This general mechanism of expectation formation encompasses different typologies of speculators which are popular in the literature, such as chartists, fundamentalists, contrarians etc. Many of these strategies fall under the domain of technical trading, which is profitable in the FX market and is widely employed by FX market professionals, under the label of feedback or momentum trading (Menkhoff and Taylor, 2007; Menkhoff, 2010) [1].

One shortcoming of HAM models is that, while they are generally estimated with a low frequency, they assume that agents react to price signals with a delay of one period. Although bounded rationality might represent a good representation for the actual behavior of at least a fraction of market participants, it is not very realistic to assume that the latter do not

[1] The adoption of price contingent strategies, such as stop-loss and profit-taking orders, which are associated with feedback trading, is widespread in the FX market (Osler, 2003, 2005; Daníelsson and Love, 2006; Osler, 2011). Froot and Ramadorai (2005) find that even flows from institutional investors, which should be more correlated with fundamentals, are instead strongly positively related, at short horizons, to transitory exchange rate shocks.

react as quickly as possible to price variations. Indeed, we should expect the contrary. For this reason, in this paper we adopt the assumption that speculators adjust their demand within the same period in which price variations occur. One possible objection to this assumption comes from the fact that demand must necessarily follow the price over time both in order-driven and in quote-driven markets. In the latter, the price is set by the dealer at request of her customers, who then decide the amount they want to trade. In the former, the price is set by market participants who post limit orders, and trading occurs when either limit orders cross or market orders are submitted for immediate execution.

The temporal precedence of price over demand in both market settings has been used to justify the restriction adopted firstly by Hasbrouck (1991), and then accepted by the MM literature, that there is no contemporaneous effect of price variations on net order flows. On the other hand, Daníelsson and Love (2006) have proven that, even assuming that price always precedes demand over time, a bivariate model will yield empirical estimates where price and demand simultaneously affect each other whenever the data is subject to time aggregation. In a subsequent paper, Love and Payne (2008) find that simultaneous feedback effects from price variations to net order flows are positive and significant at the 1 minute frequency for three major rates. Based upon these results, we consider the assumption of a simultaneous feedback effect from price variations to demand in our model as a realistic approximation, which is consistent with the subsequent empirical estimation of the model at the 5 minutes frequency.

Participants in an order-driven market can supply or demand liquidity by submitting respectively limit or market orders. Accordingly, in our model we have two basic categories of agents who interact in an order-driven market for a zero yielding asset. The first category is a representative liquidity provider, who posts limit orders to the market. The second category are a large number of heterogeneous liquidity takers, subdivided in types, who post market orders. We assume for simplicity that the liquidity provider has perfect foresight of the demand of each type of liquidity taker. Moreover, the model takes into account the institutional specificity of the FX market, which is a two tiered market. In the first tier, which is largely over the counter, FX dealers trade with customers in a quote-driven market. In the second tier, dealers trade between themselves in an order-driven market. While our agents are supposed to trade on the latter, the other tier plays a key role. In fact, we suppose that liquidity providers are always able to trade over the counter with customers, at the current interdealer market price, for an amount which is at least equal to the net demand of the liquidity takers. This supposition is consistent with the evidence that prices for customers reflect interdealer prices (Osler, 2009), and that dealers accumulate inventories by trading with their customers when they take a speculative position (Bjønnes *et al.*, 2021).

The liquidity provider computes her optimal price, taking into account a quadratic cost which reflects her aversion to inventory risk as well as her position limits. Then she posts a sequence of limit orders of the size required to match the demand of liquidity takers. The latter submit market orders according to their optimal demand in such a way that, at the end of the period, the net variation of the inventory position of the liquidity provider is zero and the interdealer market is balanced. We remark that, under the assumed market framework, both the liquidity provider and the liquidity takers find optimal to trade. On the other hand, the customers of the liquidity provider are bound to loose money. This is in line with the evidence that commercial customers on the FX market have different trading motivations than currency speculation (Osler, 2009). In other words, they behave as noise traders[2]. Instead, the assumed behavior of liquidity providers and takers is in line with the evidence that the FX dealers earn most of their profits from active currency speculation (Bjønnes and Rime, 2005).

According to the previous remarks, the profit of the liquidity provider is specified as follows:

$$\Pi_{d,t} = (p_t - p_{t-1})\, z_t - \frac{\omega_t}{2} z_t^2 \tag{1}$$

where z_t is the net market demand of liquidity takers and $\frac{\omega_t}{2} > 0$ quantifies the time varying impact of the quadratic inventory term z_t^2 on $\Pi_{d,t}$. We remark that, according to our hypotheses, the inventory cost is linked to z_t since at the end of each period the inventory is brought down to zero. In practice, it is the opportunity cost of holding an amount of risky asset equal to $z_t > 0$ until it is resold to liquidity takers[3]. We remark that, in eq. (1), p_{t-1} is the price at which liquidity providers trade over the counter at t with their customers for the amount $-z_t$, and p_t is the price associated with their limit orders at t for the amount z_t on the interdealer market.

The liquidity provider maximizes $\Pi_{d,t}$ with respect to p_t. Taking into account the effect of the optimization variable on z_t the FOC reads:

[2]We recall the following definition of liquidity, or noise, traders provided by Dow and Gorton (2008): "Noise traders are economic agents who trade in security markets for non-information-based reasons". One of the possible rational motivations of noise/liquidity trading is insurance / hedging, but other explanations have been proposed (Vitale , 2000). See Ramiah *et al.* (2015) for a recent review of the literature on this topic.

[3]In the case in which $z_t < 0$, the risky asset must be exchanged against some other asset that is costly to hold too.

$$z_t + (p_t - p_{t-1}) \frac{d}{dp_t} z_t - \omega_t z_t \, \frac{d}{dp_t} z_t = 0 \tag{2}$$

Setting $\gamma_{0,t} \equiv \frac{d}{dp_t} z_t$, we obtain

$$\Delta p_t = \left(\omega_t - \frac{1}{\gamma_{0,t}} \right) z_t \tag{3}$$

Regarding liquidity takers, we follow the literature on asset pricing mentioned in Sec. 1. In the HAM setting speculators are myopic mean-variance maximizers, since their future wealth is uncertain. Accordingly, we assume that liquidity takers of each type i maximize their expected risk adjusted profit in the next period:

$$\max_{z_{it}} \left\{ E_{it} \left[\Pi_{i,t+1} \right] - \frac{1}{2D} V_{it} \left[\Pi_{i,t+1} \right] \right\} \tag{4}$$

where D^{-1} is a risk aversion parameter linked to the variance of future profit $V_{it} \left[\Pi_{i,t+1} \right]$. Indeed the profit of liquidity takers at $t+1$ is determined by their net demand at t and they ignore the future market price when taking their decision. The current profit of liquidity takers of type i is written as follows:

$$\Pi_{it} = (p_t - p_{t-1}) \, z_{i,t-1} \tag{5}$$

where the right hand side of the equation above represents the profit obtained buying the amount $z_{i,t-1}$ at the price p_{t-1} and reselling the same amount at the price p_t.

Then we have:

$$E_{it} \left[\Pi_{i,t+1} \right] = \left(E_{it} \left[p_{t+1} \right] - p_t \right) z_{it} \tag{6}$$

$$V_{it} \left[\Pi_{i,t+1} \right] = V_{it} \left[p_{t+1} \right] z_{it}^2 \tag{7}$$

Taking into account Eqs. (6) and (7), writing $V_{it} \left[p_{t+1} \right] = \sigma_{it}^2$, and finally letting this term be absorbed by $D_{it}^{-1} = \sigma_{it}/D$, we may rewrite the objective as follows:

$$\max_{z_{it}} \left\{ E_{it}[\Delta p_{t+1}] \, z_{it} - \frac{z_{it}^2}{2D_{it}} \right\} \tag{8}$$

where $E_{it}[\Delta p_{t+1}]$ stands for the type i's expectation of Δp_{t+1}. We solve the FOC for z_{it} to obtain the optimal demand of a generic liquidity taker of type i:

$$z_{it} = D_{it} E_{it}[\Delta p_{t+1}] \tag{9}$$

Then the total market demand is

$$z_t = \sum_{i=1}^{S} D_{it} E_{it}[\Delta p_{t+1}] N_{it} \tag{10}$$

where N_{it} is the number of liquidity takers of type i at t and S is the number of different types of liquidity takers on the market. We introduce the following specification for $E_{it}[\Delta p_{t+1}]$:

$$E_{it}[\Delta p_{t+1}] = \sum_{k=0}^{K} g_{ik} \Delta p_{t-k} \tag{11}$$

where the g_{ik} are type specific fixed coefficients which measure the impact of the price increment at lag k on the expectation of liquidity takers of type i. Substituting (11) in (10) we obtain

$$z_t = \sum_{i=1}^{S} D_{it}\, N_{it} \sum_{k=0}^{K} g_{ik} \Delta p_{t-k} \tag{12}$$

Changing the order of summation we obtain

$$z_t = \sum_{k=0}^{K} \Delta p_{t-k} \sum_{i=1}^{S} D_{it} N_{it} g_{ik} \tag{13}$$

and defining

$$\gamma_{k,t} \equiv \sum_{i=1}^{S} D_{it} N_{it} g_{ik} \tag{14}$$

we obtain that market demand is a time varying function of current and past prices:

$$z_t = \sum_{k=0}^{K} \gamma_{kt} \Delta p_{t-k} \tag{15}$$

We see that, according to (15), $\frac{\partial z_t}{\partial p_t} = \gamma_{0t}$ which is consistent with our previous definition in Eq. (3). Thus we end up with a system of 2 simultaneous equations in $(\Delta p_t, z_t)$ plus lagged values of price increments:

$$\begin{cases} \Delta p_t = \left(\omega_t - \frac{1}{\gamma_{0,t}}\right) z_t + \epsilon_{0,t} \\ \\ z_t = \sum_{k=0}^{K} \gamma_{k,t} \Delta p_{t-k} + \epsilon_{1,t} \end{cases} \tag{16}$$

The bivariate random process $\epsilon_t = (\epsilon_{0,t}, \epsilon_{1,t})$ is added to take into account all the exogenous factors which impact price and demand through the actions of liquidity providers and takers respectively. We expect that this process has more structure than a simple i.i.d. white noise, since it reflects the uneven flow of information to the market.

The system (16) is equivalent to a restricted SVAR model of order K with time varying coefficients:

$$\begin{aligned} \left[\begin{array}{cc} \Delta p_t & z_t \end{array} \right] \left[\begin{array}{cc} 1 & -\gamma_{0,t} \\ -\left(\omega_t - \frac{1}{\gamma_{0,t}}\right) & 1 \end{array} \right] = \\ = \left[\begin{array}{cccc} \Delta p_{t-1} & \Delta p_{t-2} & \dots & \Delta p_{t-K} \end{array} \right] \left[\begin{array}{cc} 0 & \gamma_{1,t} \\ 0 & \gamma_{2,t} \\ \dots & \dots \\ 0 & \gamma_{K,t} \end{array} \right] + \\ + \left[\begin{array}{cccc} \Delta z_{t-1} & \Delta z_{t-2} & \dots & \Delta z_{t-K} \end{array} \right] \left[\begin{array}{cc} 0 & 0 \\ 0 & 0 \\ \dots & \dots \\ 0 & 0 \end{array} \right] + \left[\begin{array}{cc} \epsilon_{0,t} & \epsilon_{1,t} \end{array} \right] \end{aligned} \tag{17}$$

In the empirical estimation we prefer to lift the restrictions on the r.h.s., since there is evidence that microstructural effects on the market lead to autocorrelation of both price variations and demand. In particular, we assume that z_t is autocorrelated because of order splitting (Osler, 2009; Tóth *et al.*, 2015). Although the lack of autocorrelation of price increments has been widely documented at the lower frequencies, autocorrelation of Δp_t cannot be ruled out at short frequencies. Indeed, there is evidence of negative first-order autocorrelation of prices in high-frequency FX markets (Zhou, 1996; Cont, 2001). So, setting $y_t' = (\Delta p_t, z_t)$, we end up with the following formulation:

$$A_{0,t} y_t = A_{1,t} y_{t-1} + \cdots + A_{K,t} y_{t-K} + \epsilon_t \tag{18}$$

where

$$A_{0,t} = \left[\begin{array}{cc} 1 & -\left(\omega - \frac{1}{\gamma_{0,t}}\right) \\ -\gamma_{0,t} & 1 \end{array} \right] \tag{19}$$

and the coefficients in $A_{1,t}, \ldots, A_{q,t}$ are unrestricted.

3 Data description

For our empirical analysis we employ tick-by-tick transaction data, recorded on the EBS FX Spot trading platform and provided by NEX data. We recall that the participation to this order-driven platform is reserved to FX professionals, aka FX dealers. For the purpose of our analysis, the data is sampled with a 5 minutes frequency. More precisely, we investigate the following time series: the (last) Euro/ Dollar midpoint between bid and offer prices (p_t) expressed in USD cents; the total values in period t of the bid (BSZ_t) and offer (OSZ_t) transactions expressed in Millions of Euros. The sample spans the time interval from 3 January 2016, 17:55 (5.55 pm.), to 30 December 2016, 21.55 (9.55 pm.). It includes relevant events related to the final spasms of the EMU crisis, which interact with the vagaries of the British Brexit referendum campaign. A painstaking synchronization of the time series has reduced the sample length to 36,207 observations per continuous time series. Weekends, holidays and late-evening / night periods are excluded. The cleaning of data is aimed at removing the most important sources of daily and weekly seasonal patterns of volatility.

Fig. 1 exhibits the EUR/USD exchange rate in first differences (Δp_t), together with the 5 minutes difference between the total values of the offer and bid transactions, which is our measure of net demand: $z_t = OSZ_t - BSZ_t$. The outcome of the Brexit referendum (June 24) and the election of Donald Trump as president of the US (November 9) are marked with a thick vertical line in the graph. The appreciation of the dollar in the wake of the two major events of 2016 clearly stands out, although the price and demand movements which are associated with them are by no means the largest in magnitude. Indeed, the largest price swings followed a controversial announcement by the ECB of a further expansion of Quantitative Easing on March 10 [4] and the announcement of weak US jobs data on June 3[5], both of which lead to a stark appreciation of the Euro. The largest demand swing instead was triggered by the Euro falling below the critical 1.04 $ benchmark for the first time in 14 years on December 15 [6].

It should be noted that large demand swings do not necessarily correspond to large price swings and vice versa. The explanation is twofold: on the one hand, public information is incorporated directly into price and, on the other,

[4] https://www.ft.com/content/02ec97ea-e6d9-11e5-bc31-138df2ae9ee6

[5] https://www.ft.com/content/eb77d7d6-2937-11e6-8ba3-cdd781d02d89

[6] https://www.ft.com/content/25fba186-fc9f-3bf2-a020-82efe29f1f7b

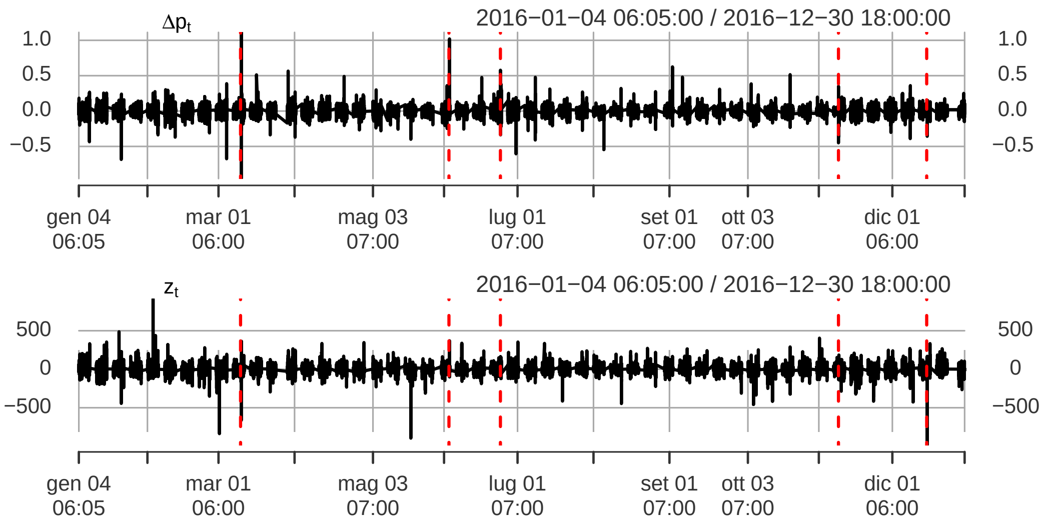

Figure 1: Time series plots. The dashed vertical lines correspond to the following events: QE announcement from ECB (March 10); weak US jobs data (June 3); Brexit referendum (June 24); Trump election (November 9); EUR/USD passing the 1.04 threshold (December 15)

the EUR/USD market is liquid enough to absorb large demand imbalances without large price effects. This goes without denying that the two variables influence each other: indeed the Pearson correlation coefficient between Δp_t and z_t is 0.305. The source of this correlation is twofold. On the one hand, we have the behavioral interaction of market participants as depicted by the model of Sec. 2. On the other, we have the exogenous flow of information affecting price and demand at the same time. The purpose of the estimation described the next section is to distinguish and quantify each of the two sources.

4 Estimation Strategy

Previous attempts to estimate a model such as (18)-(19) are apparently not available in the econometric literature. Primiceri (2005) has proposed a Bayesian approach to estimate a time-varying SVAR model, where both the regression coefficients and the covariance matrix of the shocks are allowed to vary over time. But this comes at the cost of imposing the usual *a priori* identification restrictions on $A_{0,t}$, which are unfortunately unwelcome in our case. Indeed, we have seen in Sec. 2 that feedback trading is ubiquitous in the FX market. Following the arguments of Daníelsson and Love (2006), feedback trading implies $\gamma_{0,t} \neq 0$, which means rejecting the $\gamma_{0,t} = 0$ restriction adopted by the MM literature following Hasbrouck (1991). Neither we can suppose that $\omega_t = 0$, since the latter restriction would imply that FX dealers are not adverse to inventory risk, contrary to a widespread evidence (King *et al.*, 2013). Finally, we cannot assume that $\omega_t - \frac{1}{\gamma_{0,t}} = 0$, since this would contradict one of the most fundamental results of the MM literature, namely that net order flows correlate with price variations.

A well established option, when a priori restrictions cannot be made, is to find good instruments. This is the approach pursued by Daníelsson and Love (2006). An increasingly popular alternative exploits the fact that, if the variances of the structural shocks change over time, we can obtain the coefficients of interest using the different reduced-form covariances (Rigobon, 2003). Under this approach, we need to make some assumptions on the process which generates the covariance matrices. Some commonly used options are variance regimes (Rigobon, 2003; Lanne *et al.*, 2010), restricted or unrestricted multivariate ARCH or GARCH processes (Rigobon, 2002; Sentana and Fiorentini, 2001), constant or dynamic conditional correlation processes (Weber, 2010), stochastic volatility (Lewis, 2018)[7]. In our study we envisage that a GARCH specification for volatility is the best option in order to make the best use of the information contained in our data set, provided the preliminary detection of ARCH effects in the data (not shown). In addition, according to simulation studies, a GARCH based Gaussian ML approach provides the best results when the underlying d.g.p. is conditionally heteroscedastic even if the distribution of the structural errors is misspecified (Herwartz *et al.*, 2019), so that this approach lends itself naturally to quasi-ML estimation [8].

We estimate the model (18)-(19) under the assumption that the participation of the heterogeneous liquidity takers to the market and the unconditional volatility of the structural errors follow the same hidden Markov process. For this purpose it is convenient to introduce the regime vector ξ_t:

$$\xi_t = \begin{bmatrix} \mathbb{1}\{s_t = 1\} \\ \vdots \\ \mathbb{1}\{s_t = M\} \end{bmatrix} \tag{20}$$

where $\mathbb{1}\{s_t = i\}$ represents the indicator function that the system is in state i at t. Thus, for a generic number of states M, we specify the time

[7] A detailed review is provided by Kilian and Lütkepohl (2017).

[8] In particular Herwartz *et al.* (2019) employ skewed and leptokurtic distributions which reflect the characteristics of financial time series.

varying structural coefficients in (18) and (19) as follows:

$$A_{j,t} = \sum_{i=1}^{M} \xi_{i,t} A_j^i \quad (j = 0, \dots K) \tag{21}$$

where the matrices A_j^i contain the structural parameter values at lag j when the prevailing regime is i.

The estimation proceeds through the following steps. Firstly, the parameters of the reduced form MS-VAR model are estimated using the standard approach of (Hamilton, 1989):

$$y_t = B_{1,t}\; y_{t-1} + \dots + B_{K,t}\; y_{t-K} + u_t \tag{22}$$

$$u_t \sim \mathcal{N}(0, \Sigma_t) \qquad \text{with} \qquad \Sigma_t = \sum_{i=1}^{M} \xi_{i,t} \Sigma_i \tag{23}$$

where

$$B_{j,t} = A_{0,t}^{-1} A_{j,t} = \sum_{i=1}^{M} \xi_{i,t} B_j^i \quad (j = 1, \dots K) \tag{24}$$

$$B_j^i = {A_0^i}^{-1} A_j^i \tag{25}$$

In the second step we employ the residuals of the VAR submodels obtained from the estimation of eq. (22), which we denote with u_t^i, for $i = 1, \dots, M$. In particular, we maximize the following log-likelihood:

$$L(\theta) = \sum_{t=1}^{T} \ln f_t\,(\theta) \tag{26}$$

where

$$f_t(\theta) = \sum_{i=1}^{M} P\left(s_t = i | \mathcal{I}_{t-1}\right) f_{i,t}(\theta) \tag{27}$$

$$f_{i,t}(\theta) = 2\pi^{-\frac{n}{2}} |H_t^i|^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2} {u_t^i}' {A_0^i}' {H_t^i}^{-1} A_0^i u_t^i \right\} \tag{28}$$

For this purpose, we obtain the conditional probability $P\left(s_t = i | \mathcal{I}_{t-1}\right)$ from the MS-VAR model at the first step, and we suppose that H_t follows a state-dependent GARCH(1,1) process:

$$\epsilon_t = H_t^{\frac{1}{2}} v_t \tag{29}$$
$$v_t \sim \mathcal{N}(0, I) \tag{30}$$
$$H_t = \sum_{i=1}^{M} \xi_{i,t} H_t^i \tag{31}$$
$$H_t^i = \text{diag}(h_t^i) \tag{32}$$
$$h_t^i = \overline{h}_i + \text{diag}(\alpha_i)(A_0^i u_{t-1}^*) \odot (A_0^i u_{t-1}^*) + \text{diag}(\beta_i)\ h_{t-1}^i \quad (i = 1, \dots, M) \tag{33}$$

The vector θ of eq. (26) contains the regime dependent parameters $\omega = (\omega_1, \dots \omega_M)$ and $\gamma_0 = (\gamma_{0,1}, \dots, \gamma_{0,M})$, plus the regime dependent parameters of the GARCH equation (Lanne *et al.*, 2010; Herwartz and Lütkepohl, 2014). We remark that the MS-VAR model estimated at the first step is nested in the specification for the second step, and is obtained if the A_0^i are supposed to be lower triangular matrices and the GARCH coefficients α_i and β_i are supposed to be zero.

In Appendix A we provide the details of the estimation procedure for the MS-SVAR-GARCH model described by eqs. from (22) to (33), together with a discussion of the identification conditions of the structural parameter vectors γ_0 and ω. Here we limit ourselves to the following considerations. The identification condition of Rigobon (2003) for a linear model is based on the existence of two distinct non proportional covariance matrices. This condition is reinforced by the GARCH setting of this paper, since introducing additional non proportional covariance matrices makes the structural coefficients of the linear model overidentified. Indeed, the non proportionality of the time varying covariance matrices is a. s. assured if there are ARCH effects in the errors. Following this line of reasoning, Milunovich and Yang (2013) have provided a set of sufficient identification conditions for linear models with ARCH type errors, which state that identification in a GARCH setting is achieved if no structural shock is degenerate (i.e. $\overline{h} > 0$ in eq. (33)) and at most one structural shock i is homoscedastic (i.e. $\alpha_i = 0$ for at most one shock in (33)). These conditions can be verified directly from the GARCH estimation. That they are sufficient but not necessary is obvious because, according to the argument of Rigobon, a SVAR-GARCH model (i.e. a model where the coefficients of the conditional mean equations do not vary over time) is a. s. overidentified if the GARCH process satisfies the conditions stated by Milunovic and Yang. This leaves us with enough degrees of freedom to estimate the value of the structural parameters for a limited number of different regimes as we do[9].

As a final step, we extend further our analysis by relaxing the assumption of orthogonality of H_t^i and specify the state dependent covariance matrix with a Dynamic Conditional Correlation (DCC) model (Engle, 2002):

$$H_t^i = D_t^i R_t^i D_t^i \tag{34}$$

$$D_t^i = \text{diag}(\sqrt{h_t^i}) \tag{35}$$

$$R_t^i = \text{diag}(Q_t^i)^{-\frac{1}{2}} Q_t^i \text{diag}(Q_t^i)^{-\frac{1}{2}} \tag{36}$$

$$Q_t^i = (1 - a_i - b_i)\overline{Q}_i + a_i \left((D_{t-1}^i)^{-1} A_0^i u_{t-1}^i\right) \left((D_{t-1}^i)^{-1} A_0^i u_{t-1}^i\right)' + b_i Q_{t-1}^i \tag{37}$$

where a_i, b_i are scalars and h_t^i is still given by eq. (33). This extension relaxes the identification restrictions of the approaches based on conditional heteroscedasticity, which require that the structural errors are uncorrelated (Rigobon, 2002, 2003; Love and Payne, 2008; Ehrmann *et al.*, 2011). This is accomplished thanks to a two step estimation procedure similar to the standard DCC model (Engle, 2002). Indeed, given eq. (34), the regime dependent likelihood (28) can be written as follows:

$$f_{i,t}(\theta_2|\theta_1) = 2\pi^{-\frac{n}{2}} |D_t^i|^{-1} |R_t^i|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2} u_t^{i\prime} A_0^{i\prime} D_t^{i^{-1}} R_t^{i^{-1}} D_t^{i^{-1}} A_0^i u_t^i\right\} \tag{38}$$

The parameter vector θ_1 contains the same parameters of the bivariate GARCH model. The parameter vector θ_2 contains the unknown parameters of eq. (37), which are a, b and $\overline{Q}$. These parameters are estimated conditionally on the value of the parameters in θ_1[10]. The specification (38) is reduced to the specification (28) by assuming that the a_i and b_i are zero and that $\overline{Q}_i$ is diagonal.

Thanks to the proposed MS-SVAR-GARCH-DCC framework, we are able to decompose the conditional heteroscedasticity of data in two components. The first component relates to the time variations of A_0^t, as a consequence of the changing behavior of market participants, and of the unconditional, regime dependent, volatility $\overline{H}_t$. The second component relates to the GARCH process, which reflects more closely the uneven flow of information within each regime. We believe that the possibility of discriminating between these two components of volatility is the main advantage of the proposed approach.

[9] In detail, following Rigobon (2003) we can state that, for $N = 0, 1, 2, \dots$, if there are $N + 2$ distinct and non proportional conditional covariance regimes in the d.g.p., then no more than $N + 1$ coefficients in ω and γ_0 can be identified.

[10] The DCC estimation employs the routines of the rugarch and rugarch packages (Ghalanos, 2019, 2020). The maximization of likelihood is obtained using mle2 from the bbmle package.

5 Results

We start by estimating three alternative reduced-form models: a VAR model with $K = 24$ lags[11], along with 2-state and 3-state Markov Switching models with the same number of lags as the VAR. Additionally, in the 2-state setting we restrict the coefficients respectively of the price and demand equation to be fixed across regimes in order to evaluate if regime shifts are relevant for both or just one of the two equations.

In our theoretical setting, the VAR model should fit better to the data only in the unlikely case that heterogeneity is absent. Indeed we see from Tab. 1 that the VAR model is strongly penalized according to all information criteria. Both restrictions on the 2-states MS-VAR model are rejected by the LR test, showing that non linearity matters for both price and demand. The 3-state model is selected against the 2-state model according to all information criteria.

The expected duration of regimes is on the scale of a few periods (Tab. 2). In real time, this means that the highest expected duration in the 3-states model is of 30 minutes and lowest of a bit less than 15 minutes. With low frequency data it is customary to explain regime shifts in terms of exogenous events which trigger a structural change in the system under study. In our case, considered the low duration of regimes, it seems unlikely that these might be correlated with exogenous "once-in-a-year" events. The order of the expected duration rules out, as well, that our results are related to daily or weekly patterns of volatility. Instead, the regime shifts apparently reflect the adjustment of the market to the high-frequency flow of ordinary news, which trigger seamless actions and reactions from market participants.

If this hypothesis is true, the regime shifts should reflect themselves in variations of volatility, since the arrival of news is likely to coincide with spikes of volatility. Indeed from Tab. 3 we see that the regimes are drastically separated in terms of volatility, whose values change by one order of magnitude. In particular, we see that the high and low volatility regimes of the 2-state model split further, in the 3-state model, into an extremely high volatility regime and an intermediate one. By looking at the transition probabilities of this model (Tab. 4), we see that the market is not likely to calm down immediately, after a spike of volatility, since the intermediate volatility state 3 is most likely to succeed to the high volatility state 2. On the overall, the market jumps between the low and intermediate volatility states most of the time. Entering into a high volatility state is less likely, but

[11] K is set as the maximal value among the number of lags obtained as optimal using a number of information criteria (AIC, HQ, BIC, FPE).

Model	$\mathcal{L}$	AIC	BIC	LR
VAR	-120,964	242,123	242,956	-
2-states MS-VAR (price restr.)	-104,935	210,181	211,605	286.94***
2-states MS-VAR (demand restr.)	-104,981	210,271	211,696	377.86***
2-states MS-VAR	-104,792	209,992	211,867	-
3-states MS-VAR	-102,100	204,818	207,658	-

*** significant at the 1% level. Note: $\mathcal{L}$ = likelihood; $AIC = -2 \times \mathcal{L} + 2 \times$ n of free parameters; $BIC = -2 \times \mathcal{L} + T \times$ n of free parameters; LR = loglikelihood ratio test statistics.

Table 1: Comparison of reduced-form models

	2-State MS-VAR	3-State MS-VAR
State 1	9.84	6.05
State 2	2.94	2.98
State 3		4.28

Table 2: Expected duration periods of regimes for the 2-state and 3-state MS-VAR models

	2-State MS-VAR	3-State MS-VAR
Σ_1^2	$\begin{bmatrix} 0.0008 & 0.1862 \\ 0.1862 & 323.13 \end{bmatrix}$	$\begin{bmatrix} 0.0006 & 0.1091 \\ 0.1091 & 160.18 \end{bmatrix}$
Σ_2^2	$\begin{bmatrix} 0.0064 & 1.6684 \\ 1.6684 & 4930.63 \end{bmatrix}$	$\begin{bmatrix} 0.0152 & 3.9384 \\ 3.9384 & 12471.93 \end{bmatrix}$
Σ_3^2		$\begin{bmatrix} 0.0020 & 0.5185 \\ 0.5185 & 1205.87 \end{bmatrix}$

Table 3: State dependent covariance matrices of the MS-VAR model

once this regimes takes hold, it is likely to persist for some time.

Since the MS-VAR model (22) is a non-linear model, we must adapt impulse response analysis. Ehrmann *et al.* (2003) have proposed to calculate the impulse response functions (IRFs) under the assumption that a particular regime is prevailing over the entire time span covered by the IRFs. In practice, they propose to employ the IRFs of the VAR sub-models of the MS-VAR model. The problem with this approach is that the probability

	State 1	State 2	State 3
State 1	0.83	0.00	0.17
State 2	0.01	0.50	0.06
State 3	0.16	0.50	0.77

Table 4: Transition matrix of the 3-state MS-VAR model

that these IRFs are representative of the dynamics of the MS-VAR model is rapidly converging to zero along with the probability of staying in the initial regime. We follow instead the approach proposed by Krolzig (2006) who, in the spirit of Koop *et al.* (1996), proposes the following definition:

$$\mathrm{IRF}_u(i,h) = \frac{\partial E\left[y_{t+h}|u_t, \xi_t\right]}{\partial u_{i,t}} \tag{39}$$

where ξ_t is the regime vector (20). This means that the IRFs are conditioned on the prevailing regime at t but not bounded to stay in a specific regime for the subsequent periods[12].

From the cumulative IRFs computed according to definition (39) (Fig. 2), we see that in all regimes demand responds positively and price negatively to their own shocks, as expected (see Sec. 2). The cross-effects between price and demand are negative. In particular, considering that price variations are expressed in USD cents and the unit of demand is one million Euros, a positive demand shock worth approximately one standard deviation (38 million Euros) causes a (negative) price variation worth as little as -0.0023 USD cents across regimes in the subsequent 2 hours (i.e. $h = 24$ periods), equivalent to the 4.88% of the sample volatility of price. Instead, a positive EUR/USD price shock worth one standard deviation (0.0466 cents) causes a subsequent drop of demand of up to 6.15 millions Euros across regimes in the subsequent 2 hours, equivalent to the 16% of the sample volatility of demand. A small price impact of past demand shocks is what we expect in an efficient and extremely liquid market, like the one we consider. Instead, a more pronounced impact of past price shocks on demand is what we expect as an effect of order-splitting. We interpret the negative reaction of one variable to shocks associated with the other as a sign that trades executed with a lag come mostly from noise traders, who don't speculate on the exchange rate.

The residuals of the MS-VAR estimation strongly reject the null hypothesis of homoscedasticity for a number of tests. In particular, both series display ARCH effects as required by the identification conditions discussed in Sec. 4 (data not shown). Then we are justified in going to the second

[12] For the detailed computation of the IRFs introduced in this Section, see Appendix B.

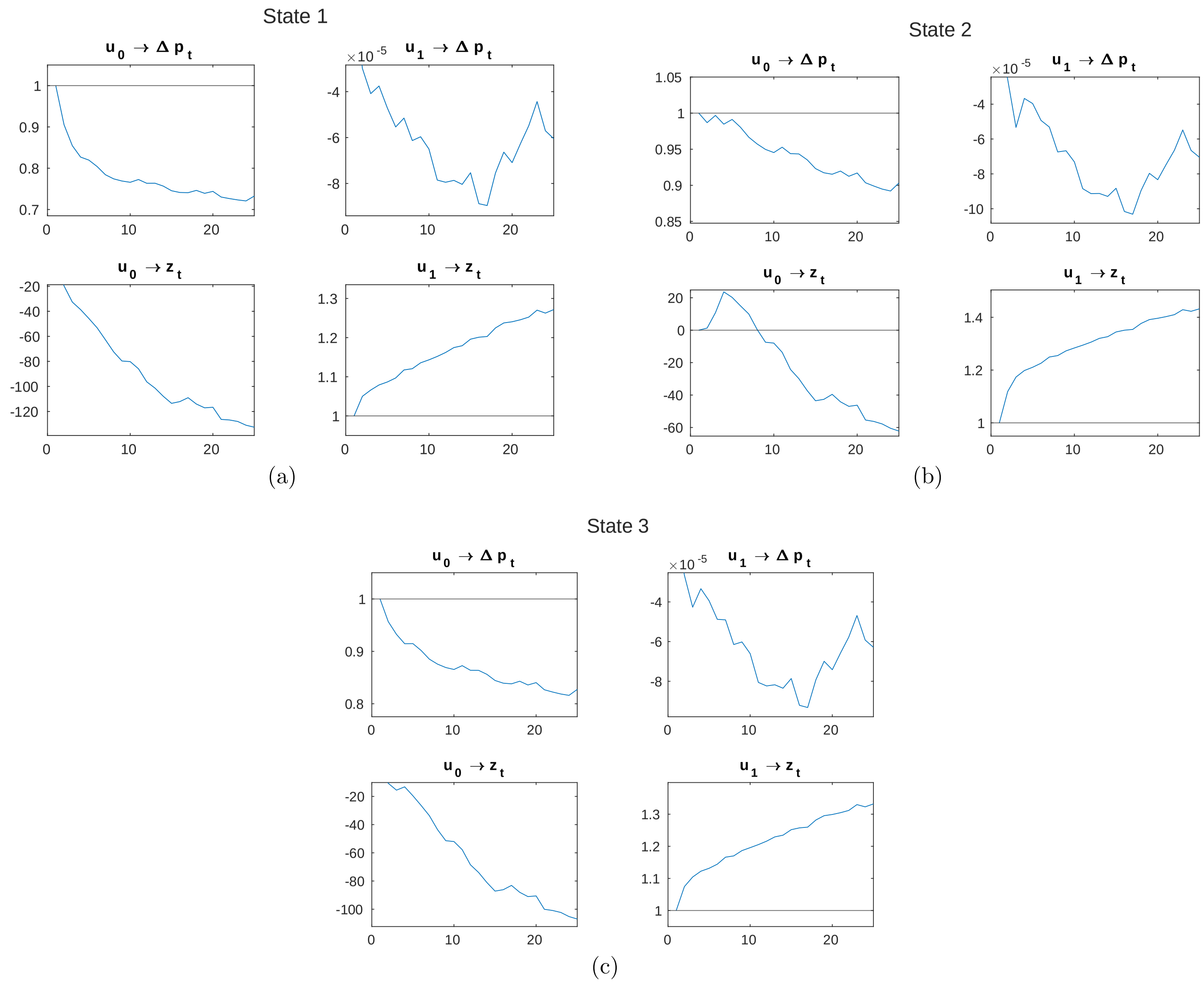

Figure 2: Cumulative IRFs to a unit shock for the MS-VAR model (see Eq. 39)

step of the estimation as described in the same section. In Tab. 5 we summarize the results obtained from the maximization of the likelihood function defined by eqs. (26)-(28). All the GARCH coefficients are highly significant, as we expected from the analysis of the MS-VAR residuals. The standardized residuals and squared residuals obtained from the GARCH estimation show no signs of serial correlation (data not shown). The signs of the parameters in the vectors ω and γ_0 are consistent with the basic hypotheses of the model in Sec. 2 ($\omega > 0$), the results of the MM literature $\left(\omega - \frac{1}{\gamma_0} > 0\right)$ and the prevalence of positive feedback traders among liquidity takers across regimes ($\gamma_0 > 0$). From the 95% confidence intervals reported in the table we see that all parameters are significantly different across regimes with the only exception of $\alpha_{z_t,i}$. In particular, we see that, contrary to $\alpha_{z_t,i}$, the impact of idiosincratic innovations on the conditional volatility of price variations, as measured by $\alpha_{\Delta p_t,i}$, is stronger in the high volatility regimes 2 and 3. These results are consistent with the interpretation that price innovations carry more information than demand innovations.

The economic implication of our estimates of ω_i and $\gamma_{0,i}$ is interesting, since it shows that the exchange rate is stabilized by the existence of feedback traders. From Eq. (3) we get that the simultaneous price impact of demand is equal to $\omega_t - \frac{1}{\gamma_{0,t}}$. From the table we see that this quantity is reduced by one order of magnitude thanks to the contribution of the positive values of γ_0. According to our model, the economic interpretation of this result is the following: thanks to the fact that a price variation coincides with a simultaneous net order flow of the same sign, the profits of liquidity providers are maximized with a smaller price increase than if this positive feedback was absent, because the actual net demand is larger in size because of this feedback.

In the high volatility states 2 and 3, liquidity providers are much less adverse to inventory build up, while liquidity takers are much more reactive to price variations. It might appear contradictory that liquidity providers become less risk adverse when volatility is high, but it all depends on who owns valuable information. Only if liquidity takers are better informed, it is rational for liquidity providers to become more risk adverse since, in this case, the valuable information is contained in demand shocks. Otherwise, information is mostly reflected in price shocks and liquidity takers will be the ones who need to react adjusting demand as quickly as possible to the latter. Indeed, this interpretation is consistent with the fact that liquidity takers become much more reactive to price variations when volatility is high.

We can get some additional indications from the CIRFs obtained from our estimates, which are depicted in Fig. 3. These are computed by adapting the definition (39) as follows:

$$\text{IRF}_{\epsilon}(i,h) = \frac{\partial E\left[y_{t+h}|A_{0,\xi_t}^{-1}\epsilon_t, \xi_t\right]}{\partial \epsilon_{i,t}} \tag{40}$$

Now that the coefficients in $A_{0,t}$ are taken into account, we see that the cross effects between price and demand are both positive thanks to the simultaneous positive impact of both shocks. The initial positive effects tend to fade away over time except that in the high volatility state 2, where a positive price shock is still causing demand to increase after 2 hours. In this regime a positive price shock worth one sample standard deviation causes an increase in Euro demand worth 750 millions after 2 hours, equal to 15 times the sample standard deviation of demand itself. Instead, a positive demand shock worth one sample standard deviation causes a price deviation of 0.00045 cents after two hours, equal to less than 1% of the sample standard deviation of price variations. Given the arguments above, these results suggest that liquidity providers have a leading role on the market when volatility is high, i.e. when valuable information arrives.

The last step is the estimation of the conditional correlation of the structural shocks according to Eqs. (37)-(38). The results are summarized in the following specifications of eq. (37):

$$Q_{1,t} = \Big(1 - \underset{(0.0098303)}{0.0204771} - \underset{(0.064483)}{0.8617819}\Big)\begin{bmatrix} 3.337646 & -2.182013 \\ -2.182013 & 6.669357 \end{bmatrix} + \\ + \underset{(0.0098303)}{0.0204771}\left(D_{1,t-1}^{-1}A_{0,1}u_{1,t-1}\right)\left(D_{1,t-1}^{-1}A_{0,1}u_{1,t-1}\right)' + \underset{(0.064483)}{0.8617819}\,Q_{1,t-1} \tag{41}$$

$$Q_{2,t} = \Big(1 - \underset{(0.0057174)}{0.0060686} - \underset{(0.3467275)}{0.624934}\Big)\begin{bmatrix} 0.178610 & -0.0697310 \\ -0.069731 & 0.125956 \end{bmatrix} + \\ + \underset{(0.0057174)}{0.0060686}\left(D_{2,t-1}^{-1}A_{0,2}u_{2,t-1}\right)\left(D_{2,t-1}^{-1}A_{0,2}u_{2,t-1}\right)' + \underset{(0.3467275)}{0.624934}\,Q_{1,t-1} \tag{42}$$

$$Q_{3,t} = \Big(1 - \underset{(0.003503)}{0.0100202} - \underset{(0.0160226)}{0.9646926}\Big)\begin{bmatrix} 1.262542 & -0.149306 \\ -0.149306 & 1.160134 \end{bmatrix} + \\ + \underset{(0.003503)}{0.0100202}\left(D_{3,t-1}^{-1}A_{0,3}u_{3,t-1}\right)\left(D_{3,t-1}^{-1}A_{0,3}u_{3,t-1}\right)' + \underset{(0.0160226)}{0.9646926}\,Q_{3,t-1} \tag{43}$$

The parameters a_i and b_i are not significantly different from zero in the high volatility regime 2. The higher standard errors in this regime suggest

	$i=1$	$i=2$	$i=3$
ω_i	0.0064991	0.0035581	0.0039837
	(0.0000112)	(0.0000423)	(0.0000091)
	[0.0064772 - 0.0065211]	[0.0034752 - 0.003641]	[0.0039658 - 0.0040015]
$\gamma_{0,i}$	173.6589	324.4846	262.3099
	(0.0007859)	(0.0000744)	(0.0003244)
$\omega_i - \frac{1}{\gamma_{0,i}}$	0.0007407	0.0004763	0.0001714
	(0.0000127)	(0.0000425)	(0.0000096)
	[0.0007158 - 0.0007656]	[0.000393 - 0.0005596]	[0.0001526 - 0.0001902]
$\overline{h}_{\Delta p_t,i}$	0.0000001	0.0013232	0.0000033
	(0.0000001)	(0.0000619)	(0.0000028)
	[0.0007158 - 0.0007656]	[0.000393 - 0.0005596]	[0.0001526 - 0.0001902]
$\alpha_{\Delta p_t,i}$	0.0003687	0.1503969	0.0941901
	(0.0000092)	(0.0000001)	(0.0000002)
	[0.0007158 - 0.0007656]	[0.000393 - 0.0005596]	[0.0001526 - 0.0001902]
$\beta_{\Delta p_t,i}$	0.9985587	0.8496011	0.9058078
	(0.0000608)	(0.0000006)	(0.0000003)
	[0.0007158 - 0.0007656]	[0.000393 - 0.0005596]	[0.0001526 - 0.0001902]
$\overline{h}_{z_t,i}$	14.788997	123.796196	99.604687
	(1.1891061)	(0.0007992)	(0.0059000)
	[12.4583 - 17.1196]	[123.7946- 123.7978]	[99.5931 - 99.6162]
$\alpha_{z_t,i}$	0.0129100	0.0129630	0.0124810
	(0.0018168)	(0.0033295)	(0.0018544)
	[0.0093491 - 0.0164709]	[0.0064372 - 0.0194888]	[0.0088464 - 0.0161156]
$\beta_{z_t,i}$	0.8311710	0.9870290	0.8860270
	(0.0117554)	(0.0004208)	(0.0025591)
	[0.8081304 - 0.8542116]	[0.9862042 - 0.9878538]	[0.8810112 - 0.8910428]

Note: standard errors in round brackets; 95% confidence intervals in square brackets.

Table 5: MS-SVAR-GARCH parameters' estimates (eqs. (26)-(33)).

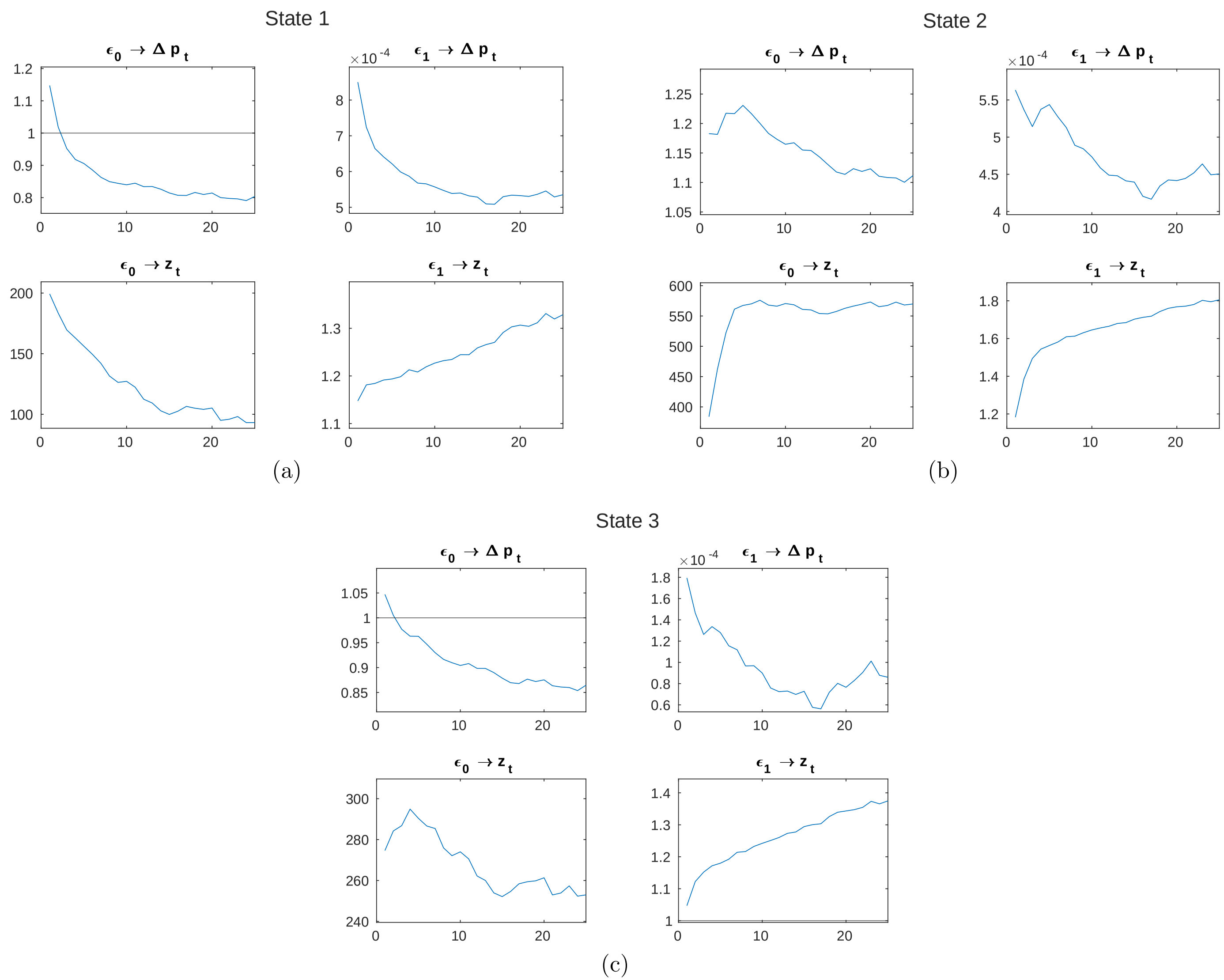

Figure 3: Cumulative IRFs to a unit shock for the MS-SVAR-GARCH model (see Eq. (40))

that these parameters are weakly identified. The parameters in the remaining regimes are significantly positive but their 95% confidence intervals ovelap. These results suggest that the conditional correlation depends only weakly on the regimes.

The time evolution of the expected conditional variances $h_{0,t}$ and $h_{1,t}$ and the expected conditional correlation ρ_t are depicted in Fig. 4[13]. We mark with a vertical line the following critical days (see Sec. 3): March 10 (QE expansion); June 3 (US Jobs announcement); June 24 (Brexit referendum); November 9 (Trump election); December 15 (Euro falls below \$ 1.04). We see that price volatility appears to be much more reactive to exogenous events (March 10, June 3, June 24, Nov 9), although the two volatilities are highly correlated (0,82). The expected unconditional correlation of the structural shocks is negative (-0.27), and the conditional correlation is mostly negative with only some few exceptions. These results are robust to an alternative estimation performed assuming that the errors follow a Student distribution (data not shown). Indeed, exogenous events do not appear to have large effects on ρ_t, with the big exception of June 3 and December 15, when ρ_t becomes strongly positive. Moreover, the movements of ρ_t result to be negatively correlated to those of $h_{0,t}$ and $h_{1,t}$ (-0.11).

A candidate explanation for the negative correlation of the structural errors is the action of liquidity / noise traders on the foreign exchange market. The latter are generally assumed to trade with a loss, a feature which might explain why a positive (negative) price shock occurs along with a negative (positive) demand shock. Moreover, the effect of the negative correlation is to balance the market. This stabilizing role is exactly the one assigned to liquidity / noise traders from the MM literature (Evans and Lyons, 2002; King *et al.*, 2013). Under this perspective, it is consistent that the magnitude of the negative correlation between the structural errors becomes stronger when h_0 and h_1 are higher (i.e. when external information arrives), because it is exactly in those moments that noise traders are likely to lose more.

In order to account for the covariance of the structural errors, we adapt our definition of impulse response function as follows:

$$\mathrm{IRF}_v(i,h) = \frac{\partial E\left[y_{t+h} | A_{0,\xi_t}^{-1} \overline{H}_{\xi_t}^{\frac{1}{2}} v_t, \xi_t\right]}{\partial v_{i,t}} \tag{44}$$

where $\overline{H}_{\xi_t}$ is the (regime dependent) unconditional covariance matrix of the structural errors. We can also define a time varying counterpart which

[13]Expectations are taken with respect to the filtered probabilities of the hidden Markov process.

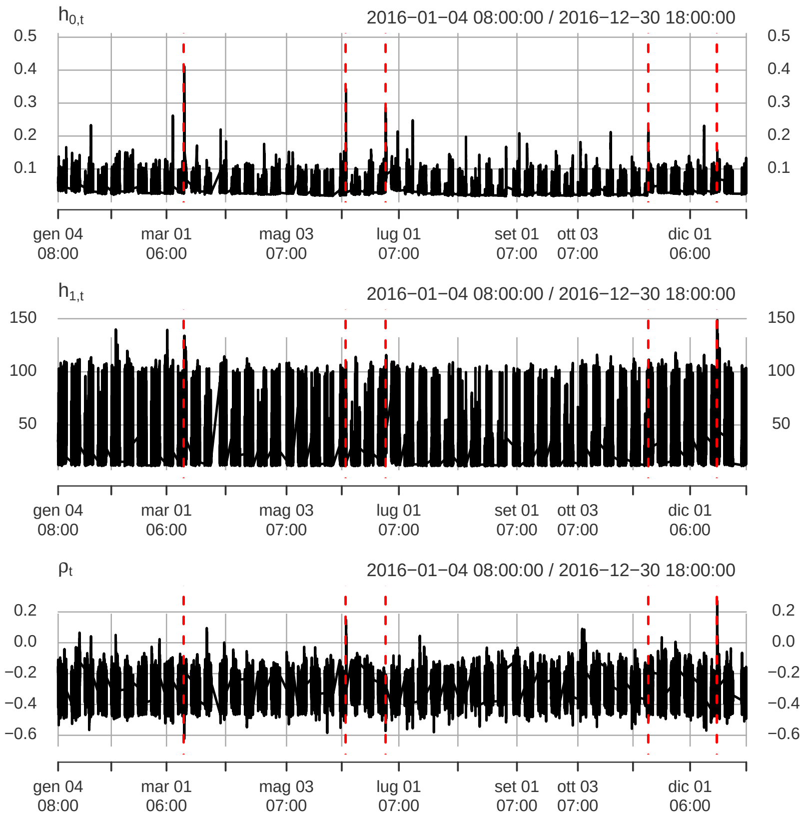

Figure 4: GARCH-DCC filters. The vertical red lines correspond to a set of "critical" days as described in the text.

depends on the regime dependent conditional covariance of the structural errors:

$$\mathrm{IRF}_v^t(i,h) = \frac{\partial E\left[y_{t+h}|A_{0,\xi_t}^{-1} H_{t,\xi_t}^{\frac{1}{2}} v_t, \xi_t\right]}{\partial v_{i,t}} \tag{45}$$

In both equations, we need to compute the square root of the covariance matrix. Since we do not wish to impose restrictions upon the result, we rely on spectral instead of Cholesky decomposition. We obtain the following results for the square roots of the unconditional covariances $\overline{H}_{\xi_t}$:

$$\overline{H}_1^{\frac{1}{2}} = \begin{bmatrix} -0.0112667 & -0.0231178 \\ 13.6319410 & -0.0000191 \end{bmatrix} \quad (46)$$

$$\overline{H}_2^{\frac{1}{2}} = \begin{bmatrix} -0.0483672 & -0.0928677 \\ 104.6265531 & -0.0000429 \end{bmatrix} \quad (47)$$

$$\overline{H}_3^{\frac{1}{2}} = \begin{bmatrix} -0.0052479 & -0.0450544 \\ 31.8160628 & -0.0000074 \end{bmatrix} \quad (48)$$

$$(49)$$

We see that there is a stark asymmetry in the square rooted matrices. While demand is expected to react positively to an orthogonal price shock, price variations are expected to react negatively to an orthogonal demand shock. The CIRFs obtained from Eq. (44), and depicted in Fig. 5, reflect this asymmetry. We see that the cumulative impact of a demand shock on price deviation turns negative under all regimes. This is consistent with the idea that orthogonal demand shocks don't carry relevant information. Instead the impact of am orthogonal price shock on demand is still positive and non decreasing under all regimes, largest by magnitude in the high volatility regime 2. These result confirm the leading informational role of liquidity providers.

We represent the conditional CIRFs obtained using eq. (45), for $h = 24$, by means of the box plots in Fig. 6. We see that the cumulative impact of price and demand shocks shifts its magnitude over time. A first look at the graph suggests that the actual reactions of the EUR/USD market to exogenous shocks are conditioned both by regime dependent volatility, as measured by A_{0,ξ_t} and $\overline{H}_{\xi_t}$, and by idiosincratic volatility, as measured by the time variation of $H_{t,\xi_t}^{\frac{1}{2}}$. A 2-sample KS test rejects the null of equal distribution for all pairwise combinations of conditional CIRF distributions across regimes, showing that the regime dependent component of volatility matters for all kinds of shock transmissions. All the median values of $\mathrm{IRF}_v^t(i,h)$ are significantly different from zero and conserve the same sign across regimes. In particular, the distribution of the conditional CIRFs shifts upwards, under regime 2, when the impact of price shocks on demand is considered (lower left panel), while the opposite happens when the impact of demand shocks on price is considered (upper right panel). This is consistent with the results of Fig. 5. A simple decomposition of variance shows that the transition among regimes explains only 14% of the variability of the impact of price shocks on price variations, while it explains 95% of the variability of the impact of demand shocks on demand itself. Similarly, the variability of cross impacts

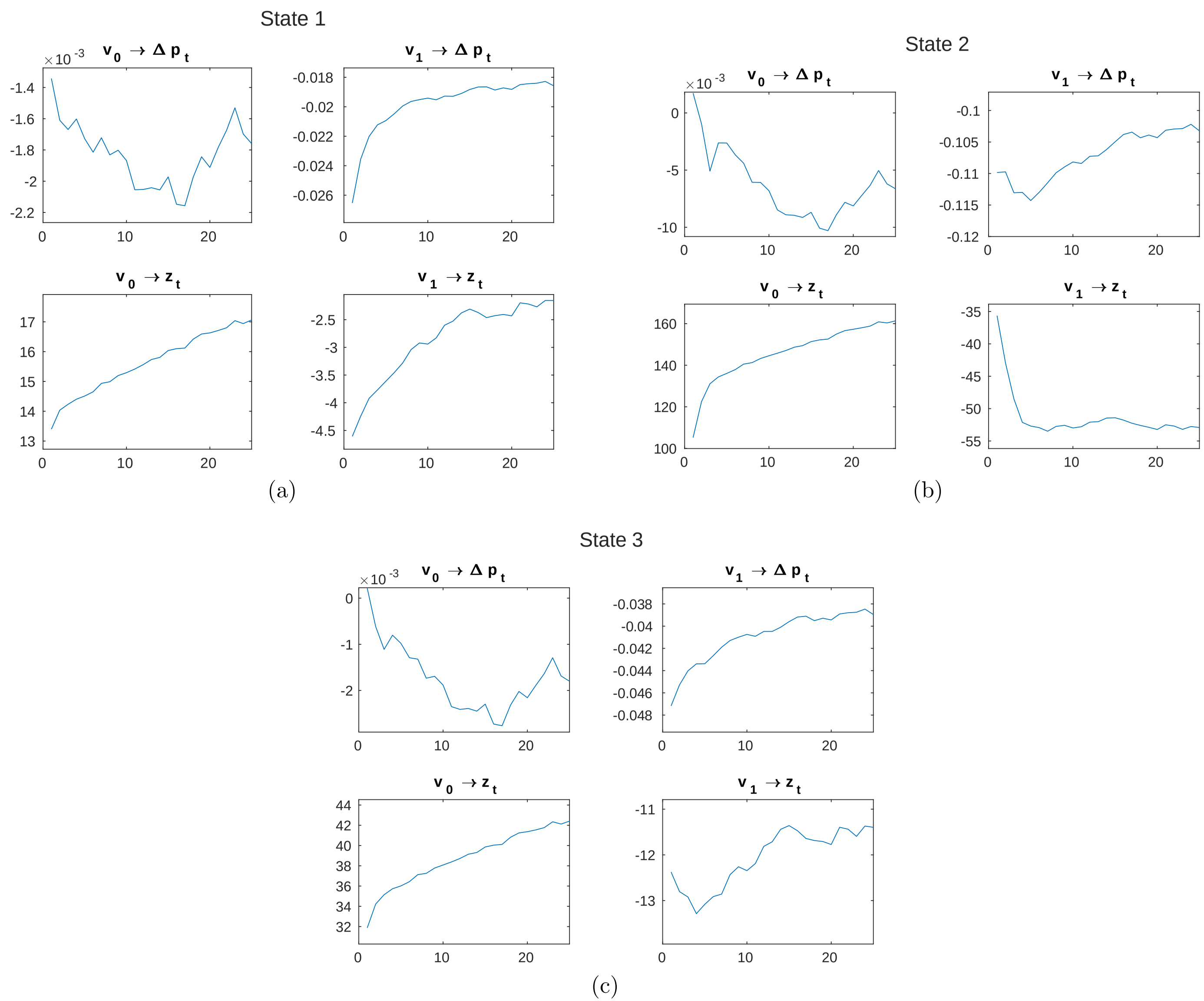

Figure 5: Cumulative IRFs for the MS-SVAR-GARCH-DCC model (see Eq. (44))

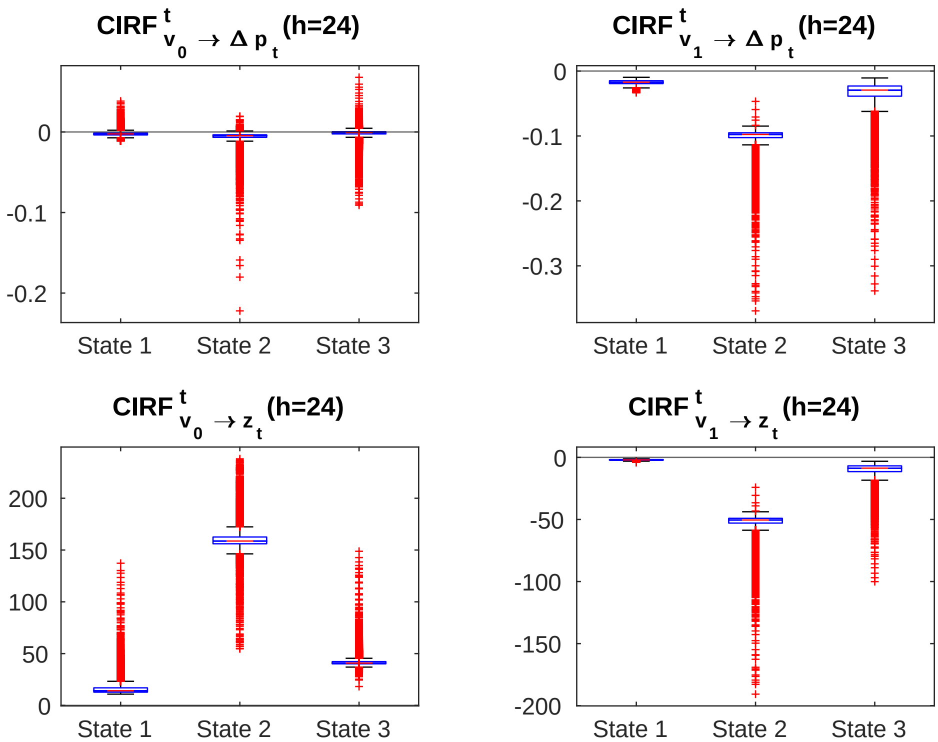

Figure 6: Box plots of time dependent CIRF functions with $h = 24$ (see Eq.(45)).

is largely explained by regime shifts (88% for the return impact of demand shocks; 98% for the demand impact of price shocks). These results indicate that price shocks are the only significant source of idiosincratic, exogenous, information on the foreign exchange market, while demand varies almost exclusively as a consequence of the endogenous response to price shocks.

6 Conclusions

The results of the reduced form MS-VAR estimation support the claim that financial markets are affected by the shifting expectations of heterogeneous speculators and their changing participation to the market. On the other hand, the reduced form coefficients explain only a small fraction of the volatility of price and demand in the FX market. This is by no means a surprise because the EUR/USD currency pair is exchanged on a highly liquid market, where we expect that lagged effects are small. Indeed, Daníelsson and Love (2006) have proved that, when data is aggregated at relatively high frequencies like the one we used, the most important component of price and demand interactions will manifest themselves under the form of simultaneous effects, which contribute to the heteroscedasticity of the reduced form errors of the MS-VAR model. We have called this component of conditional volatility endogenous since, according to the model of Sec. 2, it depends on the actions of the participants to the interdealer FX market. We have addressed the task of quantifying endogenous volatility by means of the MS-SVAR-GARCH-DCC model. The results obtained from this model show that, in the FX market, the simultaneous impact coefficients of price variation on demand and vice versa are positive across regimes (Tab. 5). This result is consistent with those of the MM literature, which require that $\omega - \frac{1}{\gamma_0} > 0$, and with the prevalence of positive feedback traders among liquidity takers, which implies that $\gamma_0 > 0$. The latter result, on its part, confirms the previous empirical results of Daníelsson and Love (2006), and rejects the restriction $\gamma_0 = 0$, proposed by Hasbrouck (1991).

After taking into account the regime dependent unconditional covariance matrices of the structural errors, the cumulative effect of a demand shock on price turns out to be negative in all regimes, while the opposite holds for the cumulative effect of a price shock on demand (Fig. 5). We relate this asymmetry to the leading informational role of liquidity providers. Indeed any piece of valuable information that is likely to raise / lower the price posted by liquidity providers is also likely to raise /lower the demand of liquidity takers at the same time. Thus the fact that demand increases with a positive price shock means that valuable information is reflected first in the price, i.e in the information set of the liquidity providers. Conversely, the fact that the price drops after a positive demand shock means that liquidity takers are less informed than the liquidity providers. In fact, if the former were better informed, the rational reaction of the latter would be to raise and not to lower prices. Instead, lowering (raising) the price is rational if the buyer (seller) is considered to be uninformed, in order to prevent liquidity based speculation to catch on (Vitale , 2000; Jeanne and Rose, 2002). Moreover, according to our results, when volatility rears up, the liquidity providers becomes less inventory adverse (ω_t falls). This result can only be rationalized if liquidity takers are no more informed than liquidity providers themselves.

Our results seem at odds with the intuition according to which informed traders should opt for aggressive trades, and thus place market orders. According to this view, liquidity takers should always be better informed. Nevertheless, our results are in line with those of Bjønnes *et al.* (2021), who show that the largest, and better informed, banks place profitable limit orders, along with market orders, on the FX market. We may synthesize our results by claiming that the FX market is efficient notwithstanding the existence of bounded rational traders and of asymmetry of information. In our framework, the price posted by liquidity providers leads the market exactly because they have access to privileged information, which may be acquired either by trading over the counter with informed customers or by their own efforts (Bjønnes *et al.*, 2021). The liquidity takers, although less informed, are able to trade according to their expectations of the future exchange rate. On the other hand, the negative correlation of the structural errors suggests that other market participants trade with a loss. Confirming this, the temporal evolution of the conditional correlation of the structural errors is weakly correlated with the evolution of regime dependent volatilities. This suggests that the conditional correlation is weakly related to the behavior of market participants described in our model. Since the effect of a negative conditional correlation of price and demand shocks is to help balancing the market, our interpretation is consistent with the stabilizing role assigned to liquidity / noise traders by the MM literature (Evans and Lyons, 2002; King *et al.*, 2013).

A Identification conditions and estimation procedure

It is known that, if the identification conditions based on conditional heteroscedasticity hold, the values of the estimated parameters are unique up to a reordering, change of sign and renormalization of the columns of A_0 (Rigobon, 2003; Ehrmann *et al.*, 2011; Lewis, 2018). This means that we need additional information to identify the structural coefficients of the model.

In order to see why this is necessary, let's start from a generic bivariate simultaneous system:

$$x_t = a\, y_t + \epsilon'_{0,t} \tag{A.1}$$

$$y_t = b\, x_t + \epsilon'_{1,t} \tag{A.2}$$

where x_t and y_t are observed variables and $\epsilon'_{0,t}$ and $\epsilon'_{1,t}$ unobserved errors. After exchanging the order of the equations, the system can be rewritten equivalently as follows:

$$x_t = \frac{1}{b}\, y_t + \epsilon''_{0,t} \tag{A.3}$$

$$y_t = \frac{1}{a}\, x_t + \epsilon''_{1,t} \tag{A.4}$$

Indeed, since we don't observe the errors, we cannot distinguish between $\epsilon'_{0,t}$ and $\epsilon''_{0,t} = -\frac{\epsilon'_{1,t}}{a}$ or between $\epsilon'_{1,t}$ and $\epsilon''_{1,t} = -\frac{\epsilon'_{1,t}}{b}$. From the two equivalent formulations we obtain the same representation, which is the only one amenable for estimation:

$$x_t = \theta_0 \, y_t + \epsilon_{0,t} \tag{A.5}$$

$$y_t = \theta_1 \, x_t + \epsilon_{1,t} \tag{A.6}$$

In order to simplify the argument, we follow Rigobon (2003) and we assume that there are two different regimes $s = 0, 1$ for the variance of $\epsilon'_{0,t}$ and $\epsilon'_{1,t}$. In this case the system (A.1)-(A.2) satisfies exactly the order condition under the assumption that $\epsilon'_{0,t}$ and $\epsilon'_{1,t}$ are uncorrelated under each regime. In particular, a and b satisfy the following couple of equations:

$$a = \frac{w_{0,1,s} - w_{1,1,s} b}{w_{0,0,s} - w_{0,1,s} b} \qquad s = 0, 1 \tag{A.7}$$

where, under each regime, $w_{0,0,s}, w_{1,1,s}, w_{0,1,s}$ are the variances and covariance of x_t and y_t, which can be estimated from the data. In order to derive (A.7), these estimates are equated to their theoretical counterparts which are on their part obtained from the following reduced form solutions for x_t and y_t:

$$x_t = \frac{\epsilon'_{0,t} + \epsilon'_{1,t} a}{1 - ab} \tag{A.8}$$

$$y_t = \frac{\epsilon'_{0,t} b + \epsilon'_{1,t}}{1 - ab} \tag{A.9}$$

Since these reduced form solutions do not depend from the ordering of equations, not even eqs. (A.7) depend from these ordering. Equating the r.h.s. of the system (A.7) we obtain a quadratic equation which yields two distinct real and finite solutions for b when the following holds (Rigobon, 2003):

$$w_{0,0,0} w_{0,1,1} - w_{0,0,1} w_{0,1,0} \neq 0 \tag{A.10}$$

If we solve the equations (A.7) for b we obtain instead the following system:

$$b = \frac{w_{0,0,s} a - w_{0,1,s}}{w_{0,1,s} a - w_{1,1,s}} \qquad s = 0, 1 \tag{A.11}$$

Equating the r.h.s of these equations it's easy to check that, if b^* is a solution for (A.7), then $a^* = \frac{1}{b^*}$ is a solution for (A.11). This shows that the two solutions obtained from either (A.7) or (A.11) correspond to the values of the estimated parameters θ_0 and θ_1 of eqs. (A.5)-(A.6), so that only the latter are identified while a and b are not.

Most of the existing literature addresses this problem by imposing inequality restrictions on the coefficients of the model (Ehrmann *et al.*, 2011; Herwartz and Lütkepohl, 2014; Lütkepohl and Netšunajev, 2014; Lanne and Luoto, 2020). In our case, we can show that the constraint imposed by the theoretical model of Sec. (2) on the reduced form coefficients allows the identification of one of the two structural coefficients. For the sake of expositional simplicity we assume that A_0 is not time varying, since the argument can be replicated for each regime dependent matrix A_0^i and the corresponding structural coefficients.

In order to illustrate the main point, let's write in vector form the two ways in which the reduced form errors can be written:

$$\begin{cases} u_t = A_0^{-1}\,\epsilon_t \\ A_0 = \begin{bmatrix} 1 & \frac{1}{\gamma_0} - \omega \\ -\gamma_0 & 1 \end{bmatrix} \end{cases} \tag{A.12}$$

$$\begin{cases} u_t^* = A_0^{*-1}\,\epsilon_t \\ A_0^* = \begin{bmatrix} 1 & -\frac{1}{\gamma_0} \\ \frac{\gamma_0}{1-\gamma_0\omega} & 1 \end{bmatrix} \end{cases} \tag{A.13}$$

Now let's suppose that θ_0 and θ_1 are the reduced form coefficients of either A_0 or A_0^*. This yields the following two systems:

$$\begin{cases} \theta_0 & = \omega - \frac{1}{\gamma_0} \\ \theta_1 & = \gamma_0 \end{cases} \tag{A.14}$$

$$\begin{cases} \theta_0 & = \dfrac{1}{\gamma_0} \\ \theta_1 & = \dfrac{\gamma_0}{\gamma_0\omega - 1} \end{cases} \tag{A.15}$$

Let's solve the two systems for the structural parameters. In the first case, we obtain:

$$\begin{cases} \omega & = \theta_0 + \dfrac{1}{\theta_1} \\ \gamma_0 & = \theta_1 \end{cases} \tag{A.16}$$

In the second case instead we obtain:

$$\begin{cases} \omega & = \theta_0 + \dfrac{1}{\theta_1} \\ \gamma_0^* & = \dfrac{1}{\theta_0} \end{cases} \tag{A.17}$$

We see that ω is identified independently from the ordering of the system while γ_0 is not identified, except in the unlikely case that $\theta_1 = \dfrac{1}{\theta_0}$.

Since γ_0 and γ_0^* yield by construction the same value of the likelihood, we estimate, for each regime, θ_0^i and θ_1^i firstly and afterwards ω_i, $\gamma_{0,i}$ and $\gamma_{0,i}^*$ according to the two orderings (A.12) and (A.13). In detail, we take the following steps:

1. Estimate the MS-VAR model (22)

2. Estimate equation-by-equation a GARCH model[14] on the regime dependent reduced form errors u_t^i

3. Use the GARCH parameters obtained with the previous step as starting values for an equation by equation maximization of the likelihood (26)-(28), in order to obtain the estimates $\hat{\theta}_0^i, \hat{\theta}_1^i$ for each regime $i = 1, 2, 3$

4. Compute the estimates $\hat{\omega}$ and $\hat{\gamma}_0$ according to the ordering (A.12): these are the ones reported in the main text

5. Compute the estimates $\hat{\gamma}_0^*$ according to the ordering (A.13), which are reported in Tab. 6

From the comparison of Tab. 6 with Tab. 5 we see that the values of $\hat{\gamma}_{0,i}^*$ are much larger than the value of $\hat{\gamma}_0$ reported in the main text. As explained above, the literature tries to overcome this source of indeterminacy relying mainly on restrictions imposed on A_0. For instance, if we deal with a standard demand-supply system, we might impose sign restrictions on the structural coefficients which translate into sign restrictions of the reduced form coefficients, making the former identifiable. In our model, the only theoretical restriction we might think of is the positivity of the adjustment coefficient in the price equation in each regime, i.e.

$$\theta_0^i = \omega_i - \frac{1}{\gamma_{0,i}} > 0 \qquad i = 1, \ldots, M \tag{A.18}$$

which is strongly supported by the MM literature. This constraint could have been informative if one of the two reduced form coefficients was negative and the other positive in at least one regime. But unfortunately this is not the case with our estimation.

If the issue is one of forecasting the response of endogenous variables to shocks, as we do in the paper, discriminating between $\hat{\gamma}_0$ and $\hat{\gamma}_0^*$ is unimportant, since the IRFs depend only on the reduced form coefficients θ_0^i and

[14] The GARCH estimations at all steps employ the routines of the rugarch package (Ghalanos, 2020). The maximization of likelihood is obtained using mle2 from the bbmle package.

	$i=1$	$i=2$	$i=3$
$\gamma^*_{0,i}$	1349.50	5835.31	2223.84
	(20.44)	(186.08)	(309.59)

Note: standard error in parentheses.

Table 6: Comparison of reduced-form models

θ_1^i. But, even if choosing between $\hat{\gamma}_0$ and $\hat{\gamma}_0^*$ is unimportant from an empirical standpoint, we nevertheless need to make a decision for the purpose of presentation. We have chosen to rely on the plausibility of the respective magnitude of the coefficients. Taking into consideration the regime dependent unconditional standard deviations of Tab. 3 and the two alternative estimates γ_0 and γ_0^*, we can compute the values for the instantaneous response of demand z_t to a price shock equal to $\sigma(\Delta p_t)$, relative to its own standard deviation $\sigma(z_t)$, which are reported in Tab. 7. The values on the first row range between 75% and 87% of $\sigma(z_t)$, while those in the second row range between 167% and 722% of $\sigma(z_t)$. We consider the latter values to be less plausible since they entail that the average instantaneous response of z_t to an average price shock is much larger than the average volatility of z_t itself.

B Impulse Response Functions for Markov Switching Models

In this appendix we detail the computation of the IRFs given by eqs. (39)-(40) and (44)-(45). For this purpose we adjust the approach of Krolzig (2006) which employs a linear state space representation of MS models. In the first place we write the system (18) in a stacked form:

	State 1	State 2	State 3
$\gamma_0 \times \frac{\sigma(\Delta p_t)}{\sigma(z_t)}$	0.75	0.87	0.22
$\gamma_0^* \times \frac{\sigma(\Delta p_t)}{\sigma(z_t)}$	1.67	2.60	7.22

Table 7: Expected simultaneous impact of a shock equal to the unconditional s.d. of Δp_t, relative to the unconditional s. d. of z_t.

$$\begin{bmatrix} A_{0,t} & 0 & \dots & 0 \\ 0 & I_n & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \vdots & I_n \end{bmatrix} \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-K+1} \end{bmatrix} =$$

$$= \begin{bmatrix} C_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} A_{1,t} & A_{2,t} & \dots & A_{K-1,t} & A_{K,t} \\ I_n & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & I_n & 0 \end{bmatrix} \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-K} \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \text{(B.1)}$$

where n is the dimension of y_t. Eq. (B.1) can be written as

$$\mathbf{A_{0,t}\, y_t = C_t + A_{1,t}\, y_{t-1}} + \epsilon_\mathbf{t} \quad \text{(B.2)}$$

It is convenient to rewrite the system (B.2) in reduced form:

$$\mathbf{y_t = D_t + B_{1,t}\, y_{t-1} + u_t} \quad \text{(B.3)}$$

We can decompose the vectors $\mathbf{y_t}$ of Eq. (B.3) and ξ_t of Eq. (20) as follows:

$$\mathbf{y_t} = E\left[\mathbf{y_t}|\xi_{t-1}\right] + \mathbf{u}_t^* \quad \text{(B.4)}$$

$$\xi_t = E\left[\xi_t|\xi_{t-1}\right] + \eta_t \quad \text{(B.5)}$$

where $\mathbf{u}_t^*$ and η_t are martingale difference sequences. Then, introducing

$\mathbf{1_n}$ as a column vector of ones of size n, we can write

$$\begin{bmatrix} \xi_{1,t}\mathbf{y_t} \\ \vdots \\ \xi_{M,t}\mathbf{y_t} \end{bmatrix} = \begin{bmatrix} p_{11}\mathbf{D_1} & \dots & p_{M1}\mathbf{D_1} \\ \vdots & \vdots & \vdots \\ p_{1M}\mathbf{D_M} & \dots & p_{MM}\mathbf{D_M} \end{bmatrix} \begin{bmatrix} \xi_{1,t-1}\mathbf{1_n} \\ \vdots \\ \xi_{M,t-1}\mathbf{1_n} \end{bmatrix} + \\ + \begin{bmatrix} p_{11}\mathbf{B_1} & \dots & p_{M1}\mathbf{B_1} \\ \vdots & \vdots & \vdots \\ p_{1M}\mathbf{B_M} & \dots & p_{MM}\mathbf{B_M} \end{bmatrix} \begin{bmatrix} \xi_{1,t-1}\mathbf{y_{t-1}} \\ \vdots \\ \xi_{M,t-1}\mathbf{y_{t-1}} \end{bmatrix} + \begin{bmatrix} \xi_{1,t}\mathbf{u_t^*} \\ \vdots \\ \xi_{M,t}\mathbf{u_t^*} \end{bmatrix} \quad \text{(B.6)}$$

or in short:

$$\psi_{y,t} = \mathbf{D}\psi_{\xi,t-1} + \mathbf{B}\psi_{y,t-1} + \varepsilon_{y,t} \quad \text{(B.7)}$$

The same arrangement can be made for the regime vector:

$$\begin{bmatrix} \xi_{1,t}\mathbf{1_n} \\ \vdots \\ \xi_{M,t}\mathbf{1_n} \end{bmatrix} = \begin{bmatrix} p_{11}\mathbf{1_n}\mathbf{1_n'} & \dots & p_{M1}\mathbf{1_n}\mathbf{1_n'} \\ \vdots & \vdots & \vdots \\ p_{1M}\mathbf{1_n}\mathbf{1_n'} & \dots & p_{MM}\mathbf{1_n}\mathbf{1_n'} \end{bmatrix} \begin{bmatrix} \xi_{1,t-1}\mathbf{1_n} \\ \vdots \\ \xi_{M,t-1}\mathbf{1_n} \end{bmatrix} + \begin{bmatrix} \xi_{1,t}\eta_t \\ \vdots \\ \xi_{M,t}\eta_t \end{bmatrix} \quad \text{(B.8)}$$

or in short:

$$\psi_{\xi,t} = \mathbf{F}\psi_{\xi,t-1} + \varepsilon_{\xi,t} \quad \text{(B.9)}$$

We see that the system (B.7)-(B.9) can be written as follows:

$$\psi_t = \mathbf{B}^*\psi_{t-1} + \varepsilon_t \quad \text{(B.10)}$$

where

$$\mathbf{B}^* = \begin{bmatrix} \mathbf{F} & \mathbf{0} \\ \mathbf{D} & \mathbf{B} \end{bmatrix} \quad \text{(B.11)}$$

Hence the moving average representation of ψ_{t+h} given ψ_t is

$$\psi_{t+h} = \mathbf{B}^{*h}\psi_t + \sum_{j=1}^{h} \mathbf{B}^{*j}\varepsilon_{t+j} \quad \text{(B.12)}$$

We can write the conditional expectation of y_{t+h} given y_t and ξ_t as a function of the conditional expectation of ψ_{t+h} given ψ_t:

$$E\left[y_{t+h}|y_t, \xi_t\right] = \sum_{i=1}^{M} E\left[\xi_{i,t+h}\, y_{t+h}|\xi_{i,t}y_t\right] = \\ = \left[\underbrace{\mathbf{0}_n \dots \mathbf{0}_n}_{n\times nM}\underbrace{I_n \dots I_n}_{n\times nM}\right] E\left[\psi_{t+h}|\psi_t\right] = \\ = \mathbf{H}\; E\left[\psi_{t+h}|\psi_t\right] \quad \text{(B.13)}$$

Using Eq. (B.12) we obtain:

$$E\left[\psi_{t+h}|\psi_t\right] = \mathbf{B}^{*h}\psi_t \tag{B.14}$$

and finally we compute the IRFs:

$$\mathrm{IRF}_u(i,h) = \frac{\partial E\left[y_{t+h}|u_t,\xi_t\right]}{\partial u_{i,t}} = \mathbf{H}\,\mathbf{B}^{*h}\begin{bmatrix}\mathbf{0}_{nm\times 1}\\ \xi_{1,t}\mathbf{e}_i\\ \vdots\\ \xi_{M,t}\mathbf{e}_i\end{bmatrix} \tag{B.15}$$

$$\mathrm{IRF}_\epsilon(i,h) = \frac{\partial E\left[y_{t+h}|\ A_{0,\xi_t}^{-1}\epsilon_t,\xi_t\right]}{\partial \epsilon_{i,t}} = \mathbf{H}\,\mathbf{B}^{*h}\begin{bmatrix}\mathbf{0}_{nm\times 1}\\ \xi_{1,t}A_{0,1}^{-1}\mathbf{e}_i\\ \vdots\\ \xi_{M,t}A_{0,M}^{-1}\mathbf{e}_i\end{bmatrix} \tag{B.16}$$

$$\mathrm{IRF}_v(i,h) = \frac{\partial E\left[y_{t+h}|A_{0,\xi_t}^{-1}\overline{H}_{\xi_t}^{\frac{1}{2}}v_t,\xi_t\right]}{\partial v_{i,t}} = \mathbf{H}\,\mathbf{B}^{*h}\begin{bmatrix}\mathbf{0}_{nm\times 1}\\ \xi_{1,t}A_{0,1}^{-1}\overline{H}_1^{\frac{1}{2}}\mathbf{e}_i\\ \vdots\\ \xi_{M,t}A_{0,M}^{-1}\overline{H}_M^{\frac{1}{2}}\mathbf{e}_i\end{bmatrix} \tag{B.17}$$

$$\mathrm{IRF}_v^t(i,h) = \frac{\partial E\left[y_{t+h}|A_{0,\xi_t}^{-1}H_{t,\xi_t}^{\frac{1}{2}}v_t,\xi_t\right]}{\partial v_{i,t}} = \mathbf{H}\,\mathbf{B}^{*h}\begin{bmatrix}\mathbf{0}_{nm\times 1}\\ \xi_{1,t}A_{0,1}^{-1}H_{t,1}^{\frac{1}{2}}\mathbf{e}_i\\ \vdots\\ \xi_{M,t}A_{0,M}^{-1}H_{t,M}^{\frac{1}{2}}\mathbf{e}_i\end{bmatrix} \tag{B.18}$$

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