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Chapter 1

Introduction

A vast majority of the applied literature in economics and finance considers models for conditional means. However, over the last two decades, an increasing attention has also been devoted to other aspects of conditional distributions, such as their quantiles (see for example White *et al.* (2015) and Koenker and Hallock (2000)). Quantile regression, originally pioneered by Koenker and Bassett (1978), extends the notion of sample quantile to a linear regression model. Specifically, it permits researchers to investigate the relationship between economic-financial variables not only at the center but across the entire conditional distribution of interest.

As pointed out by White *et al.* (2015), recent years have seen an increase in the application of quantile methodology to time series data. In my thesis, I apply the quantile regression framework to classical Structural Vector Autoregression (SVAR) models. In addition, I apply both classical and quantile regression models to currency data.

My work is aimed at introducing Quantile Vector Autoregression models and showing how to derive quantile impulse response functions, which measure the impact of a monetary policy shock on the quantile dynamics and in this way on the entire conditional distribution of a given variable. The new methodology is used to assess the impact of monetary policy innovations on the euro area economy. The results are compared to those obtained using a classical SVAR model, which focuses on the conditional mean effect of a given shock.

Another goal of my work is to empirically analyse whether the temporal variation in currency risk premia is systematically linked to changes in monetary conditions and investigate whether currency risk premia predictability provides information that is economically valuable. As argued by Menkhoff *et al.* (2012), the inter-temporal variation in currency risk premia is the most persuasive explanation for the forward premium puzzle and the resulting carry trade profitability. Concerning this, they show that global FX volatility and liquidity innovations are significant risk factors that drive the considered premia. So, focusing on monetary conditions, my work tries to propose instrumental variables that can explain the temporal variation in the price of volatility and liquidity.

Chapter 2 is a review of the empirical literature analysing the macro-financial effects of structural shocks. First, I examine the SVAR models, which are the traditional tool employed in these studies. Then, I discuss recently introduced multivariate quantile models.

In chapter 3, I propose a Quantile Vector Autoregression model and derive quantile impulse response functions. After having introduced the relevant econometric framework, I use it to empirically assess the impact of a monetary policy shock on the euro area economy.

In chapter 4, I empirically analyze the relation between currency risk premia and monetary conditions. In addition, I provide a short discussion of related research. Chapter 5 concludes my work.

Chapter 2

Means and Quantiles in Multivariate Time Series Analysis

2.1 Introduction

This chapter reviews the empirical literature that examines the macro-financial effects of structural shocks. The coventional tool employed in these studies is the Structural Vector Autoregressive (SVAR) model. By imposing a minimum set of restrictions, it permits researchers to identify the structural innovations and derive orthogonalized impulse response functions, which trace out the conditional mean effect of a given shock on current and future values of macro-financial variables.

In recent years several studies have applied the quantile regression methodology introduced by Koenker and Bassett (1978) to time series data. This modelling strategy has at least three advantages over the more traditional approaches that rely on the parameterization of the entire distribution (White *et al.* (2015)). First, regression quantile estimates are robust to outliers. Second, regression quantile is a semi-parametric technique and as such imposes minimal distributional assumptions on the underlying data generating process. Third, it enables researchers to estimate the relationship between economic variables directly on the quantiles of interest[1].

White *et al.* (2015) have introduced impulse response analysis in multivariate quantile models. However, they do not consider any dynamics in the first moments of the dependent variables. This is appropriate only if asset returns are considered. In addition, they assume that the shock is given not to the structural error but to the dependent variable. To acknowledge such fairly restrictive setting, they call the resulting function "pseudo quantile impulse response function".

The review is organized as follows. Next section examines the SVAR models. Section 2.3 provides a short overview of quantile regression and discusses multivariate quantile models. Section 2.4 concludes the paper.

[1] For an extensive review on many topics on quantile regression, see Koenker (2005).

2.2 Structural Vector Autoregressions

A Structural Vector Autoregressive model of order p (SVAR(p)) has the form:

$$\begin{aligned} y_t &= A_1 y_{t-1} + ... + A_p y_{t-p} + u_t \\ &= \mu_t(y_t) + u_t \end{aligned} \tag{2.1}$$

$$u_t = A^{-1} B \epsilon_t \tag{2.2}$$

where y_t is a $K \times 1$ vector of macroeconomic and financial variables at time t, A_i and B are a $K \times K$ coefficient matrices, $\mu_t = (\mu_t(y_{1t}), ..., \mu_t(y_{Kt}))'$ is the expected value of y_t conditional on the information set at time $t-1$, A is a $K \times K$ invertible matrix, u_t is the $K \times 1$ vector of disturbances, $\epsilon_t = (\epsilon_{1t}, ..., \epsilon_{Kt})' \sim (0, I)$ is the vector of fundamental economic shocks (e.g. monetary shock, oil price shock or exchange rate shock) and I is a $K \times K$ identity matrix.

If the process y_t is stationary, equations (2.1) and (2.2) can be written in the following way (Wold representation):

$$y_t = \Psi_0 \epsilon_t + \Psi_1 \epsilon_{t-1} + ... + \Psi_n \epsilon_{t-n} \tag{2.3}$$

where $\Psi_0 = A^{-1}B$, $\Psi_j = \Phi_j A^{-1} B$ (with $j = 1, ..., n$) and $\Phi_s = \sum_{j=1}^{s} \Phi_{s-j} A_j$, with $\Phi_0 = I$, $s = 1, ..., n$ and $A_j = 0$ for $j > p$. The elements of Ψ_i represent the orthogonalized impulse response function (IRF), which traces out the average effect of a structural shock on current and future values of the dependent variables.

In order to derive the impulse response function, A, B and the A_i's have to be calculated. While the A_i's can be estimated via ordinary least squares[2] (OLS), the computation of the stuctural matrices A and B requires identifying assumptions. Given the $K(K+1)/2$ nonredundant elements of the sample covariance matrix of u_t ($\hat{\Sigma}_u$), it is not possible to identify more than $K(K+1)/2$ structural parameters. Therefore, having the structural matrices $2K^2$ unknown parameters, $K^2 + K(K-1)/2$ restrictions are required to identify the SVAR model[3].

The necessary restrictions can be obtained by setting A equal to an identity matrix and imposing a recursive structure for the fundamental shocks. This implies that the matrix B is triangular and so each structural shock affects a subset of variables instantaneously, while another subset of variables is affected with a lag. Examples of papers with recursive restrictions are Sims (1992), Bernanke and Blinder (1992), Christiano *et al.* (2000) and Kremer (2015).

A second strategy for identifying structural shocks involves specifying economic relations between u_t and ϵ_t. In this way, contemporaneous and nonrecursive restrictions are imposed on equation (2.2). Concerning this, see for example Gordon and Leeper (1994) and Bernanke and Mihov (1998).

Restrictions on lung-run neutrality of some shocks can also be used to identify Structural Vector Autoregressive models. For example, the restriction that the s-th shock has no lung-run impact on the i-th variable can be imposed by constraining the element (i, s) of the matrix $\Psi = \sum_{j=0}^{\infty} \Psi_j$ to be equal to zero.

[2]SVAR models can be estimated using several estimation procedures, including Bayesian approaches.

[3]See Lutkepohl and Kratzig (2004) or Lutkepohl (2005)

Long-run restrictions are suggested inter alia by Blanchard and Quah (1989) and Lastrapes and Selgin (1995).

SVAR models generally give empirically plausible assessments of the macroeconomic effects of fundamental economic shocks. So, they have been widely used both by academic researchers and by practitioners in central banks to measure the effects of conventional monetary policy innovations[4]. Nevertheless, the limited conditioning information employed in this approach[5] generates three potential problems. First, if policy-makers have information not reflected in the SVAR, the measurement of policy innovations is biased. This produces the so called price puzzle. Second, representing a general economic concept using a specific data series is arbitrary to some degree. Finally, impulse response functions can be derived only for the included variables (Bernanke *et al.* (2005)).

In the next subsection I will discuss the factor-augmented VAR (FAVAR) methodology, introduced by Bernanke *et al.* (2005) to solve these problems. Then, I will consider recent empirical works employing SVAR models to analyse the macroeconomic effects of unconventional monetary policy and the interaction between monetary policy and financial instability.

[4]A survey of early papers using SVAR methodology is provided by Christiano *et al.* (2000).

[5]The degrees of freedom problem limits the inclusion of additional variables in SVAR models.

2.2.1 FAVAR framework

The FAVAR model proposed by Bernanke *et al.* (2005) consists of the following two equations:

$$C_t = \Gamma(L)C_{t-1} + v_t \tag{2.4}$$

$$X_t = \Lambda C_t + e_t \tag{2.5}$$

where $C_t = (f_t, y_t)'$, y_t is a $K \times 1$ vector of economic variables[6], f_t is a $M \times 1$ vector of unobserved factors (with M relatively small), X_t is a $N \times 1$ vector of "informational" time series (with N much greater than $(M + K)$), $\Gamma(L)$ is a conformable lag polynomial of finite order, Λ is a $N \times (M+K)$ matrix of factor loadings, v_t is an i.i.d. error term with mean zero and covariance matrix Q. The $N \times 1$ vector e_t is mean zero and contains series-specific components that are uncorrelated with C_t. These components can be either normal and uncorrelated or weakly correlated across indicators, depending on whether estimation is performed by likelihood-based Gibbs sampling techniques or principal components.

Equation (2.4) is a VAR in $C_t = (f_t, y_t)'$. So, it reduces to equation (2.1) if the terms of $\Gamma(L)$ that relates y_t to f_{t-1} are all zero. Equation (2.5) is based on the idea that both f_t and y_t are common factors that drive the dynamics of X_t.

As already mentioned, Bernanke *et al.* (2005) propose two approaches for es-

[6]Being interested in characterizing the monetary transmission mechanism, y_t includes a short-term interest rate.

timating the FAVAR model. The first one is a two-step principal component approach. The first step consists of extracting principal components from X_t in order to obtain consistent estimates of the unobserved factors f_t. As shown in Stock and Watson (2002), the principal components consistently recover the space spanned by the factors when N is large and the number of principal components used is at least as large as the true number of factors. Therefore, if y_t is really a common factor, it is captured by the principal components and estimating f_t involves removing y_t from the space covered by the principal components ($S(f_t, y_t)$). To this end, Bernanke *et al.* (2005) estimate a regression of the form $\hat{S}(f_t, y_t) = b_{S^*}\hat{S}^*(f_t) + b_y y_t + e_t$, where $\hat{S}^*(f_t)$ is an estimate of all the principal components other than y_t, obtained extracting principal components from the slow-moving variables[7]. In this way, $\hat{f}_t$ can be calculated as $\hat{S}^*(f_t) - b_y y_t$.

In the second step, equation (2.4) is estimated by OLS method. Given the presence of "generated regressors", confidence intervals for the impulse response functions are estimated following the Kilian (1998) procedure, which takes into account the uncertainty in the factor estimation. However, Bai (2003) shows that the uncertainty in factor estimates should be neglegible when N is large relative to the sample length.

The second approach is a one-step method that makes use of Bayesian likelihood methods and Gibbs sampling. However, Bernanke *et al.* (2005) find that the advantages of using this more burdersome procedure rather than the two-step method are modest.

[7]These variables do not respond contemporaneously to monetary policy shocks.

In their empirical application of FAVAR methods, Bernanke *et al.* (2005) consider a balanced panel of 120 monthly US macroeconomic time series and assume a recursive identification structure with the monetary policy instrument (the federal funds rate) ordered last in C_t. They find that a FAVAR specification with three unobserved factors and the federal funds rate successfully exploits the additional information: in particular, it removes the price puzzle and provides plausible estimates of the effects of a monetary policy shock to a wide variety of macroeconomic variables.

Boivin *et al.* (2009b) employ the FAVAR methodology to model empirically the transmission mechanism of monetary policy in the euro area (EA) and across its six largest economies (Germany, France, Italy, Spain, the Netherlands and Belgium). In this way, each country's sensitivity to EA monetary policy shocks is allowed to be different.

The model is estimated using a variant of the two-step principal component approach, a recursive identification structure and a balanced panel of 245 quarterly series covering the period from January 1980 to March 2007. Specifically, they consider 231 country-level and EA-level variables, an interest rate and real GDP for the United Kingdom, the United States and Japan, the euro/dollar exchange rate, an index of commodity price and the price of oil.

Considering a factor-augmented VAR(1) with five unobserved factors, the oil price inflation and the 3-month Euribor, Boivin *et al.* (2009b) show that there is considerable heterogeneity in the transmission of a EA monetary policy shock across countries. Nevertheless, after the creation of the euro, there is both a reduction in the effect of monetary policy innovations and a greater homogeneity in the monetary transmission mechanism across countries.

In order to remove the oil price inflation and the 3-month Euribor (which are elements of y_t in this case) from the space covered by the principal components, Boivin *et al.* (2009b) adopt the following procedure in the first step of estimation. Starting from an initial estimate ($f_t^{(0)}$) of f_t, they

1. regress X_t on $f_t^{(0)}$ and y_t to obtain the coefficient on y_t, denoted by $\hat{\lambda}_y^{(0)}$;

2. compute $\tilde{X}_t^{(0)} = X_t - \hat{\lambda}_y^{(0)} y_t$;

3. estimate $f_t^{(1)}$ as the first K principal components of $\tilde{X}_t^{(0)}$;

4. repeat steps 1. − 3. multiple times.

The same procedure is also followed by Boivin *et al.* (2009b) and Boivin and Giannoni (2010).

2.2.2 Modelling financial stress and unconventional monetary policy

After the onset of the last financial crisis, several empirical studies have employed SVAR models to analyse the effects of unconventional monetary shocks and the interaction between financial stress and economic dynamics. One of the most recent works in this field is the paper by Kremer (2015).

Kremer (2015) considers a classical Structural Vector Autoregressive framework (see equations (2.1) and (2.2)) for monthly euro area data covering the period from January 1999 to December 2013. His specification includes both core variables typically included in SVAR models and less standard variables. The former are the seasonally adjusted Harmonised Index of Consumer Prices (HICP), the seasonally adjusted real gross domestic product (GDP) and the main refinancing operations (MRO) rate: they respectively measure the aggregate price level, aggregate economic activity and stance of conventional monetary policy. The latter are the spread between the Euro Overnight Index Average (EONIA) rate and the MRO rate, the Composite Indicator of Systemic Stress (CISS) as a measure of financial instability in the euro area and the total assets of the European Central Bank (ECB) balance sheet as a measure of unconventional monetary policy.

The considered model is estimated by OLS and considering year-on-year growth rates for HICP, real GDP and and ECB total assets. Furthermore, structural shocks are identified by setting $A = I$ and imposing a recursive structure where macro variables are ordered before the financial variables.

Performing an impulse response analysis, Kremer (2015) finds that the CISS contributes significantly to the macroeconomic dynamics. In particular, after a financial stress shock, there are significant variations with the expected signs in all the endogenous variables but inflation. This also implies that the ECB reacts in a systematic way to financial instability through its conventional and unconventional monetary policy instruments. These findings are also robust to the inclusion of real and financial control variables.

Impulse response functions suggest also that expansive conventional and unconventional monetary policy shocks seem to have a positive impact on real

GDP growth rate, but no significant effect on inflation. In addition, the considered shocks help reducing financial stress.

From tests for direct and indirect causality it emerges that the CISS is directly causal for the ECB total assets growth rate, while it is indirect causal for the MRO rate. Kremer (2015) points out that this is consistent with the view that standard and non-standard monetary policy measures are guided by different motivations (separation principle).

The considered paper assumes that the linkage between financial stress and the macroeconomy is linear, ignoring potential nonlinearities in the common dynamics of the endogenous variables induced by dysfunctionalities in the financial system during periods of severe financial instability. Therefore, as highlighted by Kremer (2015), the estimated financial stress effects are an upper bound of the effects under normal times and a lower bound of the effects under times of stress. Hubrich and Tetlow (2015) analyse the interaction between financial stress, economic dynamics and monetary policy in the United States using a nonlinear multivariate framework: specifically, a Markov-switching VAR model[8].

Boeckx *et al.* (2014) also investigate the macroeconomic effects of ECB unconventional monetary policy measures using a SVAR model. They consider the same variables as Kremer (2015), although in log levels and for the period from January 2008 to December 2013. The estimation is performed using a Bayesian approach with Gibbs sampling.

In their empirical analysis, Boeckx *et al.* (2014) find that an increase in the

[8]This kind of models are out of the scope of this chapter.

ECB total assets generates a significant and temporary rise in the euro area output and prices. Extending the SVAR model, they also find that the an expansive unconventional monetary policy shock stimulates bank lending, stabilises financial markets and affects euro area countries real GDP in different ways. In particular, the impact on the output is lower in the countries more affected by the financial crisis and with a less capitalized banking system.

2.3 Multivariate quantile models

2.3.1 Quantile regression

Quantile regression was introduced by Koenker and Bassett (1978) to extend the notion of sample quantile to a linear regression model. It is specified in the following way:

$$y = Z\beta_\theta + \epsilon_\theta \tag{2.6}$$

where y is a $T \times 1$ vector of observations for the dependent variable, Z is a $T \times (K+1)$ matrix containing K explanatory variables, θ is a given confidence level, β_θ is a $K \times 1$ coefficient vector and ϵ_θ is an error term such that its θ-th conditional quantile is equal to zero.

Koenker and Bassett (1978) show that the θth regression quantile can be consistently estimated minimising the following objective function with respect to β_θ:

$$\psi_T(\beta_\theta) = \sum_{t=1}^{T}[\theta - 1(y_t \leq q_t(z_t, \beta_\theta))][y_t - q_t(z_t, \beta_\theta)] \tag{2.7}$$

where $1(\cdot)$ is an indicator function, $q_t(z_t, \beta_\theta) = z_t\beta_\theta$ is the conditional θ-quantile of y_t, y_t and z_t are respectively the t-th element of y and the t-th row of Z. Engle and Manganelli (2004) point out that the considered estimator can be applied also to a generic conditional θ-quantile $q_t(z_t, \beta_\theta)$.

Komunjer (2005) proves that there exist alternative estimators that can be used to consistently estimate the θ-th conditional quantile. The Koenker and Bassett (1978) estimator is a special case of a broader class of quasi-maximum likelihood estimators (QMLE) called "tick-exponential": when the tick-exponential density is equal to an asymmetric Laplace density, the tick-exponential QMLE coincides with the Koenker and Bassett (1978) regression quantile estimator.

If a quasi-likelihood function belongs to the tick-exponential family, then the QMLE is consistent for the true value of a correctly specified conditional quantile model (not necessarily linear). By contrast, the tick-exponential QMLE converges asymptotically to the pseudo-true value of a misspecified model. The pseudo-true parameter is defined as the unique maximizer of the expected value of the quasi log-likelihood function (Komunjer (2005)).

After having derived the semiparametric efficiency bound for conditional quantile parameters in time series models with weakly dependent and/or heterogeneous data, Komunjer and Vuong (2010b) argue that tick-exponential QMLE estimators are not semiparametric efficient in dynamic conditional quantile models[9]. In addition, they show that the considered bound is the asymptotic

[9] It is interesting to note that the Koenker and Bassett (1978) quantile estimator is semiparametric efficient only with i.i.d. data.

covariance matrix of an M-estimator β_θ^* that minimizes the following objective function:

$$\varphi_T(\beta_\theta) = \sum_{t=1}^{T} [\theta - 1(y_t \leq q_t(z_t, \beta_\theta))][F_t(y_t) - F_t(q_t(z_t, \beta_\theta))] \qquad (2.8)$$

where $F_t(\cdot)$ is the conditional distribution function.
The computation of $\varphi_T(\beta_\theta)$ requires estimating $F_t(\cdot)$. Komunjer and Vuong (2010a) derive a feasible conditional quantile estimator $\hat{\beta}_\theta^*$ replacing $F_t(\cdot)$ with a kernel estimator $\hat{F}_t(\cdot)$. Whenever $\hat{F}_t(\cdot)$ and $F_t(\cdot)$ are close, $F_t(y_t)$ is close to the probability integral transform which converts data sequences into sequences of independent uniform random variables on $(0, 1)$. Recalling that the Koenker and Bassett (1978) quantile estimator is semiparametric efficient with i.i.d. data, it follows that $\hat{\beta}_\theta^*$ is semiparametric efficient.

2.3.2 Measuring tail dependence using multivariate regression quantiles

White *et al.* (2015) have introduced a multivariate multi-quantile framework to model tail dependence among different random variables. Their model is specified in the following way:

$$q_{i,j,t}(\alpha) = z_t \beta_{i,j} + \sum_{\tau=1}^{m} q_{t-\tau}(\alpha)' \gamma_{i,j,\tau} \qquad (2.9)$$

where $q_{i,j,t}(\alpha)$ is the conditional quantile at time t of a random variable y_{it} for a given confidence level $\theta_{i,j}$, $i = 1, ..., n$ is the number of dependent variables,

$j = 1, ..., p$ is the number of quantile indexes (or confidence levels) considered[10], z_t is a $1 \times k$ vector of observable variables (whose first element is one), $\beta_{i,j}$ is a $k \times 1$ real vector, $q_{t-\tau}(\alpha)'$ is a $1 \times np$ vector, $\tau = 1, ..., m$ are the lags, $\gamma_{i,j,\tau}$ is a $np \times 1$ real vector, $\alpha'_{i,j} = (\beta'_{i,j}, \gamma'_{i,j})$, $\gamma_{i,j} = (\gamma'_{i,j,1}, ..., \gamma'_{i,j,m})'$ and $\alpha = (\alpha'_{11}, ...\alpha'_{1p}, ..., \alpha'_{n1}, ..., \alpha'_{np})'$ is the $l \times 1$ vector of coefficients to be estimated, with $l = np(k + npm)$.

White *et al.* (2015) jointly estimate all the parameters in the system (2.9) minimising the following objective function with respect to α:

$$\overline{\psi}_T(\alpha) = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{n} \sum_{j=1}^{p} [\theta_{ij} - 1(y_{it} \leq q_{i,j,t}(\alpha))][y_{it} - q_{i,j,t}(\alpha)] \right\} \tag{2.10}$$

which is a more general version of equation (2.7). In addition, they prove that the considered estimator ($\hat{\alpha}_T$) is consistent and asymptotically normal and derive a consistent estimator for its covariance matrix.

Using the proposed framework, White *et al.* (2015) introduce the concept of quantile impulse response function (QIRF): it measures the impact of a given shock on the quantile dynamics. For its derivation, they consider a simple version of the model:

$$q_t = c + A|y_{t-1}| + Bq_{t-1} \tag{2.11}$$

$$y_t = L_t \epsilon_t \tag{2.12}$$

[10] The number of quantile indexes can differ across i.

where q_t, y_t and c are 2×1 vectors, A, B are 2×2 coefficient matrices, L_t is a 2×2 time-varying lower triangular matrix and each element of $\epsilon_t = (\epsilon_{1t}, \epsilon_{2,t})'$ has a standard normal distribution and is mutually independent and identically distributed[11]. Furthermore, they assume that the shock is given to y_{it} (and not to the error term ϵ_{it}) only at time t, while in all the other periods there is no change. To acknowledge such a fairly restrictive setting, the function tracing the impact of a given shock to y_{it} on q_{it} is called "pseudo quantile impulse response function".

The pseudo θth quantile impulse response function for the variable y_{it} after a shock to y_{1t} ($\tilde{y}_{1t}$) is defined as:

$$\Delta_{i,s}(\tilde{y}_{1t}) = \tilde{q}_{i,t+s} - q_{i,t+s} \tag{2.13}$$

where s is the prediction horizon, $\tilde{q}_{i,t+s}$ is the θth conditional quantile of the shocked series at time $t + s$ and $q_{i,t+s}$ is the θth conditional quantile of the unaffected series at time $t + s$. Combining equations (2.12) and (2.11), it is straightforward to calculate $\tilde{q}_{i,t+s}$ and $q_{i,t+s}$, and in this way estimate $\Delta_{i,s}(\tilde{y}_{1t})$. The distribution of the QIRF is obtained recognising that the pseudo QIRF is a function of $\hat{\alpha}_T$ and applying the delta method[12]. In this way, the relevant standard errors and confidence intervals can be calculated.

The simple version of the model and the resulting pseudo QIRF are used to empirically assess the resilience of financial institutions to shocks to a market

[11] White *et al.* (2015) show that equation (2.12) is a possible data generating process for the multivariate regression quantile model in equation (2.11).

[12] In this case, $\hat{\alpha}_T$ includes the parameters of the simple version of the model.

index. In particular, fixing $\theta = 0.01$, White *et al.* (2015) estimate equations (2.11) and (2.12) for each of the 230 financial institutions in their sample: the first variable (y_{1t}) is the daily return on a portfolio of financial institutions and the second variable (y_{2t}) is the daily equity return on a single financial institution. Given the triangular structure of L_t, shocks to the market index can have a direct impact on the return of the specific asset, while shocks to the single asset do not have a direct impact on the large portfolio[13]. The sample covers the period from 1 January 2006 to 6 August 2010.

From the analysis it emerges that the non-diagonal coefficients of the matrices A and B are different from zero for a large fraction of the considered financial institutions. So, there is strong evidence of tail dependence between the single financial institution return and the market index return.

When averaging the pseudo QIRFs with respect to the geographical distribution or line of business of the considered financial institutions, no striking differences are revealed. The quantile impulse response analysis also suggests that a shock to the market index has a much greater impact on the risk of the largest and most leveraged financial institutions. Finally, calculating in-sample and out-of-sample quantiles for financial institutions grouped by size or leverage, it emerges that the risk of the largest and most leveraged financial institutions is very sensitive to market wide shocks during periods of market turbolence.

[13] In each of the 230 estimated models, the proxy for the market portfolio is the equally weighted average of all the financial institutions in the same geographic area.

2.4 Conclusion

Coventional SVAR analysis focuses on the conditional mean effect of structural innovations on current and future values of macro-fnancial variables. These models generally give empirically plausible results. So, they have been widely used both by academic researchers and by practitioners in central banks to measure the effects of conventional and unconventional monetary policy innovations.

The purpose of multivariate quantile models is to expand the traditional mean analysis. Specifically, they permit researchers to measure the impact of a given shock on the quantile dynamics and in this way on the entire conditional distribution of the dependent variables.

White *et al.* (2015) have introduced quantile impulse response functions in a fairly restrictive setting. First, they do not consider any dynamics in the first moments of the dependent variables: this is appropriate only if asset returns are considered. In addition, they assume that the shock is given not to the structural error but to the dependent variable.

Against this background, the next chapter proposes a generalisation of the impulse response analysis into fully dynamic quantile models. In particular, it introduces a quantile vector autoregression model and uses it to identify the structural shocks and derive quantile impulse response functions. In addition, it shows under which conditions quantile and classical impulse response functions are identical.

Chapter 3

Quantile Vector Autoregressions: an Application to Monetary Policy in the Euro Area

3.1 Introduction

Since Sims (1980), many studies have used vector autoregression (VAR) methods to examine the macroeconomic effects of monetary policy innovations: see, for example, Christiano *et al.* (2000), Bernanke *et al.* (2005), Boivin *et al.* (2009b), Boivin *et al.* (2009a), Boeckx *et al.* (2014) and Kremer (2015). Conventional VAR analysis focuses on the conditional mean effect of monetary policy schocks.

As pointed out by Kilian and Manganelli (2007), information about risk of economic variables is valuable for policy-makers in order to avoid the worst possible macroeconomic outcomes. Nevertheless, by construction, risks are not related to the conditional mean but to the tails of the distribution.

Against this background, my paper suggests a quantile vector autoregression (QVAR) model to measure the impact of a monetary policy shock on the quantile dynamics and in this way on the entire conditional distribution of a given variable (quantile impulse response function - QIRF). Despite the equivalence between QIRF and classical impulse response functions under homoscedastic error terms, I expect them to differ whenever this assumption does not hold. In particular, in presence of conditional heteroscedasticity, a given shock will affect the conditional distribution of the dependent variables in a nontrivial way.

The different equations that form the QVAR can be estimated independently from each other by regression quantiles, as introduced by Koenker and Bassett (1978). As highlighted by White *et al.* (2015), quantile methodology has at least three advantages over the more traditional approaches that rely on the parameterization of the entire distribution. First, regression quantile estimates are robust to outliers. Second, regression quantile is a semi-parametric technique and as such imposes minimal distributional assumptions on the underlying data generating process. Third, it enables researchers to estimate VAR processes directly on the quantiles of interest.

The concept of quantile impulse response function was introduced by White *et al.* (2015). However, they do not fully generalize the impulse-response function analysis into quantile models. First, they do not consider any dynamics in the first moments of the dependent variables (y_t): this is appropriate only if the dependent variables are asset returns. Then, they assume that the shock is given not to the structural error but to y_t. To acknowledge such fairly restrictive setting, they call the resulting function "pseudo quantile impulse response function".

The QVAR model and a classical VAR are used to assess the impact of a contractionary monetary policy shock on the euro area economy. First, the analysis suggests that a tightening monetary policy not only reduces the expected inflation, but it also increases the downside risk of inflation. Second, the considered shock does not have a significant impact on the expected output growth rate, while it increases the probability of left tail outcomes.

The remainder of this paper is organised as follows. Next section introduces the QVAR model and proposes the quantile impulse response function. Section 3.3 presents the empirical analysis. Section 3.4 concludes the paper.

3.2 Econometric framework

Consider a bivariate structural vector autoregression model:

$$\begin{aligned} y_t &= \omega + Ay_{t-1} + B\epsilon_t \\ &= \mu_t(y_t) + B\epsilon_t \qquad (3.1) \end{aligned}$$

where $y_t = (y_{1t}, y_{2t})'$ is a vector of two time series variables at time t, A is a 2×2 coefficient matrix, $\omega = (\omega_1, \omega_2)'$ is the intercept, $\mu_t = (\mu_t(y_{1t}), \mu_t(y_{2t}))' = \omega + Ay_{t-1}$ is the expected value of y_t conditional on the information set at time $t-1$, B is a 2×2 lower triangular coefficient matrix and the vector of error terms $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t})' \sim (0, I)$ (it can be assumed a standard multivariate normal distribution).

It follows that:

$$\sigma(y_{1t}) = b_{11} \tag{3.2}$$

$$\sigma(y_{2t}) = \sqrt{b_{21}^2 + b_{22}^2} \tag{3.3}$$

$$q_t(y_{1t}) = k_\theta b_{11} + \mu_t(y_{1t}) \tag{3.4}$$

$$q_t(y_{2t}) = k_\theta \sqrt{b_{21}^2 + b_{22}^2} + \mu_t(y_{2t}) \tag{3.5}$$

where $\sigma(y_{it})$ and $q_t(y_{it})$ are respectively the standard deviation and the quantile of y_{it} conditional on the information set at time $t-1$, k_θ is a scalar and represents the standard normal quantile, b_{ij} are the elements of B and θ is a given confidence level.

Writing equation (3.1) in terms of $q_t(y_t)$:

$$y_t = q_t(y_t) + Z\epsilon_t^\theta \tag{3.6}$$

where $q_t(y_t) = \omega_\theta + Ay_{t-1}$, $\omega^\theta = \omega + k_\theta \sigma(y_t)$, Z is a 2×2 lower triangular coefficient matrix and the 2×1 vector ϵ_t^θ is such that $q_t(Z\epsilon_t^\theta) = q_t(\epsilon_t^\theta) = 0$ and $\sigma(\epsilon_t^\theta) = I$, where I is an identity matrix.

Proposition 1. *Under the following assumptions:*

1. $\epsilon_t \sim (0, I)$;
2. ϵ_t^θ *is such that* $q_t(Z\epsilon_t^\theta) = q_t(\epsilon_t^\theta) = 0$ *and* $\sigma(\epsilon_t^\theta) = I$;
3. B *and* Z *are lower triangular matrices of constant coefficients (homoskedasticity).*

$$B = Z \tag{3.7}$$

Proof.

$$\begin{aligned} B\epsilon_t = Z\epsilon_t^\theta + (q_t(y_t) - \mu_t(y_t)) \\ \sigma^2(B\epsilon_t) = \sigma^2(Z\epsilon_t^\theta) \\ BB' = ZZ' \\ B = Z \end{aligned}$$

□

Equation (3.6) becomes:

$$y_t = q_t(y_t) + B\epsilon_t^\theta \tag{3.8}$$

This modelling framework enables us to calculate the quantile impulse response function (QIRF), which measures the impact of a shock at time t on the quantile dynamics. If the process y_t is stationary, equation (3.1) has a Wold representation and so can be written in the following way:

$$y_t = \frac{\omega}{I - A} + B\epsilon_t + AB\epsilon_{t-1} + A^2 B\epsilon_{t-2} + ... + A^n B\epsilon_{t-n} \tag{3.9}$$

where $A^i B$, with $i = 0, ...n$, defines the classical impulse response function (IRF) and I is a 2×2 identity matrix. Noting that $(y_t - B\epsilon_t) = \mu_t(y_t)$ and combining equation (3.9) with equations (3.2)-(3.5), it is straightforward to get the QIRF:

$$q_t(y_t) = k_\theta \sigma(y_t) + \frac{\omega}{I - A} + AB\epsilon_{t-1} + A^2 B\epsilon_{t-2} + ... + A^n B\epsilon_{t-n} \tag{3.10}$$

The quantile impulse response function can be also directly derived from equation (3.8). In particular:

$$y_t = \frac{\omega_\theta}{I - A} + B\epsilon_t^\theta + AB\epsilon_{t-1}^\theta + A^2 B\epsilon_{t-2}^\theta + ... + A^n B\epsilon_{t-n}^\theta \tag{3.11}$$

$$q_t(y_t) = y_t - B\epsilon_t^\theta = \frac{\omega_\theta}{I - A} + AB\epsilon_{t-1}^\theta + A^2 B\epsilon_{t-2}^\theta + ... + A^n B\epsilon_{t-n}^\theta \tag{3.12}$$

where $\omega^\theta = \omega + k_\theta \sigma(y_t)$.

It is interesting to note that considering p quantile indexes denoted by $(\theta_{i1}, \theta_{i2}, ..., \theta_{ip})$ for a given y_{it}, equations (3.4) and (3.5) become:

$$q_{jt}(y_{it}) = k_{\theta_j} \sigma(y_{it}) + \mu_t(y_{it}) \tag{3.13}$$

for $i = 1, 2$ and $j = 1, 2, ..., p$. Therefore:

$$y_{it} = q_{jt}(y_{it}) + z_i \epsilon_t^{\theta_j} \tag{3.14}$$

where z_i is the $i-th$ row of Z and the 2×1 vector $\epsilon_t^{\theta_j}$ has the same properties as ϵ_t^{θ}.

Since $Z = B$, the following must hold:

$$y_t = \frac{\omega_{\theta_j}}{I - A} + B\epsilon_t^{\theta_j} + AB\epsilon_{t-1}^{\theta_j} + A^2 B\epsilon_{t-2}^{\theta_j} + ... + A^n B\epsilon_{t-n}^{\theta_j} \tag{3.15}$$

$$q_{jt}(y_t) = \frac{\omega_{\theta_j}}{I - A} + AB\epsilon_{t-1}^{\theta_j} + A^2 B\epsilon_{t-2}^{\theta_j} + ... + A^n B\epsilon_{t-n}^{\theta_j} \tag{3.16}$$

where $j = 1, 2, ..., p$, $\omega_{\theta_j} = \omega + k_{\theta_j}\sigma(y_t)$ and $A^i B$ is the the quantile impulse response function for every j (QIRF(j)).

Proposition 2. *Under the following assumptions:*

1. $\epsilon_t \sim (0, I)$;

2. $\epsilon_t^{\theta_j}$ *is such that* $q_{jt}(Z\epsilon_t^{\theta_j}) = q_{jt}(\epsilon_t^{\theta_j}) = 0$ *and* $\sigma(\epsilon_t^{\theta_j}) = I \ \forall j$;

3. B *and* Z *are lower triangular matrices of constant coefficients (homoskedasticity);*

IRF, QIRF and QIRF(j) are identical.

Since a $VAR(p)$ can be always represented as a $VAR(1)$, the obtained results can be extended to a VAR of any order p that satisfies the aforementioned assumptions[1].

Estimation

The different equations that form $q_t(y_t)$ can be estimated independently from each other by Koenker and Bassett (1978) regression quantiles, which belong to the class of quasi-maximum likelihood estimators (see Komunjer (2005)). In this way, the residuals can be derived:

$$\hat{u}_t^\theta = y_t - \hat{q}_t(y_t) \tag{3.17}$$

At this point, it is straightforward to estimate the variance-covariance matrix of the residuals ($\hat{\Sigma}_{\hat{u}_t^\theta}$). Since Z is a lower triangular matrix, it can be obtained from a Choleski decomposition of $\hat{\Sigma}_{\hat{u}_t^\theta}$. In particular, Z is the unique solution of the following system:

$$ZZ' = \hat{\Sigma}_{\hat{u}_t^\theta} \tag{3.18}$$

Defining $\sigma_\theta^* = vech(\Sigma_{u_t^\theta})$ and α_θ as a $l \times 1$ vector containing all the QVAR coefficients to be estimated (with the exception of the structural matrix), it is possible to show that they are asymptotically normal (see Lutkepohl (2005) and White *et al.* (2015)). Recognising that the quantile impulse response function is a function of normally distributed parameters (α_θ and σ_θ^*) and

[1] For a discussion on VAR models, see Lutkepohl and Kratzig (2004) or Lutkepohl (2005).

applying the delta method[2]:

$$T^{1/2}vec(\hat{\Phi}_{i,\theta} - \Phi_{i,\theta}) \to N(0, \Sigma_{\hat{\Phi}_{i,\theta}}) \quad (3.19)$$

where $\hat{\Phi}_{i,\theta} = A^i Z$ is the structural QIRF estimator, $\Sigma_{\hat{\Phi}_{i,\theta}}$ is the variance-covariance matrix of $vec(\hat{\Phi}_{i,\theta})$, $i = 1, ..., h$ is the QIRF prediction horizon and T measures the sample size (Lutkepohl (2005)). For conciseness, a more detailed explanation of equation (3.19) is placed in Appendix A.

3.3 Empirical analysis

In this section the QVAR model and a classical VAR are used to analyse the effect of a monetary policy shock in the euro area. Based on the Schwarz and Hannan-Quinn information criteria, a lag length equal to one has been chosen for both the considered models.

3.3.1 Data

The dataset used in the estimation consists of five euro area monthly variables: the seasonally adjusted Harmonised Index of Consumer Prices (HICP), the seasonally adjusted real gross domestic product (GDP), the Composite Indicator of Systemic Stress (CISS), the Euro Overnight Index Average (EONIA) rate and the total assets of the European Central Bank (ECB) balance sheet. The sample covers the period from the introduction of the euro in January 1999 to

[2]For a discussion on delta method, see Davidson and Mackinnon (2004)

December 2013.

Following Kremer (2015), a monthly measure of GDP is constructed by state space methods, using industrial production as an interpolator variable and assuming that the interpolation error can be described as a log-linear ARIMA(1,1,0) process as in Litterman (1983). Furthermore, year-on-year (yoy) growth rates of HICP, GDP and ECB total assets are taken. The yoy transformation is preferred to limit risks of noise due to improper seasonal adjustment in the data. Finally, the square root of the CISS is considered: in this way, it is possible to control for potential nonlinearities arising from the quadratic form of the formula used to compute the CISS.

This specification should capture the main macroeconomic and financial developments during the sample period. HICP, GDP and EONIA represent core variables typically included in monetary policy VARs: they respectively measure the aggregate price level, aggregate economic activity and the stance of conventional monetary policy. By contrast, ECB total assets and CISS are less common in the literature[3]. The former represents the stance of ECB unconventional monetary policy. The latter is a financial stress index developed by Hollo *et al.* (2012) that captures the systemic dimension of financial instability in the euro area.

[3] These two variables are also considered by Kremer (2015) and Boeckx *et al.* (2014) in their VAR specifications.

3.3.2 Identification

The structural shocks are identified following Kremer (2015). Firstly, I assume that inflation and real GDP growth rate do not respond contemporaneously to the financial variables (namely, CISS, EONIA and ECB total assets growth rate), while the monetary policy variables are allowed to react instantaneously to innovations in inflation, output and the CISS. Second, inflation is ordered before GDP.

Finally, within the monetary policy block I order EONIA before ECB total assets growth rate. This assumption implies that:

- conventional monetary policy is set independently of the factors behind the decisions concerning unconventional monetary policy, at least within a given month;
- central bank assets react instantaneously to EONIA shocks.

Therefore, the final order of the considered variables within both the VAR models is the following: inflation, real GDP growth rate, CISS, EONIA and ECB balance sheet growth rate.

3.3.3 Results

Figure 3.1 displays the average reaction of the HICP and real GDP year-on-year growth rates to a one standard deviation increase in the EONIA, together with 90% confidence intervals obtained via residual bootstrap using 10000 replications[4]. Inflation shows a mild but significant decrease, while there is no significant impact on the output.

Results from the QVAR analysis are displayed in figures 3.2 and 3.3. Three different confidence levels are considered: $\theta = 0.25, 0.50, 0.75$. Two standard error confidence intervals are calculated using the asymptotic distribution of the structural QIRF (see equation A-1).

Figure 3.2 shows the quantile impulse response of the HICP yoy to a one standard deviation contactionary monetary policy shock. For $\theta = 0.25$ QIRF significantly decreases, while there are no significant variations for $\theta = 0.5$ and $\theta = 0.75$. Therefore, the effect of a contractionary monetary policy shock is not uniform across the inflation distribution. Specifically, the QVAR analysis suggests that there is a lengthening of the left tail of the considered distribution which becomes skewed to the left. This means a greater chance of left tail outcomes and an increase in the downside risk of inflation.

As highlighted by Kilian and Manganelli (2007), risks are related to the tails of the distribution. In particular, they propose to measure the risks to price stability by a probability-weighted function of the deviations of inflation from given threshold points. Their risk measure is proportionate to the probability of exceeding the considered thresholds and this explains why a a lengthening of the left tail of the inflation distribution generates an increase in the downside risk. It is also interesting to note that the risk measure proposed by Kilian

[4] These intervals are asymmetric in the sense that the estimated IRF are not in the middle between the lower and upped bound of the intervals. As pointed out by Lutkepohl (2005), this is quite common when the intervals are calculated by simulation techniques (Monte Carlo or bootstrap).

and Manganelli (2007) is consistent with a loss-function approach to risk measurement or, in other words, it is proportionate to the expected loss associated with excessive low or high inflation.

The reaction of the GDP yoy growth rate to a positive one standard deviation monetary policy shock is reported in Figure 3.3. The quantile impulse response does not show significant changes in the distribution of the output. The large confidence intervals unveil substantial estimation uncertainty in the QVAR coefficients related to the GDP yoy growth rate.

Figure 3.4 shows for both the QVAR and the VAR model the distribution of the variation of HICP yoy ($\Delta HICP_{yoy}$) after the monetary policy shock. Assuming that the distribution of HICP yoy is normal, the distribution of $\Delta HICP_{yoy}$ under the VAR methodology is also normal: its mean (standard deviation) is estimated as the average value of the IRF (difference between the IRF and the bound of its confidence interval) in the 24 months after the shock. For the QVAR model, the skewed density function of $\Delta HICP_{yoy}$ is calculated as a mixture of two gaussian distributions. In particular, I assume that one distribution has mean equal to the average value of the QIRF for $\theta = 0.25$ in the 24 months after the shock, while the other distribution has mean equal to zero since there are no significant variations in the quantile impulse response functions for $\theta = 0.50$ or $\theta = 0.75$. Again, the standard deviations are calculated as the average difference between the relevant QIRFs and the bound of their confidence intervals in the 24 months after the shock[5]. The mixing proportion

[5]For the distribution having mean zero, I calculate its standard deviation using the QIRF with lower variance (namely, that relating to $\theta = 0.75$).

(p) of the gaussian mixture distribution components is chosen minimising the following loss function (L) with respect to p:

$$L = (q_{0.25}(p) - \bar{q}_{0.25})^2 + (q_{0.50}(p) - \bar{q}_{0.50})^2 + (q_{0.75}(p) - \bar{q}_{0.75})^2 \qquad (3.20)$$

where $\bar{q}_\theta$ is the average shift of the θth quantile in the 24 months after the shock and $q_\theta(p)$ is the θth quantile of the gaussian mixture distribution, which is a function of the unknown mixing proportion p.

3.3.4 Robustness

The small sample validity of delta method results can be problematic (Lutkepohl and Kratzig (2004)). So, as a robustness check, confidence intervals for the quantile impulse response functions are built also via residual bootstrap using 10000 replications. Kilian (1998) points out that this methodology is accurate only for processes with low persistence and no deterministic time trend. Furthermore, Koenker (2005) argues that the residual bootstrap procedure assumes that quantile regression error terms are i.i.d.

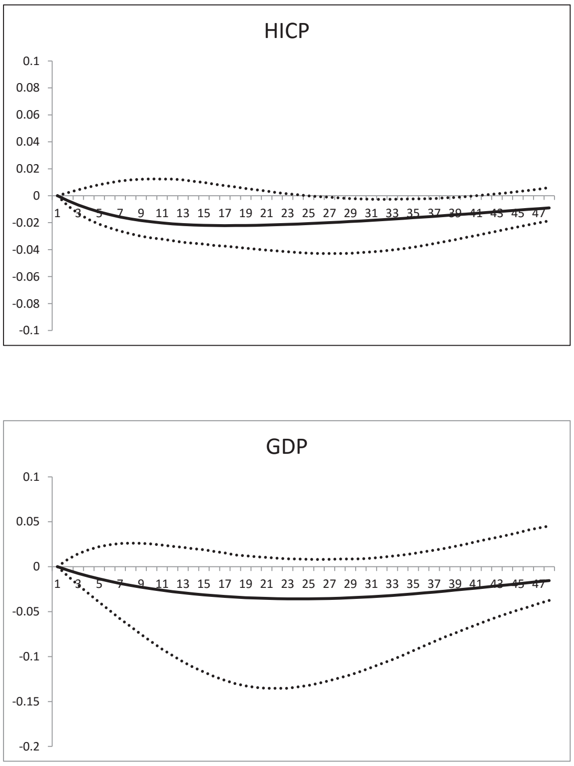
As expected, the residual bootstrap implies a lower degree of uncertainty about the estimates. So, in this case the quantile impulse response function of HICP yoy shows a mild but significant decrease also for $\theta = 0.5$ (figure 3.5). Similarly, the QIRF relating to GDP yoy significantly decreases both for $\theta = 0.25$ and $\theta = 0.5$ (figure 3.6).

3.4 Conclusion

This paper has introduced a method for measuring the impact of a monetary policy shock on the quantile dynamics of a given macroeconomic variable. Despite the asymptotic equivalence between quantile and classical impulse response functions under homoscedastic and normal error terms, they differ in finite samples where these assumptions usually do not hold. Therefore, QIRF provides valuable information about the asymmetric effects of shocks on the conditional distribution of macroeconomic variables and the consequent changes in their downside and upside risk.
Using the QVAR model and a classical VAR to assess the impact of a contractionary monetary policy shock on the euro area economy, I find that a tightening monetary policy not only reduces the expected inflation, but it also increases the probability of left tail outcomes and in this way the downside risk of inflation. The empirical analysis also suggests that the considered shock does not have a significant impact on the expected output yoy growth rate, while it generates a lengthening of the left tail of the considered distribution.
The different equations that form the QVAR are estimated independently from each other by regression quantiles, as introduced by Koenker and Bassett (1978). Nevertheless, when the data is weakly dependent this estimator is consistent but not semiparametric efficient. In order to improve the robustness of the considered results, future work should apply the robust estimator proposed by Komunjer and Vuong (2010a) to the QVAR model. This estimator is obtained by performing the standard Koenker and Bassett (1978)

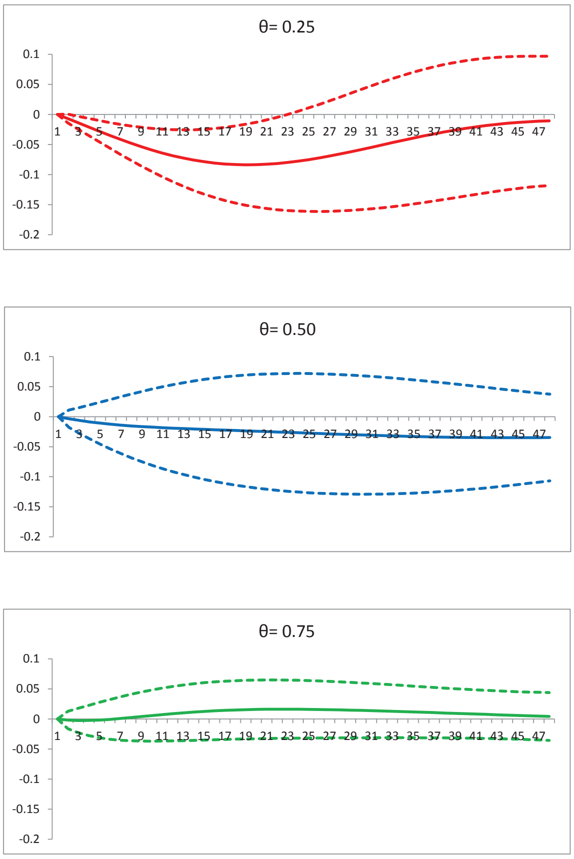
quantile regression on the conditional distribution of y_t (rather than on y_t) and then taking the inverse transformation of the obtained quantile. Another possibility is to consider a longer sample, for example using US data.

Figure 3.1: Impulse response of HICP yoy and GDP yoy to a positive one standard deviation monetary policy shock



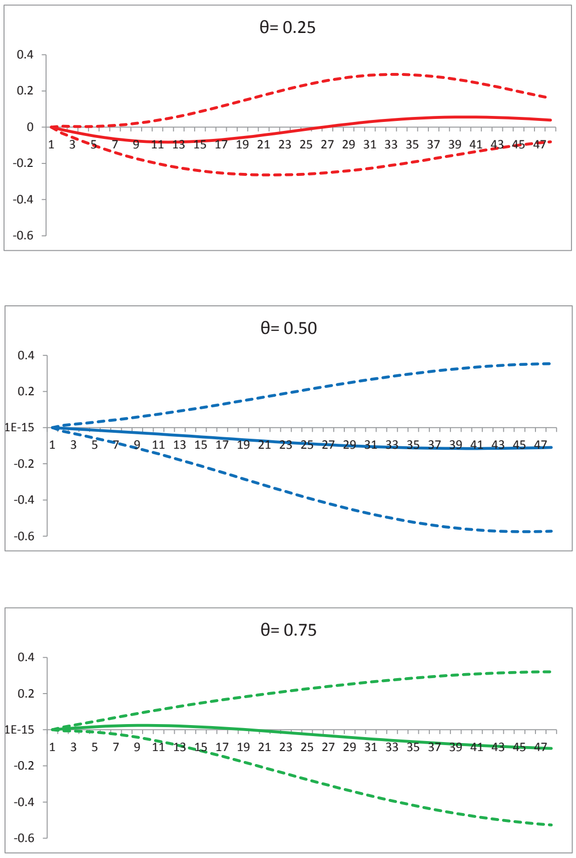
Note: Figures show the OLS impulse response function of HICP and GDP, together with their confidence intervals (dotted lines). Responses are expressed in year-on-year growth rates.

Figure 3.2: Quantile impulse response of HICP yoy to a positive one standard deviation monetary policy shock, with confidence intervals obtained via delta method



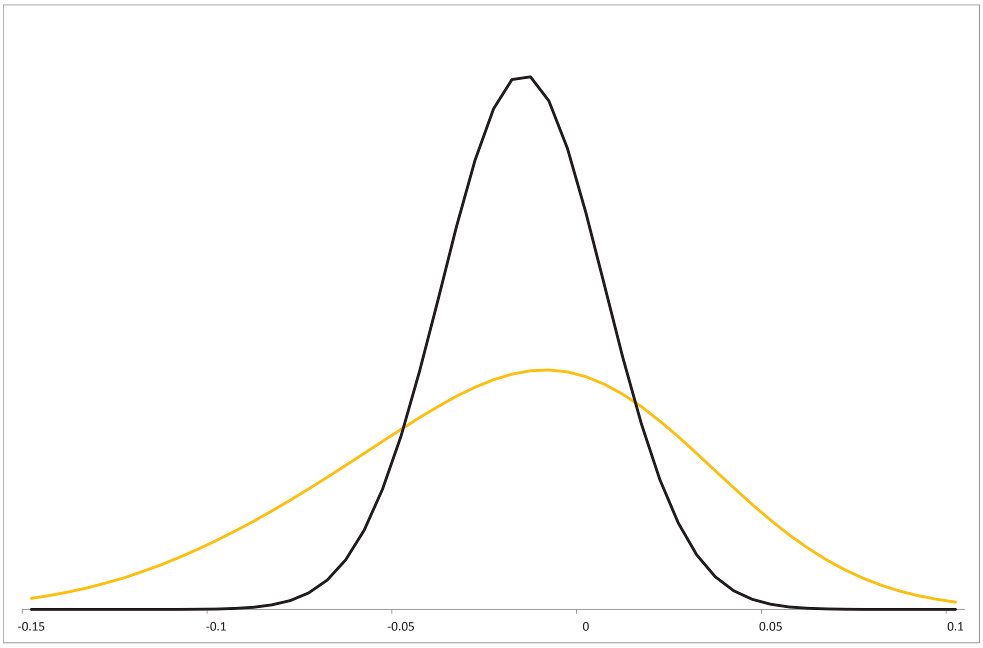
Note: Figures show the quantile impulse response functions for confidence levels equal to 0.25 (red line), 0.50 (blue line) and 0.75 (green line), together with their confidence intervals (dashed lines). Responses are expressed in year-on-year growth rates.

Figure 3.3: Quantile impulse response of GDP yoy to a positive one standard deviation monetary policy shock, with confidence intervals obtained via delta method



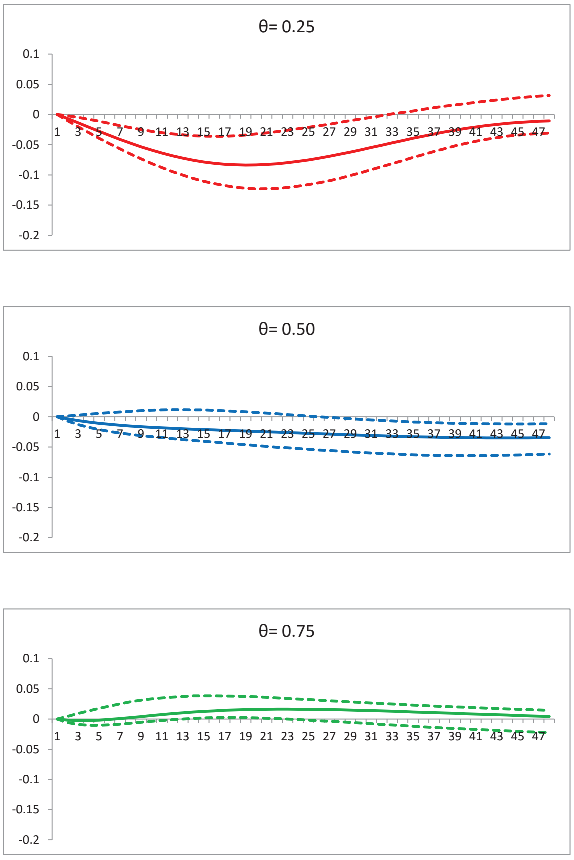
Note: Figures show the quantile impulse response functions for confidence levels equal to 0.25 (red line), 0.50 (blue line) and 0.75 (green line), together with their confidence intervals (dashed lines). Responses are expressed in year-on-year growth rates.

Figure 3.4: Density function of $\Delta HICP_{yoy}$ after a positive one standard deviation monetary policy shock



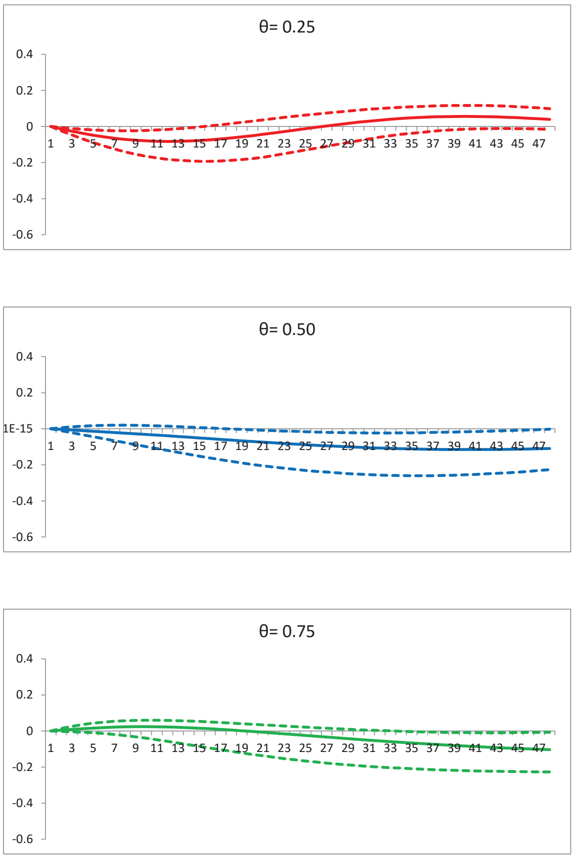
Note: This figure shows the density functions of $\Delta HICP_{yoy}$ calculated using the QVAR model (orange line) and the OLS VAR methodology (black line).

Figure 3.5: Quantile impulse response of HICP yoy to a positive one standard deviation monetary policy shock, with confidence intervals obtained via bootstrap



Note: Figures show the quantile impulse response functions for confidence levels equal to 0.25 (red line), 0.50 (blue line) and 0.75 (green line), together with their confidence intervals (dashed lines). Responses are expressed in year-on-year growth rates.

Figure 3.6: Quantile impulse response of GDP yoy to a positive one standard deviation monetary policy shock, with confidence intervals obtained via bootstrap



Note: Figures show the quantile impulse response functions for confidence levels equal to 0.25 (red line), 0.50 (blue line) and 0.75 (green line), together with their confidence intervals (dashed lines). Responses are expressed in year-on-year growth rates.

Appendix

Asymptotic distribution of quantile impulse response functions

The asymptotic distribution of the structural QIRF ($\hat{\Phi}_{i,\theta}$) is:

$$T^{1/2}vec(\hat{\Phi}_{i,\theta} - \Phi_{i,\theta}) \rightarrow N(0, C_{i,\theta}\Sigma_{\hat{\alpha}_\theta}C'_{i,\theta} + \bar{C}_{i,\theta}\Sigma_{\hat{\sigma}^*_\theta}\bar{C}'_{i,\theta}) \tag{A-1}$$

where $\Sigma_{\hat{\alpha}_\theta}$ and $\Sigma_{\hat{\sigma}^*_\theta}$ are the variance-covariance matrices of $\hat{\alpha}_\theta$ and $\hat{\sigma}^*_\theta$, $C_{1,\theta} = 0$, $C_{i,\theta} = (Z' \otimes I_n)G_{i,\theta}$ for $i = 2, ..., h$, $G_{i,\theta} = \partial vec(\Psi_{i,\theta})/\partial\alpha'_\theta$, $\Psi_{i,\theta}$ is the non-structural QIRF, n is the number of variables in the QVAR, I_n is an identity matrix $n \times n$, $\bar{C}_{i,\theta} = (I_n \otimes \Psi_{i,\theta})H$ for $i = 1, ..., h$, $H = \partial vec(Z)/\partial{\sigma^*_\theta}'$. Although the general structure of equation (A-1) is identical to the one of a classical VAR (see for example Lutkepohl (2005)), its elements are calculated in a different way.

Defining $f_{j,t}$ as the conditional density of $u^{\theta}_{j,t}$, $\nabla q_{j,t}(\alpha_\theta)$ as the $l \times 1$ gradient vector of $q_{j,t}(\alpha_\theta)$ differentiated with respect to α_θ and $1(\cdot)$ as an indicator function, White *et al.* (2015) show that the following must hold:

$$\Sigma_{\hat{\alpha}_\theta} = Q^{-1} V Q^{-1} \tag{A-2}$$

with:

$$Q = \sum_{j=1}^{n} E[f_{j,t}(0) \nabla q_{j,t}(\alpha_\theta) \nabla' q_{j,t}(\alpha_\theta)]$$
$$V = E(\eta_t \eta_t')$$
$$\eta_t = \sum_{j=1}^{n} \nabla q_{j,t}(\alpha_\theta) \psi_\theta(u^{\theta}_{j,t})$$
$$\psi_\theta(u^{\theta}_{j,t}) = \theta - 1(u^{\theta}_{j,t} \leq 0)$$

Following White *et al.* (2015), $f_{j,t}(0)$ is estimated in the following way:

$$\hat{f}_{j,t}(0) = 1(-\hat{c}_T \leq \hat{u}^{\theta}_{j,t} \leq \hat{c}_T)/2\hat{c}_T$$
$$\hat{c}_T = \hat{k}_T[\Xi^{-1}(\theta + \upsilon_T) - \Xi^{-1}(\theta - \upsilon_T)]$$
$$\upsilon_T = T^{-1/3}(\Xi^{-1}(1 - 0.05/2))^{2/3} \left(\frac{1.5(\xi(\Xi^{-1}(\theta)))^2}{2(\Xi^{-1}(\theta))^2 + 1} \right)^{1/3}$$

where $\hat{k}_T$ is the median absolute deviation of the θth quantile regression residuals and $\Xi(z)$ and $\xi(z)$ are respectively the cumulative distribution and the probability density functions of a standard normal variable.

Finally:

$$\Sigma_{\hat{\sigma}^*_\theta} = 2D_n^+(\Sigma_{u_t^\theta} \otimes \Sigma_{u_t^\theta})D_n^+ \tag{A-3}$$

where $D_n^+ = (D_n' D_n)^{-1} D_n'$ is the Moore-Penrose inverse of the duplication matrix D_n.

Chapter 4

Carry Trades and Monetary Conditions

4.1 Introduction

One of the cornerstones of international finance is uncovered interest parity (UIP), which predicts that exchange rate changes will eliminate any profit arising from the differential in interest rates across countries. Nevertheless, many studies provide empirical evidence against UIP[1]: in particular, they show that high interest rate currencies tend to appreciate rather than depreciate against low interest rate currencies (forward premium puzzle). As a consequence, one of the most popular currency speculation strategy is carry trade, which con-

[1]See Engel (1996) for a review of the empirical literature on UIP.

sists of borrowing low-interest rate currencies and investing in currencies with high interest rates (Burnside (2012)).

The most persuasive explanation for the forward premium puzzle is the intertemporal variation in currency risk premia. Nevertheless, empirical research finds it difficult to identify which risk factors drive the considered premia. As showed by Burnside *et al.* (2011), conventional factor models, i.e. those traditionally used to explain stock returns like the Capital Asset Pricing Model (CAPM), the Fama and French three factor model, the quadratic CAPM, the CAPM-volatility model and the Consumption CAPM, cannot explain currency risk premia. By contrast, less traditional factor models, which adopt empirical risk factors specifically designed to price the cross section of currency returns, are quite successful. A particularly interesting study in this field is performed by Menkhoff *et al.* (2012): guided by earlier evidence for stock markets, they show that global FX volatility innovations can explain time-varying currency risk premia and that FX volatility and liquidity innovations are related.

I contribute to this literature by empirically analyzing whether the temporal variation in currency risk premia is systematically linked to changes in monetary conditions and investigating whether currency risk premia predictability provides information that is economically valuable. Consistent with recent literature (e.g. Lustig *et al.* (2011), Menkhoff *et al.* (2012), Ahmed and Valente (2015)), currencies are allocated to six portfolios according to their forward discount at the end of each period: the zero cost strategy that goes long in portfolio 6 and short in portfolio 1 results in a carry trade portfolio. Then, following the methodology used by Jensen and Moorman (2010) to analyze the relation between the price of security liquidity and monetary policy, carry trade portfolio returns in each period t are measured based on monetary conditions in period $t-1$. Finally, carry trade portfolio average return, Sharpe ratio and 5% quantile are computed across different monetary conditions.

My main result is that carry trade portfolio average return, Sharpe ratio and 5% quantile differ substantially across expansive and restrictive conventional monetary policy before the onset of the recent financial crisis. Specifically, I find that expansive periods are characterised by significantly higher average returns and Sharpe ratios and lower downside risk. Second, I present evidence suggesting that the considered parameters are similar across aggressive and stabilising unconventional monetary policy during the recent financial crisis.

The remaining of this work proceeds as follows. Next section discusses related research and provide details on the paper's contribution and motivation. Section 4.3 presents the data and describes monetary policy indicators used in the analysis. Section 4.4 explains the methodology used to perform the empirical analysis. Section 4.5 provides a discussion of the empirical findings. Section 4.6 concludes the paper.

4.2 Related research

In the academic literature several papers analyze the risk-return profile of carry trade in order to try to explain its apparent profitability. One of the most important studies in this field is the paper by Menkhoff *et al.* (2012).

Menkhoff *et al.* (2012) perform an empirical analysis at the monthly frequency in order to show that unexpected changes (innovations) in global FX volatility are a significant risk factor in explaining the cross-section of carry trade returns. They use spot exchange rates and 1-month forward exchange rates per US dollar of 48 countries during the period November 1983 - August 2009.

First of all, they sort currencies into five portfolios based on their forward discount. Assuming that covered interest rate parity holds at monthly frequency, the forward discount is equal to the interest rate differential between two given countries. So, portfolio 1 contains currencies with the lowest interest rates or smallest forward discounts, while portfolio 5 contains currencies with the highest interest rates or largest forward discounts. The zero cost strategy that goes long in portfolio 5 and short in portfolio 1 results in the carry trade portfolio. Then, they proxy for global FX volatility in month t using the following equation:

$$\sigma_t^{FX} = \frac{1}{T_t} \sum_{\tau \in T_t} \left[\sum_{k \in K_\tau} \frac{|r_\tau^k|}{K_\tau} \right] \tag{4.1}$$

where $|r_\tau^k| = |\Delta s_\tau|$ is the absolute log return for currency k on day τ, K_τ is the number of available currencies on day τ and T_t is the number of trading days in month t. Innovations in global FX volatility ($\Delta\sigma_t^{FX}$) are computed using the residuals from an estimated AR(1) model for σ_t^{FX}.

Finally, they test whether global FX volatility innovations can explain the cross-section of currency portfolio returns using discrete net excess returns[2]. To do this, they employ a standard stochastic discount factor approach. In

[2]Discrete returns for currency k are computed as $RX_{t+1} = \frac{F_t^k - S_{t+1}^k}{S_t^k}$, where F and S are respectively the 1-month forward and spot exchange rates. Returns for portfolio j are computed as the equally weighted average of excess returns for the constituent currencies.

particular, since in absence of arbitrage opportunities excess returns have a zero price, they assume that:

$$E[m_{t+1}RX^j_{t+1}] = 0 \tag{4.2}$$
$$m_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{VOL}\Delta\sigma^{FX}_{t+1}$$

where RX^j_{t+1} is the net excess return of portfolio j, m_{t+1} is the linear stochastic discount factor (SDF), DOL_{t+1} is the average excess return of the five portfolios, $\mu_{DOL} = E(DOL_{t+1})$, b_{DOL} and b_{VOL} are the factor loadings or SDF parameters.

As pointed out by Menkhoff *et al.* (2012), this linear factor model implies:

$$E(RX^j) = \lambda'\beta_j \tag{4.3}$$

where $\lambda = (\lambda_{DOL}, \lambda_{VOL})' = \Sigma b$ is a 2×1 vector of factor prices, Σ is the 2×2 covariance matrix of risk factors, $b = (b_{DOL}, b_{VOL})'$ and β_j is a 2×1 vector containing the regression betas of portfolio j excess returns on the risk factors. Estimating parameters of equations (4.2) and (4.3) by the generalized method of moments (GMM) of Hansen (1982) and the Fama and MacBeth (1973) two-pass methodology, Menkhoff *et al.* (2012) find a significantly negative estimate for λ_{VOL} as finance theory suggests, being unexpectedly high volatility a bad state of the world for investors. Moreover, they find that estimates of β_{VOL} monotonically decrease when moving from portfolio 1 to portfolio 5: in particular, they are positive (negative) for portfolios characterized by low (high) forward discount. Therefore, high interest rate currencies perform poorly compared to low interest currency when the FX market is characterized by high volatility innovations. So, they conclude that currency risk premia can be explained by using global FX volatility innovations as a risk factor. They also point out that *DOL* does not explain the cross-section of the considered returns but it is important for the level of average returns.

Using the same methodology and introducing proxies for FX liquidity innovations , Menkhoff *et al.* (2012) show also that liquidity risk is useful to explain carry trade returns but volatility risk is the dominant risk factor. However, they point out that volatility could be simply a summary measure of various dimensions of liquidity.

In light of these results, Ahmed and Valente (2015) adopt a similar asset pricing approach to investigate the pricing power of the short and long run components of global FX volatility innovations for carry trade returns. They find that only the long-run component of global FX volatility risk is a significant risk factor in the cross-section of carry trade returns.

Lustig *et al.* (2011) were the first to propose an arbitrage pricing theory approach (Ross (1976)) to explain carry trade returns. After having built six currency portfolios according to their forward discount at the end of each month, they perform a principal component analysis on the considered portfolios and find that the first two principal components explain about 80% of the currency portfolio returns. Then, they show that the average excess return of the six portfolios (i.e. the Dollar risk factor) and the return difference between portfolio 6 and portfolio 1 (i.e. the carry trade risk factor) are strongly correlated respectively with the first and the second principal component. Using the same asset pricing approach already mentioned for Menkhoff *et al.* (2012), they find that the carry trade risk factor explains the cross-section of carry trade returns and the Dollar risk factor is important only for the level of average returns. Finally, they show that the carry tade risk factor is closely related to innovations in global equity volatility, although the former is the dominant factor.

Summing up, recent studies analyzing the risk-return profile of carry trade returns show that FX and global equity volatilities and FX liquidity play an important role in understanding the cross-section of carry trade returns. My work, analyzing whether currency risk premia are conditional on prevailing monetary policy, tries to propose instrumental variables that can explain the temporal variation in the price of volatility and liquidity and investigates whether currency risk premia predictability provides information that is economically valuable.

Jensen and Moorman (2010) show that monetary policy is crucial to understand the relation between expected security returns and illiquidity, which contains a significant time-varying component. In their empirical analysis, they use monthly returns of all stocks in the Center for Research in Security Prices database during the period September 1954 - December 2006 and three alternative liquidity measures. Furthermore, they identify shifts in Federal Reserve monetary policy looking at changes in the federal funds rate and in the Fed discount rate. The former is used as an indicator of the stringency of Federal Reserve monetary policy, while the latter is used as an indicator of

Fed's monetary policy stance.

They sort stocks into five portfolios according to their illiquidity and show that monthly average returns of the considered portfolios are increasing in stock illiquidity, namely, when moving from portfolio 5 to portfolio 1. They compute also returns for the zero-cost portfolio, which is long the quintile of most illiquid stocks and short the quintile of the most liquid stocks. These returns are statistically different from zero.

Then, they show that there is a statistically significant relation between monetary conditions and next period's aggregate liquidity innovations. In particular, they find that after expansive (restrictive) monetary policy shifts, liquidity increases (decreases). Furthermore, by refining the analysis, they find that portfolio 1 level of illiquidity is very sensitive to monetary policy shifts: following expansive (restrictive) monetary policy shifts, liquidity improves (deteriorates) significantly. By contrast, the most liquid portfolio experiences almost no change.

Guided by these findings, they investigate whether the inter-temporal variation in the price of liquidity is systematically linked to changes in monetary policy. To this end, they compute zero-cost portfolio monthly returns across different monetary conditions: they find that when both monetary policy indicators are expansive, zero-cost portfolio returns are statistically significant and more than twice than the unconditional return; otherwise, zero-cost portfolio returns are statistically insignificant. Furthermore, when considering separately the two policy indicators, they prove that the considered returns differ between expansive and restrictive monetary conditions.

Finally, they analyze zero-cost portfolio mean returns during 100 days after and before a shift in monetary policy stance and find that these values change much more around shifts to an expansive policy than around restrictive policy shifts. In particular, the considered returns are substantially below (above) average before (after) an expansive policy shift, while they are slightly above (below) average before (after) a restrictive policy shift. They point out that this can be explained noting that in order to avoid a liquidity crisis, the Federal Reserve will implement a restrictive monetary policy only when liquidity is abundant and so investors are not concerned about it; by contrast, when liquidity concerns are high, the Fed will implement an expansive monetary policy.

Using daily data for nine currency pairs over the period January 2007 - December 2009, Mancini *et al.* (2013) provide empirical evidence that when uncertainty in the economy (proxied by the Chicago Board Options Exchange Volatility Index - VIX) increases and traders' funding liquidity (proxied by the TED spread[3]) decreases, FX liquidity drops. This is consistent with a theory of liquidity spirals (see Brunnermeier and Pedersen (2009)). Considering different measures of liquidity, Mancini *et al.* (2013) show also strong comovements among FX, US equity and bond market liquidities. Taken together, these findings support the assumption of a relation between Fed monetary policy and FX liquidity.

Finally, my work is related to recent studies analyzing the role of interest rate

[3]The TED spread is the difference between one-month LIBOR interbank market interest rate and the risk-free T-Bill rate.

rules for monetary policy in exchange rate determination: for example, Engel and West (2006) and Mark (2009) show that exchange rate models based on Taylor rule perform quite well empirically. Modern monetary macroeconomic models assume the endogeneity of monetary policy and take the interest rate as the instrument of policy. By contrast, classic monetary exchange rate models assume less realistically that monetary policy is exogenous and take the money supply as an indicator of policy. So, in this kind of models the amount of money supply does not depend on economic fundamentals and nominal interest rates move to clear money market (Engel *et al.* (2008)).

4.3 Data and variables

Data

The dataset consists of daily spot and one month forward exchange rates per US dollar covering the period from November 1983 to December 2013. These data are available on Datastream. Following the relevant literature since Fama (1984), logarithms of spot and forward rates will be considered: they will be denoted as s and f respectively.
The sample contains the following countries: Australia, Austria, Belgium, Canada, Hong Kong, Czech Republic, Denmark, euro area, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Swe-

den, Switzerland, Taiwan, Thailand and the United Kingdom. The euro series starts in January 1999. Euro area countries are excluded after this date.

Following Lustig *et al.* (2011), the following observations are not taken into account due to large failures of covered interest parity: South Africa from the end of July 1985 to the end of August 1985, Malaysia from the end of August 1998 to the end of June 2005, Indonesia from the end of December 2000 to the end of May 2007 and Turkey from the end of October 2000 to the end of November 2001.

Monetary policy measures

To proxy for changes in monetary conditions, Federal Reserve (Fed) monetary policy is considered. In particular, shifts in its policy are identified by changes in the federal funds rate and the Fed total assets: the former captures conventional monetary policy, while the latter is an indicator of Fed unconventional monetary policy.

The dummy variable *Conventional* is used to identify changes in conventional monetary policy over the period November 1983 to December 2007 (namely, prior to the onset of the recent financial crisis). When the federal funds rate decreases from month $t-1$ to month t, *Conventional* is labelled "expansive" for month t, while if the previous change in the federal funds rate was an increase, *Conventional* is considered "restrictive". When there are no changes in the federal funds rate, *Conventional* does not change its prior label.

The dummy variable *Unconventional* is considered for the period January 2008 to December 2013. It is labelled "aggressive" for a given month t whenever the Fed total assets increase from month $t-1$ to month t by more than 10000 millions of dollars. By contrast, it is "stabilising" for a given month t if the previous change in the Fed total assets was smaller than 10000 millions of dollars. This threshold is chosen in order to have a balanced number of "aggressive" and "stabilising" unconventional monetary policy periods[4].

4.4 Methodology

In order to investigate whether the temporal variation in currency risk premia is systematically linked to changes in monetary conditions, currency portfolios are considered[5]. In particular, currencies are allocated to six portfolios according to their forward discounts $f_t - s_t$ observed at the end of each month t. If the covered interest parity holds empirically at the frequency analyzed, then the forward discount is equal to the interest rate differential versus US interest rate: therefore, sorting on forward discount is equivalent to sorting on interest rate differentials. Concerning this, Akram *et al.* (2008) show that covered interest parity holds at daily and lower frequency.

Currencies are ranked from low to high interest rates (or forward discounts): therefore, currencies with the lowest interest rates or smallest forward discounts are contained in portfolio 1, while currencies with the highest interest rates or largest forward discounts are contained in portfolio 6. The zero cost

[4]Results do not change by choosing a threshold equal to 15978 millions of dollars, which is the exact median.

[5]I am considering currency portfolio data available at the following website: https://sites.google.com/site/lustighanno/data. These portfolios are built following Lustig *et al.* (2011).

strategy that goes long in portfolio 6 and short in portfolio 1 (the high-minus-low strategy H/L) is labelled carry trade portfolio.

Monthly excess returns for buying a foreign currency k in the forward exchange market and selling it in the spot market after one month are:

$$rx_{t+1}^{k} \approx f_t^k - s_{t+1}^k \tag{4.4}$$

where s_{t+1}^k and f_t^k are respectively the logarithm of daily spot and one month forward exchange rates at the end of month $t+1$ and t. Gross returns for portfolio j are computed as the equally weighted average of excess returns for the constituent currencies. Net excess returns are derived using the bid-ask quotes for spot and forward contracts and assuming that investors go short in portfolio 1 and long in all the other foreign currencies.

Carry trade portfolio returns are measured for every month t based on monetary conditions in month $t-1$. In this way, carry trade portfolio average return, Sharpe ratio and quantiles can be computed across different monetary conditions.

To formally test the relation between carry trade portfolio average return and monetary policy shifts, the classical regression model is used:

$$rx_t^{H/L} = \omega + x_{t-1}\beta + \epsilon_t \tag{4.5}$$

where x_{t-1} is a $1{\times}2$ vector containing rx_{t-1} and a dummy variable ($Conventional_{t-1}$ or $Unconventional_{t-1}$) that measures monetary conditions, β is a 2×1 coefficient vector, ω is the intercept and ϵ_t is an error term such that its conditional mean $E(\epsilon_t/x_{t-1}) = 0$. $Conventional_{t-1}$ ($Unconventional_{t-1}$) is equal to one in month $t-1$ when monetary policy is expansive (aggressive) and it is zero when monetary policy is restrictive (stabilising).

Carry trade portfolio quantiles across expansive and restrictive monetary periods are formally compared using the Koenker and Bassett (1978) quantile regression framework:

$$rx_t^{H/L} = \omega_\theta + x_{t-1}\beta_\theta + \epsilon_{t,\theta} \tag{4.6}$$

where θ is a given confidence level, β_θ is a 2×1 coefficient vector, ω_θ is the intercept and $\epsilon_{t,\theta}$ is an error term such that its θth conditional quantile $q_t(\epsilon_{t,\theta}/x_{t-1}) = 0$.

The relation between carry trade portfolio Sharpe ratio and monetary policy shifts is tested using the symmetric studentized bootstrap confidence interval proposed by Ledoit and Wolf (2008). In their paper Ledoit and Wolf (2008) assume that data are strictly stationary time series and define the difference between Sharpe ratios of two investment strategies x and y as:

$$\begin{aligned} \Delta &= Sh_x - Sh_y \\ &= \frac{\mu_x}{\sigma_x} - \frac{\mu_y}{\sigma_y} \end{aligned} \tag{4.7}$$

where μ_x and σ_x are respectively the mean and the standard deviation of investment strategy x excess returns (over a given benchmark) and μ_y and

σ_y are the mean and the standard deviation of investment strategy y excess returns. They propose to test the null hypothesis $H_0 : \Delta = 0$ by constructing a two-sided bootstrap confidence interval for Δ: if zero is not contained in this interval, then the null hypothesis is rejected at the chosen significance level.
They proxy for the distribution function of the studentized statistic using the bootstrap in the following way:

$$\psi\left(\frac{|\hat{\Delta}-\Delta|}{s(\hat{\Delta})}\right) \approx \psi\left(\frac{|\hat{\Delta}^*-\hat{\Delta}|}{s(\hat{\Delta}^*)}\right) \tag{4.8}$$

where Δ is the true difference between the Sharpe ratios, $\hat{\Delta}$ is the estimated difference computed from the original sample, $s(\hat{\Delta})$ is the standard error for $\hat{\Delta}$, $\hat{\Delta}^*$ is the estimated difference computed from bootstrap data, $s(\hat{\Delta}^*)$ is the standard error for $\hat{\Delta}^*$ and $\psi()$ is the distribution function. So, the bootstrap $1-\alpha$ confidence interval for Δ is:

$$CI = \hat{\Delta} \pm z^*_{1-\alpha} s(\hat{\Delta}) \tag{4.9}$$

where $z^*_{1-\alpha}$ is the $1-\alpha$ quantile of $\psi\left(\frac{|\hat{\Delta}^*-\hat{\Delta}|}{s(\hat{\Delta}^*)}\right)$.
Bootstrap data are generated by resampling block of pairs from the observed pairs with replacement and each block has a fixed size $b \geq 1$. Ledoit and Wolf (2008) propose a calibration method in order to choose b.
The choice of using this inference method is due to the fact that other Sharpe ratio tests assume that data are normally distributed and do not exhibit persistence. Since it is well known that financial returns are not normally distributed

and are characterized by volatility clustering, these other tests are not valid. By contrast, the inference method proposed by Ledoit and Wolf (2008) assumes only that excess returns are strictly stationary time series.

4.5 Results

4.5.1 Currency portfolio returns

For comparison with prior research (e.g. Lustig *et al.* (2011), Menkhoff *et al.* (2012), Ahmed and Valente (2015)), descriptive statistics for the five currency portfolios and the carry trade portfolio are presented in tables 4.1 and 4.2 without regard to monetary conditions. Table 4.1 considers the sample period November 1983 to December 2007, while table 4.1 contains results for the period January 2008 to December 2013 (namely, after the outbreak of the recent financial crisis). Panel A provides results for gross excess returns in US dollars, while panel B reports results for excess returns net of transaction costs.

In table 4.1 unadjusted and adjusted annualized average returns and Sharpe ratios increase (although not monotonically) when moving from portfolio 1 to portfolio 6 and the H/L portfolio. When transaction costs are considered, the average return on the carry trade portfolio decreases from 967 basis points to 562 basis points, while the Sharpe ratio decreases from 1.08 to 0.63. No clear pattern emerges for the standard deviation and the 5% quantile[6].

Concerning skewness and kurtosis, I consider both standard measures based on averages and measures based on quantiles. Kim and White (2004) and White *et al.* (2010) point out that averages are sensitive to outliers and so moments of order three and four are influenced by any outlier that may be present. In their paper, Kim and White (2004) propose the use of the following robust measures of skewness ($SK(q)$) and kurtosis ($KR(q)$) based on sample quantiles:

$$SK(q) = \frac{q_{0.75} + q_{0.25} - 2q_{0.50}}{q_{0.75} - q_{0.25}} \tag{4.10}$$

$$KR(q) = \frac{q_{0.975} - q_{0.025}}{q_{0.75} - q_{0.25}} - 2.91 \tag{4.11}$$

where $q_{0.025}$, $q_{0.25}$, $q_{0.50}$ $q_{0.75}$ and $q_{0.975}$ are the unconditional quantiles for $\theta = 0.025, 0.25, 0.50, 0.75, 0.975$.

When the standard measure of skewness (SK) is considered, SK shows a decreasing pattern when moving from portfolio 1 to portfolio 6 and the H/L portfolio. This is true for both gross and net excess returns (table 4.1). Nevertheless, these results do not hold when a quantile-based measure of skewness is used. In this case there is no clear pattern for skewness. It is also interesting to point out that carry trade portfolio excess returns are skewed to the left according to SK, while they are slightly skewed to the right according to $SK(q)$. No clear pattern emerges for kurtosis, independently of which measure is used.

[6] For portfolio 1, 95% quantile is considered because the investor is short in these currencies.

In table 4.2, which considers the period after the onset of the recent financial crisis, it is interesting to note that portfolio 1 is characterised by positive net average excess returns[7], while the payoff to the carry trade portfolio is negative. Furthermore, portfolio 1 has a lower 95% quantile during the recent financial crisis than during the period November 1983 to December 2007, while H/L portfolio has a lower 5% quantile during the crisis. These results are consistent with the findings by Menkhoff *et al.* (2012): namely, high interest currencies offer exposure to FX volatility and liquidity risk, while low interest rate currencies provide insurance against them.

From table 4.2 it also emerges that the H/L portfolio is skewed to the left according to both standard and quantile-based measures. However, surprisingly SK is greater during the crisis than during the period November 1983 to December 2007. The opposite is true for $SK(q)$. So, the quantile-based measure of skewness seems to perform better empirically.

4.5.2 Monetary conditions and carry trade portfolio returns

Table 4.3 reports annualized means, Sharpe ratios and 5% quantiles for excess returns of the carry trade portfolio across expansive and restrictive monetary periods, as measured by shifts in the Fed conventional monetary policy. Panel A provides results for gross excess returns, while panel B reports results for excess returns net of transaction costs. Figures are reported in percentage

[7] In this case, the investor should go long in portfolio 1 in order to make profits.

points and refer to the sample period November 1983 to December 2007.
Average excess returns seem to be related to conventional monetary policy: specifically, gross and net returns are equal respectively to 13.07% and 9.07% after expansive monetary periods, while they are equal to 6.73% and 2.63% after a restrictive policy. This is confirmed by a p-value equal to 0.04 for the coefficient of the dummy variable $Coventional_{t-1}$ in equation (4.5), estimated for excess returns without and with transaction costs adjustments. Newey and West (1987) standard error is considered to perform the relevant tests.
From both panels in table 4.3 it also emerges that the Sharpe ratio for the H/L portfolio differs substantially across expansive and restrictive conventional monetary policy. This is formally tested using the symmetric studentized bootstrap confidence interval proposed by Ledoit and Wolf (2008). When considering gross excess returns, the p-value of the test is about 0.02 and so the null $H_0 : \Delta = 0$ is rejected at 5% significance level. When considering net excess returns, the null is also rejected since the p-value of the test is about 0.04.
Table 4.3 shows also that the 5% quantile for gross and net excess returns of the H/L strategy seems to be linked to conventional monetary policy. In order to find statistical support for this hypothesis, equation (4.6) is estimated and the coefficient covariance matrix is calculated via XY-pair bootstrap. When considering excess returns without transaction costs adjustments, the coefficient relating to $Conventional_{t-1}$ is significant at 10% confidence level. However, removing rx_{t-1} from the independent variables, the same coefficient becomes significant at 5% significance level. The same happens for net excess returns.
Table 4.4 reports annualized means, Sharpe ratios and 5% quantiles for excess

returns of the carry trade portfolio across expansive and restrictive unconventional monetary policy. Panel A provides results for gross excess returns, while panel B reports results for excess returns net of transaction costs. Figures are reported in percentage points and refer to the sample period January 2008 to December 2013.

Surprisingly, from table 4.4 it emerges that means and Sharpe ratios for excess returns without and with transaction costs adjustments are higher after a less expansive unconventional monetary policy. However, testing these hypotheses using equation (4.5) and the symmetric studentized bootstrap confidence interval by Ledoit and Wolf (2008), I find that carry trade average returns and Sharpe ratios are not statistically different across monetary conditions during the recent financial crisis.

Table 4.4 shows also that carry trade portfolio 5% quantile could be related to unconventional monetary policy. Employing the quantile regression framework to formally test this hypothesis, it emerges that 5% quantile of the H/L strategy is not systematically linked to monetary conditions during the sample period January 2008 to December 2013.

4.5.3 Terminal wealth in different monetary conditions

To provide further information about the relation between carry trade average excess returns and monetary conditions, figures 4.1 and 4.2 show the monthly growth of one dollar invested in the the carry trade portfolio under different policies. The former considers conventional monetary policy and the sample period November 1983 to December 2007, while the latter considers unconventional monetary policy and refers to the recent financial crisis.

Figure 4.1 illustrates the striking difference in the growth of gross and net H/L portfolio value in expansive monetary conditions (black line) versus restrictive monetary conditions (red line). In particular, the black dotted line shows that compounded net excess returns for the carry trade portfolio grow substantially during expansive periods, while the red dotted line indicates nearly zero growth during restrictive periods.

Figure 4.2 shows how compounded gross and net excess returns of the H/L portfolio are similar across monetary conditions during the recent financial crisis. Furthermore, it confirms the poor performance of the carry trade strategy during the considered period.

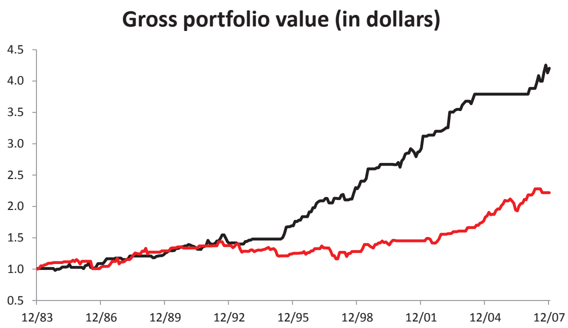
4.6 Conclusion

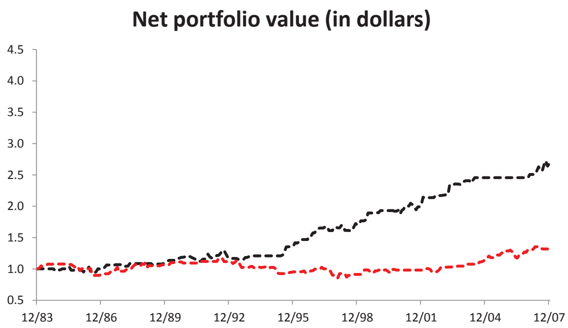
The empirical failure of uncovered interest parity is one of the enduring puzzles in international finance: many studies show the existence of the forward premium puzzle, namely, the trend for high interest rate currencies to appreciate rather than to depreciate against low interest rate currencies. This leads investors to engage in the carry trade, which is an investment strategy consisting of borrowing low-interest rate currencies and investing in currencies with high interest rates. The major avenue of research to explain this puzzle and the resulting carry trade profitability is the consideration of time-varying currency risk premia (Menkhoff *et al.* (2012)).

My paper is aimed at investigating whether the temporal variation in currency risk premia is systematically linked to changes in monetary conditions and whether currency risk premia predictability provides information that is economically valuable. To this end, an empirical analysis is carried out at the monthly frequency considering Federal Reserve monetary policy as a proxy for changes in monetary conditions and using daily spot and one month forward exchange rates per US dollar. Currencies are sorted into six portfolios according to their forward discounts and carry trade portfolio returns are measured at time t based on monetary conditions at time $t-1$: in this way, average returns, Sharpe ratios and 5% quantiles are computed across different monetary conditions.

Firstly, the analysis shows that carry trade portfolio average return, Sharpe ratio and 5% quantile differ substantially across expansive and restrictive conventional monetary policy before the onset of the recent financial crisis. In particular, I find that expansive periods are characterised by significantly higher average returns and Sharpe ratios and lower risk. Second, I find that the considered parameters are similar across aggressive and stabilising unconventional monetary policy during the recent financial crisis.

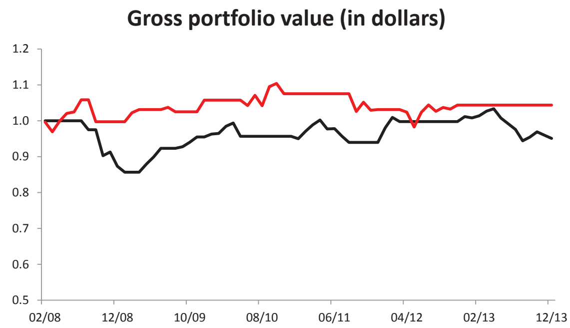
Figure 4.1: Growth of the H/L portfolio across monetary conditions (Conventional)

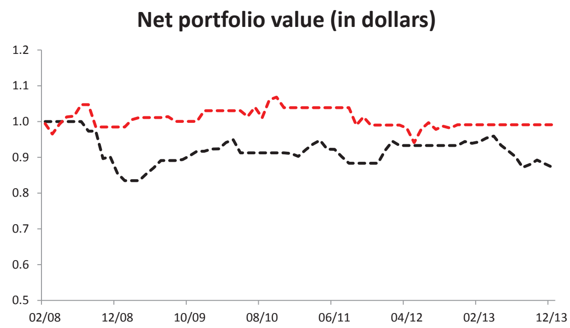




Note: This figure shows the monthly growth of one dollar invested in the carry trade portfolio in different monetary conditions over the sample period November 1983 to December 2007. The black line shows the dollar growth for investing in the considered portfolio after expansive conventional monetary policy and not investing after restrictive states. The red line shows the dollar growth for investing in the carry trade portfolio after restrictive periods and not investing after expansive states. Solid lines refer to cost unadjusted excess returns, while dotted lines refer to net excess returns.

Figure 4.2: Growth of the H/L portfolio across monetary conditions (Unconventional)





Note: This figure shows the monthly growth of one dollar invested in the carry trade portfolio in different monetary conditions over the sample period January 2008 to December 2013. The black line shows the dollar growth for investing in the considered portfolio after aggressive unconventional monetary policy and not investing after less expansive states. The red line shows the dollar growth for investing in the carry trade portfolio after stabilising periods and not investing after aggressive states. Solid lines refer to cost unadjusted excess returns, while dotted lines refer to net excess returns.

Table 4.1: Descriptive Statistics (pre-crisis period)
The table reports annualized mean, standard deviation, Sharpe ratio and 5% quantile for excess returns of currency portfolios sorted monthly according to their forward discounts. For portfolio 1, the table reports 95% quantile and *minus* the actual average excess return because the investor is short in these currencies. Means, standard deviations and quantiles are reported in percentage points. Portfolio 1 contains currencies with the lowest forward discount, while portfolio 6 contains currencies with the highest forward discount. H/L denotes the zero cost strategy that goes long in portfolio 6 and short in portfolio 1. Annualized means are computed multiplying monthly means by 12, while annualized standard deviations and quantiles are computed multiplying monthly standard deviations and quantiles by $\sqrt{12}$. The Sharpe ratio is the ratio of annualized mean to the annualized standard deviation. The table also reports skewness (SK and SK(q)) and kurtosis (KR and KR(q)) of currency portfolios. Panel A and panel B consider excess returns in US dollars without and with transaction costs adjustments respectively. The sample period is November 1983 to December 2007.

Panel A: Gross Excess Returns							
Portfolio	1	2	3	4	5	6	H/L
Mean	-2.00	0.13	1.59	4.30	3.99	7.67	9.67
St. Dev.	8.08	7.39	7.48	7.39	8.00	9.30	8.96
Sharpe Ratio	-0.25	0.02	0.21	0.58	0.50	0.82	1.08
Quantile	13.07	-11.74	-12.27	-10.19	-11.39	-13.63	-13.59
SK	0.24	0.16	0.13	0.10	-0.47	0.07	-0.64
SK(q)	-0.05	-0.06	0.03	0.18	-0.002	0.12	0.14
KR	4.08	4.25	4.10	6.08	5.37	3.87	4.65
KR(q)	4.04	3.94	4.01	4.65	4.24	4.10	3.62
Panel B: Net Excess Returns							
Mean	-0.86	-0.85	0.34	2.97	2.44	4.76	5.62
St. Dev.	8.10	7.38	7.44	7.33	7.99	9.21	8.95
Sharpe Ratio	-0.11	-0.12	0.05	0.41	0.31	0.52	0.63
Quantile	13.33	-12.03	-12.64	-10.45	-11.87	-14.24	-14.71
SK	0.27	0.15	0.09	0.06	-0.53	-0.01	-0.68
SK(q)	-0.07	-0.08	-0.01	0.17	-0.07	0.04	0.17
KR	4.13	4.26	4.13	6.04	5.59	3.76	4.56
KR(q)	4.01	3.91	3.92	4.64	4.28	3.87	3.70

Table 4.2: Descriptive Statistics (crisis period)
The table reports annualized mean, standard deviation, Sharpe ratio and 5% quantile for excess returns of currency portfolios sorted monthly according to their forward discounts. For portfolio 1, the table reports 95% quantile and *minus* the actual average excess return because the investor is short in these currencies. Means, standard deviations and quantiles are reported in percentage points. Portfolio 1 contains currencies with the lowest forward discount, while portfolio 6 contains currencies with the highest forward discount. H/L denotes the zero cost strategy that goes long in portfolio 6 and short in portfolio 1. Annualized means are computed multiplying monthly means by 12, while annualized standard deviations and quantiles are computed multiplying monthly standard deviations and quantiles by $\sqrt{12}$. The Sharpe ratio is the ratio of annualized mean to the annualized standard deviation. The table also reports skewness (SK and SK(q)) and kurtosis (KR and KR(q)) of currency portfolios. Panel A and panel B consider excess returns in US dollars without and with transaction costs adjustments respectively. The sample period is January 2008 to December 2013.

Panel A: Gross Excess Returns							
Portfolio	1	2	3	4	5	6	H/L
Mean	1.00	-0.88	0.96	0.28	4.85	1.03	0.03
St. Dev.	7.22	6.52	7.77	9.08	10.78	11.83	8.48
Sharpe Ratio	0.14	-0.14	0.12	0.03	0.45	0.09	0.004
Quantile	9.93	-9.13	-14.28	-17.73	-19.16	-21.67	-14.47
SK	0.41	-0.60	-0.19	-0.52	-0.47	-0.98	-0.51
SK(q)	0.15	-0.33	-0.04	-0.01	0.07	-0.05	-0.27
KR	6.13	5.59	3.62	3.43	3.57	4.64	3.18
KR(q)	3.54	3.20	5.28	3.45	4.43	3.66	2.86
Panel B: Net Excess Returns							
Mean	1.97	-1.53	-0.16	-1.07	3.54	-0.31	-2.28
St. Dev.	7.24	6.54	7.78	9.05	10.78	11.87	8.54
Sharpe Ratio	0.27	-0.23	-0.02	-0.12	0.33	-0.03	-0.27
Quantile	10.26	-9.40	-14.69	-17.99	-19.59	-22.39	-15.29
SK	0.54	-0.61	-0.19	-0.52	-0.47	-1.00	-0.56
SK(q)	0.15	-0.33	0.01	-0.005	0.08	-0.06	-0.25
KR	6.45	5.63	3.62	3.42	3.56	4.73	3.33
KR(q)	3.45	3.17	5.37	3.37	4.35	3.68	2.94

Table 4.3: H/L performance across monetary conditions (Conventional)
The table shows annualized mean, Sharpe ratio and 5% quantile for excess returns of the H/L portfolio across different monetary conditions. Returns are measured in month t based on changes in conventional monetary policy at time $t-1$. H/L denotes the zero cost strategy that goes long in portfolio 6 and short in portfolio 1: portfolio 6 contains currencies with the highest forward discount, while portfolio 1 contains currencies with the lowest forward discount. Means and quantiles are reported in percentage points. Annualized means are computed multiplying monthly means by 12, while annualized standard deviations and quantiles are computed multiplying monthly standard deviations and quantiles by $\sqrt{12}$. The Sharpe ratio is the ratio of annualized mean to the annualized standard deviation. Panel A and panel B consider excess returns in US dollars without and with transaction costs adjustments respectively. The sample period is November 1983 to December 2007.

Panel A: Gross Excess Returns				
Conventional	Expansive	Restrictive	P-value	All
Mean	13.07	6.73	0.04	9.67
Sharpe Ratio	1.59	0.71	0.02	1.08
5% Quantile	-10.43	-16.27	0.09	-13.59
Panel B: Net Excess Returns				
Mean	9.07	2.63	0.04	5.62
Sharpe Ratio	1.10	0.28	0.04	0.63
5% Quantile	-11.59	-17.57	0.06	-14.71

Table 4.4: H/L performance across monetary conditions (Unconventional)
The table shows annualized mean, Sharpe ratio and 5% quantile for excess returns of the H/L portfolio across different monetary conditions. Returns are measured in month t based on changes in unconventional monetary policy at time $t-1$. H/L denotes the zero cost strategy that goes long in portfolio 6 and short in portfolio 1: portfolio 6 contains currencies with the highest forward discount, while portfolio 1 contains currencies with the lowest forward discount. Means and quantiles are reported in percentage points. Annualized means are computed multiplying monthly means by 12, while annualized standard deviations and quantiles are computed multiplying monthly standard deviations and quantiles by $\sqrt{12}$. The Sharpe ratio is the ratio of annualized mean to the annualized standard deviation. Panel A and panel B consider excess returns in US dollars without and with transaction costs adjustments respectively. The sample period is January 2008 to December 2013.

Panel A: Gross Excess Returns				
Unconventional	Aggressive	Stabilising	P-value	All
Mean	-1.16	2.14	0.53	0.03
Sharpe Ratio	-0.14	0.23	0.60	0.004
5% Quantile	-12.89	-15.00	0.94	-14.47
Panel B: Net Excess Returns				
Mean	-3.63	0.06	0.50	-2.28
Sharpe Ratio	-0.45	0.01	0.55	-0.27
5% Quantile	-13.32	-15.49	0.90	-15.29

Chapter 5

Conclusion

Recent years have seen an increase in the application of quantile methodology to time series data. As stated by White *et al.* (2015), this modelling strategy has at least three advantages over the more traditional approaches that rely on the parameterization of the entire distribution. First, regression quantile estimates are robust to outliers. Second, regression quantile is a semi-parametric technique and as such imposes minimal distributional assumptions on the underlying data generating process. Third, it enables researchers to estimate the relationship between economic variables directly on the quantiles of interest.
In this work, I apply the quantile regression framework to classical Structural Vector Autoregression models. In addition, I apply both classical and quantile regression models to currency data.
The aims of my thesis are:

1. introduce Quantile Vector Autoregression models;

2. derive quantile impulse response functions;

3. assess the impact of monetary policy shocks on the euro area economy considering the quantiles (rather than the average) of the macroeconomic variables;

4. analyse whether the temporal variation in currency risk premia is systematically linked to changes in monetary conditions;

5. investigate whether currency risk premia predictability provides information that is economically valuable.

My analysis uncovers a host of interesting results. Firsly, it shows that quantile impulse response functions provide valuable information about the asymmetric effects of monetary policy shocks on the conditional distribution of macroeconomic variables. In particular, from the empirical assessment of the impact of a monetary policy shock on the euro area economy it emerges that a tightening monetary policy not only reduces the expected inflation, but it also increases its downside risk. In addition, the considered shock has no effect on the expected output growth rate, while it increases the probability of left tail outcomes.

Second, my thesis shows that rewards from engaging in carry trade vary with changes in monetary conditions during "normal times". Specifically, expansive periods are characterised by significantly higher average returns and Sharpe ratios and lower risk. So, monetary conditions drive FX liquidity and volatility innovations and in this way currency risk premia.

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