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Journal of Banking & Finance 28 (2004) 1385–1411

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Conditional covariances and direct central bank interventions in the foreign exchange markets

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Received 4 November 2002; accepted 26 March 2003

Abstract

In this paper, we investigate the effects of central bank interventions (CBIs) on the ex post correlation and covariance of exchange rates. Using a multivariate GARCH model with time-varying conditional covariances, we estimate the effects of CBIs on both the variances and covariance between the yen and the deutsche mark (the Euro) in terms of the US dollar. Our results suggest that coordinated CBIs not only tend to increase the volatility of exchange rates but also explain a significant amount of the covariance between the major currencies. We show that this result can be useful for short-run currency portfolio management. © 2003 Elsevier B.V. All rights reserved.

JEL classification: C32; E58; F31; G15

Keywords: Central bank interventions; Foreign exchange markets; Conditional correlations; Multivariate GARCH; Portfolio management

1. Introduction

Estimates of correlations between financial asset prices, such as exchange rates, are of tremendous importance in financial applications. For instance, reliable estimates of correlation are required for the mean/variance optimization of financial asset portfolios, for modelling asset returns, or for computing value-at-risk measures

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of asset portfolios (Jorion, 2001). Most empirical studies (for example, Bollerslev et al., 1988) emphasize that conditional covariances and conditional correlations are variable over time. This throws doubt on the usual implicit or explicit assumption that correlations among financial assets are constant. This calls both for econometric approaches aimed at capturing the way these covariances evolve over time, and for a better understanding of their determinants.

Simple methods such as rolling historical correlations provide a first step toward a better understanding of the correlation process. They are, however, insufficient to capture the full dynamics of this process. There is, therefore, significant econometric literature concerned with developing econometric tools that can capture the (unobservable) time-varying covariances. These approaches basically extend the existing multivariate constant correlation GARCH model of Bollerslev (1990). Bollerslev et al. (1988) had earlier developed the VECH model in which each element of the variance/covariance matrix follows a univariate GARCH model driven by the corresponding cross-product of the return innovations. ¹ While interesting, these approaches should be extended by introducing explanatory variables of the conditional variances and covariances. ² This would permit a clearer understanding of the way correlations react to financial events and policy interventions. In turn, such an analysis should be valuable for forecasting purposes.

To improve the relevance of these econometric models, the financial variables that are thought to affect the dynamics of the second moment of these asset prices have to be considered as well. In this paper, we are interested in the correlation among the major exchange rates and hence we examine the direct central bank interventions (CBIs) in these markets. The gradual release of data relative to official CBIs has prompted the development of an extensive empirical literature concerned with the effects of these interventions (Dominguez and Frankel, 1993; Baillie and Osterberg, 1997; Dominguez, 1998; Beine et al., 2002). A significant part of this literature has attempted to assess the efficiency of CBIs by estimating their impact on the ex post dynamics of exchange rates. More precisely, these studies have investigated the effects of CBIs on exchange rate returns and their volatility. Most papers have relied extensively on univariate GARCH-type models and on distinguishing the various types of interventions (official vs. reported, coordinated vs. unilateral, dummies vs. amounts).

The literature in general points out that CBIs are not very efficient, at least in the very short run. There is some limited evidence that interventions can affect the exchange rate level (Baillie and Osterberg, 1997). Nevertheless, attention has gradually shifted to the effects on higher moments and especially on the volatility of exchange rates (which was the main concern of the 1987 Louvre Agreement). The conclusions appear much more clear-cut with respect to exchange rate volatility. The literature

¹ Sometimes this model yields variance/covariance matrices that are not positive definite. With this in mind, Engle and Kroner (1995) have derived useful restrictions that led to a new model, the so-called BEKK model.

² It is thus hardly surprising that Engle and Sheppard (2001, p. 21) call for such developments in empirical investigations of correlation dynamics.

on the whole emphasizes that there is a significant increase in volatility as a result of foreign exchange rate interventions carried out by the major central banks, namely the Federal Reserve (Fed), the Bundesbank (BB) and the Bank of Japan (BoJ). ³ These studies cover periods of heavy central bank activity in the foreign exchange market, especially between 1985 and 1995. Given that the BoJ and the European Central Bank (ECB) have quite recently been enthusiastic about using CBIs, it is definitely worthwhile to update these estimates. Furthermore, the very recent release of official data by the BoJ allows us to estimate the impact of official interventions without resorting to the use of proxies.

The main purpose of this paper is to assess the extent to which direct interventions by the major central banks have influenced the dynamics of covariances and correlations among exchange rates. To the best of our knowledge, such an empirical investigation has not been proposed in the existing literature. This paper hopes to reconcile the two extensive empirical literatures mentioned above, namely the empirical analyses aimed at measuring the impact of these CBIs on the dynamics of exchange rates, and the econometric approaches that permit the estimation of time-varying covariances between financial assets. Our approach allows to capture potential spillover effects and to bring further evidence in favor of the so-called signalling channel of CBIs. Understanding the link between CBIs and covariances may also be valuable, for instance, for forecasting purposes and thus for optimizing currency portfolios. ⁴ Quite recently, robust stylized facts have been proposed by several authors (Andersen et al., 1999; Chesnay and Jondeau, 2000), emphasizing that covariances and correlations increase during periods of relatively high volatility. Since CBIs have in general been found to be a source of market uncertainty, one could expect some CBIs to be associated with a significant increase in the covariances. Our results tend to be consistent with these expectations, at least for concerted CBIs.

The paper is organized as follows. Section 2 looks at the methodology used to capture the time-varying correlations between exchange rates and provides some striking evidence that the correlation and covariance between the yen (JPY) and the deutsche mark (DEM) – Euro (EUR) from 1999 on – are highly variable over time. Section 3 presents and discusses the CBI data. Section 4 reports the estimation results while Section 5 examines the various implications of these findings in terms of transmission channels of CBI, of short-run forecasting and of portfolio optimization. Section 6 concludes.

 $^{^{3}}$ Exceptions to these widespread results have nevertheless been found by Beine et al. (2003) and Mundaca (2001).

⁴ Of course, depending on the forecast horizon, one sometimes needs to forecast the CBIs. While this is obviously beyond the scope of this paper, one should make use of the extensive literature focusing on the motivations of the central bank in intervening (see Almekinders and Eijffinger, 1996). In this respect, our estimates could be used in the very short-run (at a one-day forecast horizon) because we do not use the amount of intervention but focus only on dummies capturing the fact that one or two central banks are in the market. Also, in Section 5.3, we provide some examples showing the implications of our results for short-run portfolio management. It should be stressed that in this particular case, one does not need to forecast CBIs since the interventions are known *before* the estimation of the variances and the covariance.

2. A multivariate GARCH approach

To study the impact of CBIs on the evolution of the conditional correlation between exchange rates, we use multivariate GARCH models with time-varying conditional correlations. We use these models, rather than the Dynamic Conditional Correlation (DCC) approach of Engle (2000), because they are estimated using a one-step procedure. It is therefore possible to estimate simultaneously the impact of CBIs on the dynamics of exchange rate returns, their volatility and their correlation. Such models are sometimes difficult to estimate for large systems, calling for new approaches like the DCC. In this paper, as we are focusing on the correlation between the JPY and the DEM (EUR), the VECH model can be used, provided some additional restrictions are imposed.

2.1. The VECH approach

To capture the dynamics of the conditional variances and covariance, we rely on the VECH model with a GARCH(1,1) specification for the variances and covariances, as in Bollerslev et al. (1988). We find that (i) maximum likelihood estimates seem consistent with the empirical results obtained in general with multivariate GARCH models and seem to capture a global maximum, and (ii) the estimated variance/covariance matrix is positive definite at each point of time. This suggests that the VECH model is a satisfying starting point to model the dynamics of the second moments of the returns.

In its general form, the so-called multivariate GARCH(p,q) VECH model introduced in Bollerslev et al. (1988) may be written as

$$y_{t} = b + \epsilon_{t},$$

$$\operatorname{vech}(H_{t}) = C + \sum_{l=1}^{q} A_{i} \operatorname{vech}(\epsilon_{t-l} \epsilon_{t-l}') + \sum_{m=1}^{p} B_{j} \operatorname{vech}(H_{t-m}),$$

$$(1)$$

$$\epsilon_{t} | \Omega_{t-1} \sim N(0, H_{t}),$$

where y_t is a $(N \times 1)$ vector of exchange rate returns, vech (\cdot) denotes the matrix operator stacking the lower part of a symmetric matrix into a column vector, b is a $(N \times 1)$ vector of constants, ϵ_t is a $(N \times 1)$ innovation vector, C is a $((N(N+1)/2) \times$ 1) vector of constants capturing the unconditional variances and covariances, A_t (l = 1, ..., q) and B_m (m = 1, ..., p) are $(N(N+1)/2) \times (N(N+1)/2)$ matrices of parameters representing the GARCH process. H_t is the $(N \times N)$ conditional variance–covariance matrix of the returns. Note that we do not include any autoregressive or moving average terms in the conditional mean since this basic specification yields satisfying results in terms of diagnostic tests of serial correlation. ⁵

⁵ Of course, such a specification is consistent with the efficient-market hypothesis.

This model is estimated using the two major exchange rates against the US dollar (USD), the JPY and the DEM (EUR). The reasons for choosing these exchange rates are obvious. First, these currencies are the major ones and their prevailing flexible exchange rate regime has not been undermined by any international monetary arrangement – at least over the period we are investigating. Second, since the beginning of the 1980s, the Federal Reserve has intervened only in these two markets. Choosing the JPY and the DEM (EUR) therefore allows us to make a clear distinction between unilateral and coordinated interventions. Coordinated interventions are defined as simultaneous interventions conducted by the two involved central banks. Finally, the BoJ and the ECB have recently favored the use of the direct intervention instrument on the foreign exchange markets, in either a concerted or unilateral way. Our investigation covers the period from 1 April 1991 to 19 October 2001, amounting to 2609 data points. ⁶ We use daily data since the intervention policy is thought to be conducted on a daily basis, although one could argue that the weekly frequency may also be relevant.

The estimation of the VECH model may be cumbersome due to the high number of parameters to be estimated. Therefore, it is advisable to use a parsimonious specification. So, apart from choosing N = 2, following Bollerslev et al. (1988), we fit a GARCH(1, 1) specification (m = l = 1) and will impose diagonality on the A_l and B_m matrices.⁷ We rely on a normal multivariate distribution for ϵ_l . The model is estimated by maximum likelihood with the conditional likelihood function given by

$$L(\theta) = \sum_{i=1}^{T} \left[-\frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln|H_{t}(\theta)| - \frac{1}{2} \epsilon_{t}(\theta)' H_{t}^{-1}(\theta) \epsilon_{t}(\theta) \right],$$
(2)

where θ' includes all the parameters of the model, i.e. $\theta' = (b', C', \operatorname{vech}(A_1))$, $\operatorname{vech}(B_1)$). With this parsimonious specification, the model may be written in the following extended form:

$$y_{1,t} = b_1 + \epsilon_{1,t},$$

$$y_{2,t} = b_2 + \epsilon_{2,t},$$

$$h_{11,t} = \gamma_{11} + \alpha_{11}\epsilon_{1,t-1}^2 + \beta_{11}h_{11,t-1},$$

$$h_{12,t} = \gamma_{12} + \alpha_{12}\epsilon_{1,t-1}\epsilon_{2,t-1} + \beta_{12}h_{12,t-1},$$

$$h_{22,t} = \gamma_{22} + \alpha_{22}\epsilon_{2,t-1}^2 + \beta_{22}h_{22,t-1},$$

$$\epsilon_t | \Omega_t \sim N(0, H_t),$$
(3)

where Ω_t denotes the information set available at time t. Throughout the rest of the paper, i = 1 will refer to the JPY/USD exchange rate while i = 2 will denote the DEM (or EUR)/USD exchange rate. Thus, for instance, $y_{1,t}$ and $h_{22,t}$ denote the

⁶ This choice stems from the availability of official intervention data for the BoJ. See Section 3 for further details.

⁷ Nevertheless, relaxing the diagonality assumption of the A_i matrix produces very similar estimates.

exchange rate returns of the JPY/USD and the conditional volatility of the DEM/ USD at time *t* respectively.

2.2. Estimation results and conditional correlations

Table 1 reports the estimates of model (3) for the two currencies. The estimates suggest that this model fits the data rather well: all the parameters are highly significant at conventional levels. The very simple specification used for the conditional mean seems sufficient to capture the dynamics of the returns, as suggested by the absence of serial correlation (see the Ljung–Box statistics Q_{11} on the standardized residuals reported for 30 lags). The estimated values for the β_{ij} parameters suggest that both the conditional variances and covariances display a high degree of persistence. The GARCH(1, 1) specification seems rich enough to capture the dynamics of these variances and covariances, as suggested by the Ljung–Box statistics on the squared (Q_{11} and Q_{22}) and the cross-products of residuals (Q_{12}).

2.3. Some evidence on time-varying correlations

Direct tests on the estimated model support the time-varying specification of both the covariance and the correlation between the JPY and the EUR. In particular, likelihood ratio tests of a constant covariance specification (LRT1) and of a constant correlation specification (LRT2) (Bollerslev, 1990) strongly support the VECH specification (3). From Table 1, it is of interest to extract the dynamics of the correlations between the JPY/USD and the DEM/USD. The unconditional correlation amounts to 0.37, while the unconditional covariance is equal to 0.19. Fig. 1 plots the correlation over the full period. The variation over time of the correlation between the currencies seems highly significant, ranging from -0.2 to 0.8. This confirms that the assumption of constant correlation (often used in financial applications) obviously has not held and that failing to update these estimates regularly may lead to suboptimal choices. Identifying some of the determinants of the correlation dynamics is thus called for. The basic question addressed in this paper is whether the CBIs belong to the set of relevant explanatory variables. Before turning to this investigation, we shall examine the CBI data.

3. The intervention data

In this paper, we focus on the impact of official CBIs. Other types of CBIs have been used in the literature, such as reported interventions (see Dominguez, 1998; Beine et al., 2002). Basically, the use of reported interventions may be useful for two reasons. The first one is related to the unavailability of data concerning official interventions. For instance, up until quite recently, the BoJ did not release the official CBI data for several reasons (including legal constraints). In this case, some authors (Bonser-Neal and Tanner, 1996; Beine et al., 2002) used reported interventions as proxies for official ones. Quite recently, however, the BoJ and the Japanese Ministry Table 1

Basic specification: VECH model; JPY/USD and DEM (EUR)/USD (1991-2001)

$\begin{array}{cccc} \mbox{Conditional mean} & JPY/USD $$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$	1		. ,		
$\begin{array}{c cccc} \text{DEM/USD } y_{2,t} & b_2 & - & \begin{bmatrix} [0,3/9] \\ 0,0079 \\ 0,0079 \\ [0,646] \end{bmatrix} \\ \hline \\ \text{Conditional variance} & JPY/USD h_{11,t} & \gamma_{11} & 0.0079^{**} & 0.0080^{**} \\ [4,016] & [3,982] \\ \alpha_{11} & 0.0610^{**} & 0.0612^{**} \\ [6,397] & [6,347] \\ 0.9278^{**} & 0.9275^{**} \\ [84.456] & [83.218] \\ \hline \\ \text{Conditional covariance} & h_{12,t} & \gamma_{12} & 0.0022^{**} & 0.0022^{**} \\ [84.456] & [83.218] \\ \hline \\ \text{Conditional covariance} & h_{12,t} & \gamma_{12} & 0.0022^{**} & 0.0022^{**} \\ [3,090] & [3,087] \\ \alpha_{12} & 0.0349^{**} & 0.0349^{**} \\ [6,913] & [6,870] \\ \beta_{12} & 0.9570^{**} & 0.9569^{**} \\ [157.680] & [156.066] \\ \hline \\ \text{Conditional variance} & \text{DEM/USD } h_{22,t} & \gamma_{22} & 0.0068^{***} & 0.0067^{***} \\ [3,645] & [3,656] \\ \alpha_{22} & 0.0365^{***} & 0.0365^{***} \\ [12,595] & [113.112] \\ \hline \\ \beta_{22} & 0.9497^{***} & 0.9500^{**} \\ [12,595] & [113.112] \\ \hline \\ \beta_{22} & 0.9497^{***} & 0.9500^{**} \\ [12,595] & [113.112] \\ \hline \\ \rho_{23} & 0.344 & 21.14 \\ \hline \\ Log Lik & -5108.422 & -5108.213 \\ LRT1 & 171.35^{***} & 171.51^{***} \\ LRT2 & 182.68^{***} & 182.16^{***} \\ \hline \end{array}$	Conditional mean	JPY/USD $y_{1,t}$	b_1	_	0.0046
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		DEM/USD	L		[0.379]
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		$DEM/USD y_{2,t}$	b_2	_	0.0079
$\begin{array}{c ccccc} \mbox{Conditional variance} & JPY/USD $h_{11,t}$ & γ_{11} & 0.0079^{***} & 0.0080^{***} \\ $[4.016]$ & $[3.982]$ \\ α_{11} & 0.0610^{***} & 0.0612^{***} \\ $[6.397]$ & $[6.347]$ \\ β_{11} & 0.9278^{***} & 0.9275^{***} \\ $[84.456]$ & $[83.218]$ \\ \hline $Conditional covariance $h_{12,t}$ & γ_{12} & 0.0022^{***} & 0.0022^{***} \\ $[3.090]$ & $[3.087]$ \\ α_{12} & 0.0349^{***} & 0.0349^{***} \\ $[6.913]$ & $[6.870]$ \\ β_{12} & 0.9570^{***} & 0.9569^{***} \\ $[157.680]$ & $[156.066]$ \\ \hline $Conditional variance $DEM/USD $h_{22,t}$ & γ_{22} & 0.0068^{***} & 0.0067^{***} \\ $[3.645]$ & $[3.656]$ \\ α_{22} & 0.0367^{***} & 0.0365^{***} \\ $[12.595]$ & $[113.112]$ \\ β_{22} & 0.9497^{***} & 0.9500^{***} \\ $[112.595]$ & $[113.112]$ \\ $\rho_{1}(30$ & 24.47 & 24.38 \\ $\rho_{2}(30$ & 25.31^{***} & 5.50 \\ $\rho_{22}(30$ & 21.34 & 21.14 \\ $Log Lik.$ -5108.422 & -5108.213 \\ $LRT1$ & 171.35^{***} & 171.51^{**} \\ $LRT2$ & 182.68^{***} & 182.16^{***} \\ \hline $\end{tabular}$					[0.040]
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Conditional variance	JPY/USD $h_{11,t}$	γ_{11}	0.0079***	0.0080***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$				[4.016]	[3.982]
$ \begin{array}{c} \left[\begin{array}{c} [6.397] & [6.347] \\ 0.9278^{***} & 0.9275^{***} \\ [84.456] & [83.218] \end{array} \right] \\ \mbox{Conditional covariance} & h_{12,t} & \gamma_{12} & 0.0022^{***} \\ [3.090] & [3.087] \\ \alpha_{12} & 0.0349^{***} & 0.0349^{***} \\ [6.913] & [6.870] \\ \beta_{12} & 0.9570^{***} & 0.9569^{***} \\ [157.680] & [156.066] \end{array} \right] \\ \mbox{Conditional variance} & DEM/USD h_{22,t} & \gamma_{22} & 0.0068^{***} & 0.0067^{***} \\ [3.645] & [3.656] \\ \alpha_{22} & 0.0367^{***} & 0.0365^{***} \\ [6.235] & [6.225] \\ \beta_{22} & 0.9497^{***} & 0.9500^{***} \\ [112.595] & [113.112] \end{array} \right] \\ \mbox{Q}_1(30) & 28.71 & 28.68 \\ Q_2(30) & 30.41 & 30.40 \\ Q_{11}(30) & 24.47 & 24.38 \\ Q_{12}(30) & 255.31^{***} & 5.50 \\ Q_{22}(30) & 21.34 & 21.14 \\ \mbox{Log Lik.} & -5108.422 & -5108.213 \\ \mbox{LRT1} & 171.35^{***} & 171.51^{***} \\ \mbox{LRT2} & 182.68^{***} & 182.16^{***} \end{array} \right] $			α ₁₁	0.0610***	0.0612***
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$				[6.397]	[6.347]
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$			β_{11}	0.9278***	0.9275***
$\begin{array}{c ccccc} \mbox{Conditional covariance} & h_{12,t} & \gamma_{12} & 0.0022^{***} & 0.0022^{***} \\ & [3.090] & [3.087] \\ & \alpha_{12} & 0.0349^{***} & 0.0349^{***} \\ & [6.913] & [6.870] \\ & \beta_{12} & 0.9570^{***} & 0.9569^{***} \\ & [157.680] & [156.066] \end{array}$				[84.456]	[83.218]
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Conditional covariance	$h_{12,t}$	¥12	0.0022***	0.0022***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		r		[3.090]	[3.087]
$ \begin{array}{c} \beta_{12} & \begin{bmatrix} [6.913] & [6.870] \\ 0.9570^{***} & 0.9569^{***} \\ [157.680] & \begin{bmatrix} [156.066] \end{array} \\ \end{array} \\ \\ \hline \\ Conditional variance & DEM/USD $h_{22,t}$ & γ_{22} & 0.0068^{***} & 0.0067^{***} \\ \hline \\ [3.645] & [3.656] \\ \alpha_{22} & 0.0367^{***} & 0.0365^{***} \\ \hline \\ [6.235] & [6.225] \\ \beta_{22} & 0.9497^{***} & 0.9500^{***} \\ \hline \\ [112.595] & [113.112] \\ \hline \\ Q_1(30) & 28.71 & 28.68 \\ Q_2(30) & 30.41 & 30.40 \\ Q_{11}(30) & 24.47 & 24.38 \\ Q_{12}(30) & 255.31^{***} & 5.50 \\ Q_{22}(30) & 21.34 & 21.14 \\ \hline \\ \\ Log Lik. & -5108.422 & -5108.213 \\ LRT1 & 171.35^{***} & 171.51^{***} \\ LRT2 & 182.68^{***} & 182.16^{***} \\ \end{array} $			α ₁₂	0.0349***	0.0349***
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$				[6.913]	[6.870]
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $			β_{12}	0.9570***	0.9569***
$\begin{array}{c ccccc} \mbox{Conditional variance} & \mbox{DEM/USD } h_{22,i} & & & & & & & & & & & & & & & & & & &$				[157.680]	[156.066]
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Conditional variance	DEM/USD $h_{22,t}$	Y22	0.0068***	0.0067***
$\begin{array}{cccccccc} \alpha_{22} & 0.0367^{***} & 0.0365^{***} \\ & & [6.235] & [6.225] \\ \beta_{22} & 0.9497^{***} & 0.9500^{***} \\ & & [112.595] & [113.112] \end{array} \\ \begin{array}{ccccccccccccccccccccccccccccccccccc$				[3.645]	[3.656]
$ \begin{array}{ccccc} & [6.235] & [6.225] \\ \beta_{22} & 0.9497^{***} & 0.9500^{***} \\ [112.595] & [113.112] \end{array} \\ \begin{array}{ccccc} Q_1(30) & 28.71 & 28.68 \\ Q_2(30) & 30.41 & 30.40 \\ Q_{11}(30) & 24.47 & 24.38 \\ Q_{12}(30) & 255.31^{***} & 5.50 \\ Q_{22}(30) & 21.34 & 21.14 \\ \\ Log Lik. & -5108.422 & -5108.213 \\ LRT1 & 171.35^{***} & 171.51^{***} \\ LRT2 & 182.68^{***} & 182.16^{***} \end{array} $			α ₂₂	0.0367***	0.0365***
$ \begin{array}{cccccc} \beta_{22} & 0.9497^{***} & 0.9500^{***} \\ & [112.595] & [113.112] \end{array} \\ \begin{array}{ccccccccccccccccccccccccccccccccccc$				[6.235]	[6.225]
$ \begin{bmatrix} [112.595] & [113.112] \\ Q_1(30) & 28.71 & 28.68 \\ Q_2(30) & 30.41 & 30.40 \\ Q_{11}(30) & 24.47 & 24.38 \\ Q_{12}(30) & 255.31^{***} & 5.50 \\ Q_{22}(30) & 21.34 & 21.14 \\ \\ \text{Log Lik.} & -5108.422 & -5108.213 \\ \text{LRT1} & 171.35^{***} & 171.51^{***} \\ \text{LRT2} & 182.68^{***} & 182.16^{***} \\ \end{bmatrix} $			β_{22}	0.9497***	0.9500***
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$\begin{array}{ccccc} Q_2(30) & 30.41 & 30.40 \\ Q_{11}(30) & 24.47 & 24.38 \\ Q_{12}(30) & 255.31^{***} & 5.50 \\ Q_{22}(30) & 21.34 & 21.14 \\ \\ \text{Log Lik.} & -5108.422 & -5108.213 \\ \text{LRT1} & 171.35^{***} & 171.51^{***} \\ \text{LRT2} & 182.68^{***} & 182.16^{***} \end{array}$			$Q_1(30)$	28.71	28.68
$\begin{array}{ccccc} Q_{11}(30) & 24.47 & 24.38 \\ Q_{12}(30) & 255.31^{***} & 5.50 \\ Q_{22}(30) & 21.34 & 21.14 \\ \\ \text{Log Lik.} & -5108.422 & -5108.213 \\ \text{LRT1} & 171.35^{***} & 171.51^{***} \\ \text{LRT2} & 182.68^{***} & 182.16^{***} \end{array}$			$Q_2(30)$	30.41	30.40
$\begin{array}{cccc} Q_{12}(30) & 255.31^{***} & 5.50 \\ Q_{22}(30) & 21.34 & 21.14 \\ \\ \text{Log Lik.} & -5108.422 & -5108.213 \\ \text{LRT1} & 171.35^{***} & 171.51^{***} \\ \text{LRT2} & 182.68^{***} & 182.16^{***} \end{array}$			$Q_{11}(30)$	24.47	24.38
$\begin{array}{cccc} Q_{22}(30) & 21.34 & 21.14 \\ Log Lik. & -5108.422 & -5108.213 \\ LRT1 & 171.35^{***} & 171.51^{***} \\ LRT2 & 182.68^{***} & 182.16^{***} \end{array}$			$Q_{12}(30)$	255.31***	5.50
Log Lik5108.422 -5108.213 LRT1 171.35*** 171.51*** LRT2 182.68*** 182.16***			$Q_{22}(30)$	21.34	21.14
LRT1 171.35*** 171.51*** LRT2 182.68*** 182.16***			Log Lik.	-5108.422	-5108.213
LRT2 182.68*** 182.16***			LRT1	171.35***	171.51***
			LRT2	182.68***	182.16***

Estimated model:

 $y_{1,t} = b_1 + \varepsilon_{1,t}; y_{2,t} = b_2 + \varepsilon_{2,t};$ $h_{11,t} = \gamma_{11} + \alpha_{11}\varepsilon_{1,t-1}^2 + \beta_{11}h_{11,t-1};$ $h_{12,t} = \gamma_{12} + \alpha_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{12}h_{12,t-1};$ $h_{22,t} = \gamma_{22} + \alpha_{22}\varepsilon_{2,t-1}^2 + \beta_{22}h_{22,t-1}.$

Notes:

- (a) t-statistics of maximum likelihood estimates are in brackets. *, ** and *** indicate rejection respectively at the 10%, 5% and 1% level.
- (b) $Q_i(30)$ denotes the Ljung-Box statistics computed from the standardized residuals of y_{it} at a lag equal to 30. $Q_{ij}(30)$ denotes the Ljung-Box statistics computed from the cross product of ε_{it} and ε_{jt} at a lag equal to 30.
- (c) LRT1 is the value of the likelihood ratio test with respect to a model with constant covariance $(a_{12} = \beta_{12} = 0)$.
- (d) LRT2 is the value of the likelihood ratio test with respect to the constant correlation model of Bollerslev (1990).



Fig. 1. Correlation JPY-EUR: April 2, 1991-October 19, 2001.

of Finance made the official data freely available, at least those data concerning operations conducted after April 1991. Reported interventions may also be of interest to separate official operations into secret and reported ones. However, although they are interesting, we are not focusing on secret interventions that were used mostly during the 1980s.⁸

Another meaningful distinction concerns coordinated versus unilateral interventions. Several authors (for instance, Catte et al., 1992) have found that coordinated operations turned out to be more powerful than unilateral ones. This is explained more by the signal that is conveyed through these coordinated operations than by the absolute size of concerted sales or purchases of foreign currency. It might thus be interesting to assess the extent to which the impact of CBIs on the covariance and correlation between exchange rates depends on whether they are concerted or not. Given that, choosing the JPY and the DEM (or EUR) as the currencies to investigate seems straightforward. Indeed, the Federal Reserve has intervened in the foreign exchange market only against these two major currencies. The distinction between unilateral and coordinated interventions thus suggests that we focus on these markets. ⁹

⁸ By contrast, in the 1990s, there was some tendency (at least in flexible exchange rate arrangements) toward a more transparent intervention policy. For instance, in its FX reports, the Federal Reserve tended to justify (ex post) each intervention in the foreign exchange market. This is understandable since the signalling channel of CBIs emphasizes the importance of the ambiguous or unambiguous nature of the signal that is conveyed to the market through such an intervention. This in turn raises the question why the central banks in the 1980s made use of secret interventions (the so-called "secret puzzle") (see Sarno and Taylor, 2001 on this point).

⁹ It should be emphasized that since 1995, the Federal Reserve has carried out only coordinated interventions in the JPY or DEM (EUR) markets. By contrast, the BoJ and the ECB have also relied on unilateral operations.

	Number	Average amount (USD billions)
JPY/USD		
Unilateral FED	1	0.2
Unilateral BoJ	180	0.79
Coordinated	19	1.44
EUR/USD		
Unilateral FED	12	0.45
Unilateral Bundesbank/ECB	6	na ^a
Coordinated	12	1.03 ^b

Table 2	
Official central bank interventions: A	pril 1, 1991–October 19, 2001

. . .

^a The mean of the amounts is unavailable since the official amounts of the three unilateral interventions of the ECB (in November 2000) are not known.

^b Assuming that the intervention of the ECB in September 2000 amounts to USD 3 billion (using estimates provided by Gros and Ritter (2000)); other estimates of *The Economist* report ECB's intervention to amount to USD 2.1 billion.

Table 2 reports the number of CBIs carried out over our period of investigation, 1991–2001. As mentioned before, the choice of this period is dictated by the availability of official data of CBIs undertaken by the BoJ. The average amounts involved in these interventions are also reported. It should also be emphasized that the official amounts of ECB interventions have not been made available to researchers. ¹⁰ Table 2 shows that the BoJ has been by far the most active central bank on the foreign exchange market. By contrast, the Federal Reserve has relied almost solely on coordinated interventions in the JPY/USD market. This rules out investigating the impact of unilateral Fed interventions in the JPY/USD market. The Bundesbank and ECB have been much less active during this period than during the so-called Plaza and Louvre periods in the 1980s. ¹¹ The ECB, while reluctant to use CBIs as a policy instrument, has nevertheless conducted four operations at the end of 2000 to support the EUR against the USD.

A final choice involves the use either of dummy variables that capture the presence of the central bank(s) in the market, or of variables expressed in terms of the purchased amounts. Using dummy variables usually refers more to the so-called signalling channel (see Mussa, 1981; Lewis, 1995), while working with the amounts refers more specifically to the well-known portfolio channel. While the signalling channel seems to have received much more support in the empirical literature, we do not intend here to assume a specific transmission scheme of CBIs. However, the use of dummies rather than the variables expressed in amounts may be justified by the practical implications of our work. As said before, the estimates of CBIs on the conditional covariances of exchange rates may be useful for portfolio optimization, provided of course that CBIs have been reported to the market participants or

¹⁰ However, some conjecture about the effective amounts involved in the recent interventions has been made (Gros and Ritter, 2000).

¹¹ See Beine et al. (2002) on this point.

have been forecast. With respect to the forecasting issue, one can rely on previous work trying to estimate reaction functions of the central banks, either in terms of deviation of the exchange rate from a given target (the well-known leaning against, or with the wind, behavior for instance) or in terms of volatility (see, for instance, Almekinders and Eijffinger, 1996). One should nevertheless recognize that forecasting the probability of intervention is much easier than predicting the involved amounts of such an intervention. Similarly, reports of CBIs mainly concern the fact that one or several central bank(s) have intervened (in a particular direction) but do not often mention the amounts involved. ¹² Therefore, throughout the rest of the analysis, we will capture the CBIs by dummy variables. ¹³

4. The impact of CBI

In order to estimate the impact of CBIs on exchange rate dynamics, model (3) can be extended in a straightforward way:

$$y_{1,t} = b_1 + \delta_1 x'_{t-1} + \epsilon_{1,t},$$

$$y_{2,t} = b_2 + \delta_2 x'_{t-1} + \epsilon_{2,t},$$

$$h_{11,t} = \gamma_{11} + \alpha_{11} \epsilon_{1,t-1}^2 + \beta_{11} h_{11,t-1} + \psi_{11} |x'_{t-1}|,$$

$$h_{12,t} = \gamma_{12} + \alpha_{12} \epsilon_{1,t-1} \epsilon_{2,t-1} + \beta_{12} h_{12,t-1} + \psi_{12} |x'_{t-1}|,$$

$$h_{22,t} = \gamma_{22} + \alpha_{22} \epsilon_{2,t-1}^2 + \beta_{22} h_{22,t-1} + \psi_{22} |x'_{t-1}|,$$

$$\epsilon_t |\Omega_t \sim N(0, H_t),$$

(4)

where x_t denotes the set of central bank interventions at time t. ^{14,15} In the following sections, we report estimates using various definitions for x_t . First, we focus on the role of coordinated and unilateral interventions, both in the mean and in the second moment equations. We then estimate their joint influence, disregarding any influence on the level of exchange rates (as suggested by the previous results). We use the raw

¹² Most central banks usually publish the official data with a lag of several months. The Fed releases the data in its foreign exchange reports, usually with a lag of six months. Since August 2000, the Japanese Ministry of Finance has decided to update the intervention data four times a year (freely available on the Web site, www.mof.go.jp./english/elc021.htm). The delay in disclosure ranges between one and four months.

 $^{^{13}}$ We use the following definition: 1 refers to a purchase of USDs by the central bank(s), 0 to a nonintervention, and -1 to a sale of USDs.

¹⁴ More precisely, we use CBIs occurring at time t - 1 to account for differences in market opening times. Our exchange rate quotations are taken from the Tokyo market and recorded at 10 a.m. local time, i.e. 1:00 GMT. Therefore, all interventions dated at time t, including those of the BoJ, occur *after* the quotation of the exchange rate.

¹⁵ In order to assess the robustness of the results, we also estimated a more general model, relaxing the diagonality assumption by adding cross-innovations terms. In particular, the following specification for the covariance was also used: $h_{12,t} = \gamma_{12} + \delta_{11}\epsilon_{1,t-1}^2 + \alpha_{12}\epsilon_{1,t-1}\epsilon_{2,t-1} + \delta_{22}\epsilon_{2,t-1}^2 + \beta_{12}h_{12,t-1} + \psi_{12}|x_{t-1}'|$. Due to space restrictions, we do not report the estimation results. However, these are available upon request. We obtain very similar estimates for both the GARCH terms and the parameters capturing the impact of CBIs.

data; that is, we do not make any distinction between unilateral and coordinated interventions. This is justified by the fact that estimated reaction functions of CBIs are designed mainly for individual central banks.

4.1. Coordinated interventions

We first focus on the impact of coordinated interventions. Results reported in Table 3 show that coordinated CBIs had very weak impact on the exchange rate levels. By contrast, they have quite a significant effect on the variances. In this respect, our results are fully consistent with those of the empirical literature: CBIs are associated with increases in exchange rate volatility. Not surprisingly, the coordinated CBIs tend to increase volatility in their target market, i.e., coordinated BoJ–Fed interventions in the JPY market and coordinated ECB–Fed interventions in the EUR market. Interestingly, the coordinated interventions in the JPY market tended also to have spillover effects in terms of volatility on the EUR. Turning to the impact on the covariance, it turns out that coordinated BoJ–Fed CBIs increased the covariance between the EUR (the DEM) and the JPY significantly, while the effect of coordinated CBIs on the EUR was not significant. ¹⁶ As expected, this impact is positive, which is consistent with the stylized fact that covariances and correlations tend to be higher during periods of rather high volatility.

4.2. Unilateral interventions

The results obtained with unilateral CBIs are shown in Table 4. In contrast to the results of coordinated interventions, the impact of unilateral interventions on covariances seems much less obvious. The results concerning the conditional mean and variances are identical to those arising from coordinated interventions: unilateral CBIs do not appear to influence exchange rate levels and tend to increase exchange rate volatility. These results are once more consistent with those of the main body of the literature (Baillie and Osterberg, 1997; Dominguez, 1998). The impact on the covariances seems less significant. The unilateral interventions of the Fed in the EUR/USD market turn out to be significantly positive but at a lower significance level (5%), which is questionable given the number of data points (2609). This result is consistent, to a certain extent, with previous findings that emphasize the fact that coordinated CBIs are more powerful than unilateral operations (Catte et al., 1992, among others).

4.3. Joint introduction

By definition, unilateral and coordinated interventions are orthogonal, which reduces or rules out the potential problems of multicollinearity associated with the

¹⁶ This result, nevertheless, may be related to the small number of occurrences of coordinated interventions in this market.

Table 3

Conditional mean	JPY/USD $y_{1,t}$	b_1		0.0039
		$\delta_{1 \text{ coord-ven}}$	0.0046	
		1,coold-yen	[0.379]	
		$\delta_{1 \text{ coord-euro}}$	0.0000	_
		- 1,0010-0110	[0.002]	
	DEM/USD v2	b_2		0.0055
	<i>y</i> 2,4	-		[0.349]
		$\delta_{2 \text{ coord-ven}}$	0.0079	_
		_,,	[0.644]	
		$\delta_{2,\text{coord-ven}}$	0.0071	_
		_,,	[0.582]	
Conditional	IPV/USD h		0.0000***	0 0000***
Variance	$JF 1/03D n_{11,t}$	¥11	0.0090	[4 017]
variance			[4.043] 0.0504***	[4.01/]
		α_{11}	0.0094	0.0594***
		D	[0.391]	[0.339]
		ρ_{11}	0.9224	0.9224
			[80.394]	[80.067]
		$\psi_{11, ext{coord-yen}}$	0.3843	0.3843
		1	[3.043]	[3.038]
		$\psi_{11,\text{coord-euro}}$	0.0301	0.0301
			[0.681]	[0.6/9]
Conditional	$h_{12,t}$	γ ₁₂	0.0021***	0.0021***
covariance			[3.078]	[3.071]
		α_{12}	0.0347***	0.0347***
			[6.550]	[6.532]
		β_{12}	0.9538***	0.9537***
			[155.881]	[155.129]
		$\psi_{12,\text{coord-ven}}$	0.1612***	0.1615***
		,	[3.482]	[3.482]
		$\psi_{12 \text{ coord-euro}}$	0.0196	0.0196
		/ 12,0014-0410	[0.492]	[0.490]
Conditional	DEM/USD have	Vac	0.0083***	0 0084***
variance	, 0.000	122	[3.893]	[3.885]
		X22	0.0376***	0.0377***
		22	[5.949]	[5.920]
		β22	0.9418***	0.9517***
		r 22	[99,216]	[98.525]
		V 22 against and	0.1482***	0.1488***
		r 22,coord-yen	[2,734]	[2.736]
		V22 against and	0.2008***	0.2007***
		r 22,coord-euro	[2.202]	[2.200]
		O(30)	28 07	21 00
		$\mathcal{Q}_1(30)$	∠0.0/ 21.00	24.00 21.00
		$Q_2(30)$	21.00	51.00 27.24
		$Q_{11}(50)$	21.22	Z1.24

()			
	$Q_{12}(30)$	67.81	0.63
	$Q_{22}(30)$	17.22	17.23
	Log Lik.	-5077.74	-5077.71
	P-value of LRT	< 0.001	< 0.001

Estimated model:

Table 3 (continued)

$$\begin{split} y_{1,t} &= b_1 + \delta_1 x'_{t-1} + \varepsilon_{1,t}; y_{2,t} = b_2 + \delta_2 x'_{t-1} + \varepsilon_{2,t}; \\ h_{11,t} &= \gamma_{11} + \alpha_{11} \varepsilon^2_{1,t-1} + \beta_{11} h_{11,t-1} + \psi_{11} |x'_{t-1}|; \\ h_{12,t} &= \gamma_{12} + \alpha_{12} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + \beta_{12} h_{12,t-1} + \psi_{12} |x'_{t-1}|; \\ h_{22,t} &= \gamma_{22} + \alpha_{22} \varepsilon^2_{2,t-1} + \beta_{22} h_{22,t-1} + \psi_{22} |x'_{t-1}|. \end{split}$$

Notes:

(a) See also Table 1.

(b) *P*-value of LRT denotes the significance level associated to a likelihood ratio test based on a comparison of estimates of model (3) reported in Table 1 and estimates of model (4) reported in this table.

joint introduction of these CBIs. We disregard any effect in the conditional mean since previous results tend to show that the impact of CBIs on exchange rate returns is highly insignificant. The estimations reported in Table 5 confirm that conditional covariances are influenced only by the coordinated interventions of the BoJ and the Fed on the JPY/USD market. Through the joint introduction of unilateral and coordinated interventions, one sees that the impact of unilateral CBIs on the covariances becomes insignificant. Thus, for forecasting purposes, one should focus mainly on coordinated interventions of the BoJ and the Fed in the JPY/USD market.

4.4. Raw data

Finally, it would be of interest to estimate the model using the "raw" CBI data (that is, without distinguishing unilateral and coordinated interventions), for two reasons. First, it may be cumbersome to forecast the occurrence of coordinated interventions. In contrast, most studies have focused on reaction functions of individual central banks and emphasized the determinants of such interventions (see Almekinders and Eijffinger (1996) and, for a survey, Sarno and Taylor (2001)). ¹⁷ Second, reports do not always indicate whether a particular intervention is coordinated or unilateral. For instance, while the ECB quickly confirmed its intervention on 22 September 2000, there was a significant lag in information stating that the Fed, the BoJ, the Bank of England and the Bank of Canada had supported this intervention.

Columns 4–6 of Table 6 report the estimations of CBIs on the variances and covariances. Quite surprisingly, the estimates of the Fed's interventions in the EUR market turn out to be significant. However, the interventions of the Fed in the JPY market, while positive, are significant only at a 10% level. Nevertheless, this result may be explained by problems of multicollinearity triggered by the nonadjustment of CBI data and the use of dummies rather than amounts. Indeed, the

¹⁷ Basically, the usual determinants are the past depreciation trend, excess volatility and past CBIs.

та	hla	4	
та	.Die	4	

Conditional mean	JPY/USD <i>y</i> _{1,<i>t</i>}	b_1	-	0.0038 [0.312]
		$\delta_{1, ext{unil-Boj}}$	0.0012	_
		2	[0.107]	
		$\partial_{2,\text{unil-Boj}}$	0.0000	—
			[0.011]	
	DEM/USD $y_{2,t}$	b_2		0.0055
				[0.456]
		$\delta_{2,\text{unil-FeD}}$	0.0064	
			[0.011]	-
		$\delta_{2,\text{unil-Bce}}$	0.0000	_
			[0.110]	
Conditional	JPY/USD $h_{11,t}$	γ ₁₁	0.0065***	0.0066***
variance			[3.844]	[3.806]
		α_{11}	0.0477***	0.0480***
			[5.576]	[5.516]
		β_{11}	0.9414***	0.9410***
			[91.110]	[89.424]
		$\psi_{11, ext{unil-boj}}$	0.0065	0.0067
			[0.742]	[0.748]
		$\psi_{11,\mathrm{unil-fed}}$	0.1830	0.1822
			[1.465]	[1.450]
		$\psi_{11,\text{unil-bce}}$	-0.062***	-0.062***
			[-3.338]	[-3.322]
Conditional	$h_{12,t}$	γ ₁₂	0.0016***	0.0016***
covariance			[2.666]	[2.659]
		α_{12}	0.0286***	0.0287***
		.12	[5.100]	[5.074]
		β^{12}	0.9631***	0.9629***
			[149.909]	[148.056]
		$\psi_{12,\mathrm{unil-boj}}$	0.0042	0.0042
		1	[0.987]	[0.992]
		$\psi_{12,\text{unil-fed}}$	0.180/***	0.1803
			[2.088]	[2.070]
		$\psi_{12,\text{unil-bce}}$	-0.0003	-0.0004
			[-0.020]	[-0.010]
Conditional	DEM/USD $h_{22,t}$	V22	0.0072***	0.0072***
variance			[3.799]	[3.792]
		α ₂₂	0.0347***	0.0349***
		0	[6.275]	[6.248]
		β_{22}	0.9469***	0.9468***
		,	[113.435]	[112.594]
		$\psi_{22,\mathrm{unil-boj}}$	0.0006	0.0007
		,	[0.109]	[0.113]
		$\psi_{22,\text{unil-fed}}$	0.5978***	0.5983***
			[3.730]	[3.722]

Table 4 (communed)			
	$\psi_{22,\text{unil-bce}}$	0.1586*	0.1590*
	,	[1.893]	[1.888]
	$Q_1(30)$	28.84	27.81
	$Q_2(30)$	31.94	31.94
	$Q_{11}(30)$	25.28	25.23
	$Q_{12}(30)$	136.59***	174.69***
	$Q_{22}(30)$	17.23	20.60
	Log Lik.	-5077.71	-5074.56
	P-value of LRT	< 0.001	< 0.001

Table 4 (continued)

Estimated model:

$$\begin{split} y_{1,t} &= b_1 + \delta_1 x'_{t-1} + \varepsilon_{1,t}; y_{2,t} = b_2 + \delta_2 x'_{t-1} + \varepsilon_{2,t}; \\ h_{11,t} &= \gamma_{11} + \alpha_{11} \varepsilon^2_{1,t-1} + \beta_{11} h_{11,t-1} + \psi_{11} |x'_{t-1}|; \\ h_{12,t} &= \gamma_{12} + \alpha_{12} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + \beta_{12} h_{12,t-1} + \psi_{12} |x'_{t-1}|; \\ h_{22,t} &= \gamma_{22} + \alpha_{22} \varepsilon^2_{2,t-1} + \beta_{22} h_{22,t-1} + \psi_{22} |x'_{t-1}|. \end{split}$$

Notes: (a) See Tables 1 and 3.

correlation between the Fed interventions in both markets turns out to be quite high (0.52), suggesting that the Fed has a global intervention strategy. Furthermore, the correlation between the Fed interventions in the EUR market and those of the ECB (Bundesbank) also amounts to 0.57, which results in a poor estimation of the standard errors of the parameters.

In order to reduce these issues of multicollinearity, we run the model estimation, excluding the insignificant variables (see column 6). The results are strikingly different: the conditional covariances are once more influenced only by the Fed interventions in the JPY market. They are thus fully consistent with the fact that only coordinated CBIs matter – at least in explaining the dynamics of conditional covariances – as almost all Fed interventions in the JPY/USD market were coordinated (see Table 2). This is consistent with the recent Fed strategy with respect to intervention policy (see Humpage and Osterberg, 2000). Therefore, if one plans to use our results for forecasting purposes, one should focus on the probability of the Fed to follow certain BoJ interventions in the JPY/USD market.

4.5. Impact on conditional correlations

As mentioned before, our primary aim is to capture the impact of CBIs on both conditional variances and covariance, for two main reasons. First, this allows us to test the robustness of previous results concerning the impact of CBIs that were obtained with univariate frameworks (see, for instance, Baillie and Osterberg, 1997; Dominguez, 1998; Beine et al., 2002). Second, the variances and covariances are of course the basic features needed for mean-variance optimization of portfolios, as illustrated in Section 5.3. Nevertheless, it may be interesting to assess the direct impact of CBIs on the conditional correlations. While such an analysis is better conducted in more recent frameworks such as the DCC model developed by Engle

Table 5

Impact of unilateral and coordinated central bank interventions: JPY/USD and DEM (EUR)/USD (1991–2001)

Conditional mean	JPY/USD $y_{1,t}$	b_1	_	0.0047
				[0.390]
	DEM/USD $y_{2,t}$	b_2	_	0.0061
				[0.503]
Conditional	JPY/USD $h_{11,t}$	γ ₁₁	0.0089***	0.0089***
variance			[4.093]	[4.061]
		α_{11}	0.0533***	0.0535***
			[6.024]	[5.978]
		β_{11}	0.9288***	0.9284***
			[82.093]	[80.820]
		$\psi_{11, ext{coord-yen}}$	0.3497***	0.3511***
			[3.703]	[3.693]
		$\psi_{11, ext{coord-euro}}$	0.0634	0.0637
			[1.293]	[1.301]
		$\psi_{11,\mathrm{unil-fed}}$	-0.1185	-0.1184
			[-1.389]	[-1.388]
		$\psi_{11,\text{unil-bce}}$	-0.0504**	-0.050/***
			[-2.260]	[-2.260]
Conditional	$h_{12,t}$	γ ₁₂	0.0021***	0.0021***
covariance			[3.150]	[3.144]
		α_{12}	0.0314***	0.0314***
			[5.652]	[5.627]
		β_{12}	0.9571***	0.9570***
			[147.588]	[146.143]
		$\psi_{12, ext{coord-yen}}$	0.1083***	0.1083***
			[2.649]	[2.646]
		$\psi_{12,\text{coord-euro}}$	0.0078	0.0081
			[0.180]	[0.188]
		$\psi_{12,\text{unil-fed}}$	0.10/5	0.10/6
		.1.	[0.980]	[0.976]
		$\psi_{12,\text{unil-bce}}$	0.0038	0.0039
			[0.130]	[0.138]
Conditional	DEM/USD $h_{22,t}$	γ_{22}	0.0089***	0.0089***
variance			[3.636]	[3.643]
		α_{22}	0.0353***	0.0352***
			[6.764]	[5.753]
		β_{22}	0.9416***	0.9418***
			[92.923]	[93.253]
		$\psi_{22, ext{coord-yen}}$	0.02/4	0.02/1
		.1.	[0.644]	[0.638]
		$\psi_{22,\text{coord-euro}}$	0.11//	0.1184
		, le	[1.311]	[1.323]
		$\psi_{22,\text{unil-fed}}$	[2 022]	0.000
		ale	[2.932] 0.1748*	[2.929] 0.1748
		Ψ 22,unil-bce	[] \$40]	[1 853]
			[1.042]	[1.055]
		$Q_1(30)$	24.17	24.12

$Q_2(30)$	31.85	31.83
$Q_{11}(30)$	27.32	27.18
$Q_{12}(30)$	1.30	4.67
$Q_{22}(30)$	19.16	19.15
Log Lik.	-5057.36	-5057.23
P-value of LRT	< 0.001	< 0.001

Table 5 (continued)

Estimated model:

$$\begin{split} y_{1,t} &= b_1 + \delta_1 x'_{t-1} + \varepsilon_{1,t}; y_{2,t} = b_2 + \delta_2 x'_{t-1} + \varepsilon_{2,t}; \\ h_{11,t} &= \gamma_{11} + \alpha_{11} \varepsilon^2_{1,t-1} + \beta_{11} h_{11,t-1} + \psi_{11} |x'_{t-1}|; \\ h_{12,t} &= \gamma_{12} + \alpha_{12} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + \beta_{12} h_{12,t-1} + \psi_{12} |x'_{t-1}|; \\ h_{22,t} &= \gamma_{22} + \alpha_{22} \varepsilon^2_{2,t-1} + \beta_{22} h_{22,t-1} + \psi_{22} |x'_{t-1}|. \end{split}$$

Notes: (a) See Tables 1 and 3.

(2000), one can compute this impact using our estimates. Denoting the correlation between $y_{1,t}$ and $y_{2,t}$ by ρ_{12} , one gets

$$\frac{\partial \rho_{12,t}}{\partial x_t} = \frac{\partial [h_{12,t}/h_{1,t}h_{2,t}]}{\partial x_t} = \frac{\partial \rho_{12,t}}{\partial h_{12,t}} \frac{\partial h_{12,t}}{\partial x_t} + \frac{\partial \rho_{12,t}}{\partial h_{1,t}} \frac{\partial h_{1,t}}{\partial x_t} + \frac{\partial \rho_{12,t}}{\partial h_{2,t}} \frac{\partial h_{2,t}}{\partial x_t} = \frac{1}{h_{1,t}h_{2,t}} \psi_{12} - \frac{h_{12,t}}{h_{11,t}h_{2,t}} \frac{\partial h_{1,t}}{\partial x_t} - \frac{h_{12,t}}{h_{1,t}h_{22,t}} \frac{\partial h_{2,t}}{\partial x_t},$$
(5)

where $h_{1,t} = \sqrt{h_{11,t}}$ and $h_{2,t} = \sqrt{h_{22,t}}$. Expression (5) involves the direct impact of CBI on the conditional standard errors $(\frac{\partial h_{1,t}}{\partial x_t} \text{ and } \frac{\partial h_{2,t}}{\partial x_t})$ while our estimates capture the effect of CBIs on conditional variances. Therefore, in order to get an expression in terms of estimates, this may be rewritten as

$$\frac{\partial \rho_{12,t}}{\partial x_t} = \frac{1}{h_{1,t}h_{2,t}} \left(\psi_{12} - \frac{h_{12,t}}{2h_{11,t}} \psi_{11} - \frac{h_{12,t}}{2h_{22,t}} \psi_{22} \right). \tag{6}$$

Eq. (6), not surprisingly, suggests that the impact of CBIs on the correlation between exchange rates is highly nonlinear with respect to $h_{12,t}$, $h_{2,t}$ and $h_{1,t}$. It is nevertheless useful to evaluate this expression using estimates of ψ_{12} , ψ_{22} and ψ_{11} at longrun values of $h_{12,t}$, $h_{2,t}$ and $h_{1,t}$. The unconditional historical values equal 0.19 for the covariance between the JPY and DEM, and 0.54 and 0.48 for the variance of the JPY and DEM respectively. Table 7 reports the value of (6) for the impact of coordinated interventions in the JPY/USD market, using estimates of Tables 3 and 5, as well as the impact of Fed interventions in the JPY/USD market using estimates of Table 6.

Table 7 confirms that, at long-run values of variances and covariance, the net effect of a coordinated or a Fed intervention in the JPY/USD market on the correlation is positive. 18

¹⁸ Of course, one obvious limitation of this analysis is that this effect is evaluated in terms of point estimates. The assessment of the significance of such an effect would be captured better in other models such as the DCC model (Engle, 2000) but is clearly beyond the scope of this paper.

Table 6

Impact of central bank interventions: raw data; JPY/USD and DEM (EUR)/USD (1991-2001)

I		· · ·		(-) (,
Conditional	JPY/USD y _{1,t}	b_1	_	0.0033	_
mean				[0.268]	
	DEM/USD $y_{2,t}$	b_2	-	0.0062	-
				[0.515]	
Conditional	JPY/USD $h_{11,t}$	211	0.0073***	0.0073***	0.0091***
variance			[3.890]	[3.856]	[4.062]
		α_{11}	0.0472***	0.0473***	0.0586***
			[5.492]	[5.449]	[6.475]
		β_{11}	0.9391***	0.9390***	0.9231***
			[84.993]	[83.990]	[80.389]
		$\psi_{11,\mathrm{Fed}}$ on yen	0.2828***	0.2828***	0.3331***
			[3.340]	[3.334]	[3.479]
		$\psi_{11,\mathrm{Boj}}$	-0.0108	-0.0107	-
			[-1.352]	[-1.340]	
		$\psi_{11,\mathrm{Fed}}$ on euro	0.1190**	0.1192**	0.0232**
			[2.468]	[2.471]	[0.679]
		$\psi_{11,\mathrm{Ecb}}$	-0.0682^{***}	-0.0684^{***}	-
			[-3.494]	[-3.494]	
Conditional	$h_{12,t}$	Ÿ12	0.0018***	0.0018***	0.0021***
covariance			[2.763]	[2.756]	[3.075]
		α ₁₂	0.0301***	0.0300***	0.0344***
			[5.521]	[5.489]	[6.488]
		β_{12}	0.9604***	0.9605***	0.9542***
			[151.892]	[150.822]	[154.553]
		$\psi_{12,\mathrm{Fed}}$ on yen	0.0795*	0.0789*	0.1011***
			[1.874]	[1.863]	[2.594]
		$\psi_{12,\text{Boj}}$	-0.0003	-0.0003	-
			[-0.070]	[-0.059]	
		$\psi_{12,\mathrm{Fed}}$ on euro	0.0908**	0.0906**	0.0499
			[2.018]	[2.015]	[1.459]
		$\psi_{12,\mathrm{Ecb}}$	-0.0232	-0.0231	_
			[-1.105]	[-1.101]	
Conditional	DEM/USD h _{22,t}	γ_{22}	0.0090***	0.0090***	0.0080***
variance			[3.828]	[3.836]	[4.020]
		α ₂₂	0.0353***	0.0351***	0.0370***
			[5.885]	[5.869]	[6.277]
		β_{22}	0.9413***	0.9416***	0.9430***
			[96.759]	[97.303]	[107.314]
		$\psi_{22,\mathrm{Fed}}$ on yen	0.0238	0.0226	0.0287
			[0.475]	[0.453]	[0.725]
		$\psi_{22,\mathrm{Boj}}$	0.0011	0.0012	_
			[0.142]	[0.159]	
		$\psi_{22,\mathrm{Fed}}$ on euro	0.2559***	0.2548***	0.2772***
		,	[3.033]	[3.027]	[3.791]
		$\psi_{22,\mathrm{Ecb}}$	0.0780	0.0782	_
			[1.219]	[1.228]	
		$Q_1(30)$	24.35	24.32	25.00
		$Q_2(30)$	32.83	32.82	32.83

Table 6 (continued)				
	$Q_{11}(30)$	26.75	26.67	27.36
	$Q_{12}(30)$	23.35	22.16	49.43**
	$Q_{22}(30)$	18.09	18.07	18.00
	Log Lik.	5065.01	-5064.88	-5070.12
	P-value of	< 0.001	< 0.001	< 0.001
	LRT			

Estimated model:

$$\begin{split} y_{1,t} &= b_1 + \delta_1 x'_{t-1} + \varepsilon_{1,t}; y_{2,t} = b_2 + \delta_2 x'_{t-1} + \varepsilon_{2,t}; \\ h_{11,t} &= \gamma_{11} + \alpha_{11} \varepsilon^2_{1,t-1} + \beta_{11} h_{11,t-1} + \psi_{11} | x'_{t-1} |; \\ h_{12,t} &= \gamma_{12} + \alpha_{12} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + \beta_{12} h_{12,t-1} + \psi_{12} | x'_{t-1} |; \\ h_{22,t} &= \gamma_{22} + \alpha_{22} \varepsilon^2_{2,t-1} + \beta_{22} h_{22,t-1} + \psi_{22} | x'_{t-1} |. \end{split}$$

Notes: (a) See Tables 1 and 3.

Table 7

Impact of central bank interventions on the exchange rates correlation: JPY/USD and DEM (EUR)/USD (1991–2001)

Coordinated (Table 3)	Coordinated (Table 5)	Fed interventions (Table 6)
0.265	0.175	0.162

5. Implications

The econometric results of our analysis yield a set of important implications. First, there is a possible connection of these results with the findings of the literature concerned with market contagion issues (Section 5.1). Second, the econometric outcomes may be assessed in order to identify empirically the transmission channel of CBIs at work (Section 5.2). Third, given the impact of CBIs on the dynamics of exchange rates second moments, we show that these results may be used for short-run currency portfolio management (Section 5.3). Finally, we stress the importance of the coordinated interventions for explaining the differences in the implied correlations extracted from the multivariate GARCH estimates (Section 5.4).

5.1. Contagion versus interdependence

The increase in the covariance of exchange rates related to coordinated interventions and the weak impact of unilateral interventions shed an interesting light on the economic and financial interpretation of these results. Following Forbes and Ribogon (1999), market contagion is defined as a significant increase in the cross-market correlation or covariance during periods of turmoil. Several theories of contagion have recently been advanced and can be used to explain our empirical results. Among these theories, Mullainathan (1998) focuses on investor psychology, emphasizing that the investor's priors or memories are highly correlated. In this perspective, interventions in a particular market that result in higher costs (such as coordination costs) are likely to convey a strong signal to traders on both foreign exchange markets. Many traders in foreign exchange markets are often involved simultaneously on the two major exchange rate markets or at least pay attention to news related to both currency markets. Thus, information specific to one particular market is likely to be used by agents involved in the other major exchange rate market. This spillover effect results mainly from coordinated interventions as these operations require some active involvement of the Fed (which is thought to carry out some global foreign exchange policy).¹⁹ In other words, it may be that coordinated interventions in the JPY/USD market could be interpreted by traders as a strong signal that the Fed is also ready to intervene in the DEM/USD market in the near future. The strength of this signal is fostered by the increasing reluctance of the Fed to intervene in the FX markets. Therefore, this spillover effect is to a certain extent a specific "Fed effect". While this effect does not entail a systematic impact in terms of level, it tends to drive the JPY and the DEM in the same direction against the USD. This could explain why coordinated interventions are significantly associated with higher covariance and correlation between exchange rates.

The previous interpretation obviously refers to a specific transmission channel of CBI, i.e. the so-called signalling channel. However, the signalling channel is not the only possible channel through which CBI could theoretically affect the exchange rates. Therefore, it might be interesting to discuss these various CBI channels and to emphasize the way our results can shed some light on the effective channel at work.

5.2. Transmissions channels of CBI

Basically, three main channels of influence of CBI have been identified at a theoretical level. First, to the extent that CBIs are not sterilized, direct purchases or sales of foreign currency may affect the domestic monetary base and the relative interest rates, leading to a change in the level of exchange rates. Nevertheless, as it has been acknowledged for a long time by the major central banks, most of the FOREX operations were fully sterilized. This is especially true for the CBI considered in our analysis. The second channel through which sterilized interventions can affect the exchange rate is the portfolio channel. According to this theoretical explanation, as long as foreign and domestic assets are imperfect substitutes, some intervention that modifies the relative outstanding supply of domestic assets will involve a change in the relative returns, leading to a change in the value of the exchange rate. The main drawback of such an explanation is that the usual size of CBIs is very small relative to the average daily turnover in the major exchange rate markets, so that the impact is likely to be very limited. Our results do not identify any impact on the level of exchange rates, confirming the weakness of this channel.

The third theoretical channel of influence is the so-called signalling channel (Mussa, 1981; Lewis, 1995). The signalling hypothesis allows intervention to be interpreted as

¹⁹ As mentioned above, this global policy is illustrated by the relatively high correlation coefficient between the Fed interventions in the JPY and EUR markets.

information conveyed to the market. In turn, this will affect market participants' expectations, both in terms of level and volatility of exchange rate. As recalled by some authors (Baillie et al., 2000, for instance), the signalling channel has received much more support in the empirical literature and is considered as the most plausible explanation of the influence channel of CBIs.

Basically, our results provide three original pieces of evidence in favor of the signalling channel hypothesis. First, while we abstract from the size of the interventions, our results suggest a different impact of coordinated interventions compared to unilateral operations. The signal conveyed by coordinated operations seems to lead to stronger effects of CBIs, both in terms of volatility and co-movements of exchange rates. Second, unlike the rest of the empirical literature, ²⁰ our estimations capture a first type of spillover effect, i.e. coordinated operations on the JPY/USD market leading to an increase of the DEM/USD exchange rate volatility.²¹ Third, as mentioned above, these coordinated interventions on the YEN/USD trigger a second type of spillover effect in terms of co-movement of the two exchange rates. These spillover effects suggest that a particular intervention conveys some signal which is not only useful for the participants of the market on which this intervention takes place but also leads to some important reactions of agents involved in another exchange rate market. On the whole, these results bring further evidence that CBIs do not affect exchange rates through a pure portfolio effect but through a signalling impact altering agents' expectations of the future exchange rates.

5.3. Portfolio management

The previous econometric results in terms of second moments of exchange rates may be used for short-run portfolio management, as illustrated by the following example. Assume that both variances and the covariance are at their unconditional historical values. As mentioned above, these equal 0.19 for the covariance between the JPY and the DEM, and 0.54 and 0.48 for the variance of the JPY and the DEM respectively. This amounts to a correlation value equal to 0.37. Suppose now that the Fed intervened (the day before) in the JPY market. If one accounts for the effect of this intervention on the covariance (and, of course, on the variances), the correlation rises to a predicted value of 0.45. Failing to account for the impact on the covariance (for instance, through univariate GARCH models for each currency), one would predict that this correlation would decrease to 0.29. Thus in this particular case, ignoring the impact of CBIs on the conditional covariance would result in a forecasting error about the sign of the variation of the correlation and in a significant underestimation of its level.

This of course has direct implications for portfolio management. Consider a riskadverse US investor dealing with a currency portfolio involving the JPY and

²⁰ For instance, using univariate GARCH models of DEM/USD and YEN/USD exchange rates over the 1985–1995 period, Dominguez (1998) does not detect any robust spillover effect, i.e. interventions on a particular market affecting the dynamics of exchange rate moments of the other currency market.

²¹ See ψ_{22} parameters associated to coordinated interventions on the YEN/USD market in Table 3.

the EUR. As suggested by the previous estimation results (and consistent with the efficient-market hypothesis), the expected return of both currencies is equal to zero. Furthermore, as suggested by the results reported in Tables 3–6, CBIs do not seem to influence these expected returns in a systematic way so that we can disregard return considerations and focus on the risk of the portfolio. Suppose, therefore, that this investor is looking for the global minimum variance portfolio. Using the results of the Capital Asset Pricing Model (see for instance, Campbell et al., 1997), the optimal vector of portfolio weights (ω_g) is given by

$$\omega_{\rm g} = \frac{\widehat{H}^{-1}i}{i'\widehat{H}^{-1}i},\tag{7}$$

where \hat{H} is the estimate of the covariance matrix of the returns and i' = [1, 1]. The variance of the global minimum variance portfolio (σ_g^2) is given by

$$\sigma_{g}^{2} = \frac{1}{i'\widehat{H}^{-1}i}.$$
(8)

Using the unconditional values for the variances and the covariance, the optimal proportion of JPY and EUR would be 45.3% and 54.7% respectively, while the variance associated with this portfolio (called A) is equal to 0.348.

Now, assume that the Fed has intervened the day before (day t - 1) in the JPY/ USD market in a coordinated way with the BoJ. Fig. 2 summarizes the sequence of key events. The main difference between the DEM/USD market and the JPY/USD market lies in the existence of an overlap between European and American trading, i.e. between 13.00 GMT and 17.00 GMT. Usually, coordinated interventions between the Fed and the Bundesbank take place during that particular period. In this sense, these coordinated interventions are simultaneous operations. By contrast, on



Fig. 2. Timing of CBI, update of forecasted moments and portfolio rebalancing.

the JPY/USD market, there is no overlap between American and Asian trading. Therefore, coordinated interventions are observed after the Fed's intervention on the American market, i.e. after 13.00 GMT but before the New York market close at 21.00 GMT, while the corresponding operation conducted by the BoJ took place after the opening of the Japanese market.²² Suppose now that this intervention has been reported overnight to portfolio managers. This assumption is not as strong as it seems *prima facie*. Indeed, using Reuters news reports of CBIs, Dominguez (2003) shows that trader's reactions occur within the next hour, confirming that traders pay much attention to this kind of news, and that some traders typically know that the Fed is intervening at most 1 hour before the diffusion of the report, suggesting that the delay between the effective operation and the reports is quite short. Using the estimates of Table 6, the investor can therefore update the estimation of the covariance matrix \hat{H} .²³ This update of the covariance matrix and the related portfolio rebalancing using Eq. (7) occur between the release of the news and the next quotation of our exchange rate, i.e. at 1.00 GMT of day t. 24

Fig. 3 summarizes the various portfolio allocations. Ignoring the direct impact of the intervention on the covariance between the JPY and the EUR would lead to a portfolio (denoted B) with 24.4% JPY and 75.6% EUR. Furthermore, the variance associated with such a portfolio would be erroneously considered equal to 0.43, while the true value amounts to 49.8%. If one accounts for the direct impact of the CBIs on the covariance, the optimal portfolio (denoted C) would comprise about 6.6% JPY and 93.3% EUR. The variance associated with this portfolio is equal to 0.478, that is, about 3% lower than the risk associated with portfolio B.

Therefore, failing to account for the impact of CBIs on the covariance results in a portfolio that is too diversified and thus suboptimal. This is understandable since, in this case, one underestimates the correlation between the currencies. Accounting for the rise in the correlation and the covariance (and thus the decrease in the benefits drawn from diversification) leads to a rebalancing of the portfolio by increasing the share of the less-risky asset, that is, the EUR currency.

 $^{^{22}}$ As recalled by Dominguez (2003), the major central banks usually operate during business hours in their own respective markets.

²³ Given the GARCH(1, 1) structure that applies to the dynamics of both the variances and the covariance (see model [4]), the one-day-ahead forecast of $h_{ij,t}$ (i = 1, 2; j = 1, 2) denoted $h_{ij,t+1|t}$ may be written as: $h_{ij,t+1|t} = \gamma_{ij} + (\alpha_{ij} + \beta_{ij})(h_{ij,t} - \gamma_{ij}) + \psi_{ij}|x'_{1}|$. Here we make use of the fact that we are assuming $h_{ij,t}$ equals γ_{ij} (the conditional second moment is at its unconditional value) and the investor knows the value of x'_{t} .

²⁴ Therefore, it should be clear here that the portfolio manager does not need either to forecast the coordinated interventions neither to rebalance in advance. It is assumed here that a couple hours are needed for the CBI to exert their full impact on exchange rate moments, which is consistent with the intradaily estimate of Dominguez (2003). We also neglect transaction costs. In contrast, the use of CBI for currency portfolios over a longer horizon would imply to forecast the occurrence of these CBI, which may be cumbersome.



Fig. 3. Portfolio management and CBI.

5.4. Differences in the extracted correlations associated to CBIs

Another way to assess the importance of this issue is to compare the dynamics of the correlation, obtained both with and without the impact of CBIs. Fig. 4 plots the difference of the correlation implied by model (4) estimated with and without the raw CBI data (last column of Table 6). Fig. 4 also reports the dates of the Fed interventions in the JPY/USD market. Fig. 4 obviously suggests that a significant portion of the dynamics of this difference is related to the occurrence of Fed interventions. This is clearly obvious, for instance, for the Fed interventions occurring in May and June 1993 (three coordinated interventions), in November 1994 (one coordinated inter-



Fig. 4. Difference in correlations and Fed interventions: April 1, 1991–October 19, 2001.

vention), and in June 1998 (last Fed intervention on the JPY market). Furthermore, due to the GARCH(1, 1) specification fitted to the covariance, this difference tends to persist over some time.²⁵

6. Conclusion

In this paper, we have provided evidence that CBIs in foreign exchange markets tend to influence the conditional correlation between the major exchange rates, that is, the Japanese yen and the Euro against the USD. Focusing on the period 1991–2001, we show that this impact not only increases the conditional variances but also accounts for a significant increase in the covariance. Hence, one can expect that failing to account for this direct impact could result in significant errors in the estimation and the forecasting of the correlations. The new spillover effects documented in this paper, both in terms of volatility and co-movement of exchange rates bring further empirical evidence in favor of the signalling channel of CBI.

Estimates of the time-varying correlations between exchange rates are of overwhelming importance in numerous applications such as portfolio optimization and estimation of value-at-risk measures of currency portfolios. The results of this paper may therefore provide a framework for forecasting correlations between the major currencies. In this respect, our analysis shows that this can be used for the purpose of short-run currency portfolio optimization. This in turn raises the question whether CBIs can be predicted in the context of long-run forecasts of the correlations. Our estimation results suggest – given the Fed's recent intervention strategy of employing only coordinated interventions – that one should focus on Fed interventions in the JPY and EUR markets. This amounts to predicting when the Fed will follow the BoJ and/or the ECB to intervene simultaneously in the foreign exchange market. We leave this important issue for further research.

Acknowledgements

I am indebted to K.F. Kroner for making available the codes necessary to run the estimations reported in this paper. This paper has benefited from useful comments by A. Bénassy, B. Candelon, J. Coackley, S. Coulombe, F. Docquier, E. Farvaque, E. Girardin, A. Hecq, F. Huart, S. Laurent, R. MacDonald, J. Melitz, F. Palm, P.-Y. Preumont, H. Raymond, A. Szafarz, C. Tavera, M.P. Taylor, from participants of seminars held at the universities of Lille, Rennes, Maastricht, Oxford, Strathclyde and participants at the T2M meeting in Evry and the 14th IEA World

²⁵ There are other reasons to explain the sudden spikes in the difference in the correlations. For instance, the seemingly unintuitive negative discrepancy in the estimated correlations observed in November 1994 is due to the fact that the Fed intervened in both the JPY and the DEM markets, causing a significant rise in the variance of the DEM against the USD. Also, the positive difference observed in September and November 2000 is due as well to the Fed intervention in the EUR market.

Congress in Lisbon. The author of the paper remains, of course, responsible for all errors and omissions.

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