A Markov Switching Analysis of Contagion in the EMS

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Abstract

This paper applies the multivariate version of the Forbes and Rigobon (2002) contagion test, as proposed by Dungey et al. (2005a), to detect contagion effects in the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS). Crisis and non-crisis observations are determined endogenously via a Markov-switching vector autoregression (MS-VAR). We show that the MS-VAR is suitable for this purpose as it does particularly well in identifying the 11 realignments of the ERM. We examine whether Denmark’s rejection of the Maastricht Treaty and Italy’s competitiveness problems have affected other EMS participants and find evidence for contagion.

JEL Classification: F31, F33

Keywords: Currency crisis, volatility transmission, Markov switching

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1 INTRODUCTION

The frequency of currency and banking crises has increased significantly in the last 25 years (e.g. Bordo et al., 1998). Similarly, the crisis literature has grown and evolved to offer different explanations for the apparently ever-changing phenomena. The initial approach of ‘bad’ fundamentals (see Krugman, 1979), indicating that crises could be avoided with sound fiscal and monetary policies, were followed by game-theoretic models with multiple equilibria (e.g. Obstfeld, 1986). The latter predict that circumstances can arise in which investors’ perception of the government’s objectives can lead to a crisis even when the fundamentals are good. More recently, and as a result of the inability of existing models to predict the Asian crisis, so called third generation models evolved. These explain crises in terms of moral hazard, contagion effects and highlight the role of banking supervision (e.g. Corsetti et al. 1999).

In this paper, we propose a Markov regime-switching methodology to model movements in the foreign exchange (FX) markets and their transmission across countries. Such models have been extensively used in the business cycle literature (e.g. see Hamilton, 1989 and Krolzig, 2001) but have only recently generated active interest in currency crisis research. This is rather surprising since a crisis can be thought of as a switch from a state of the world with zero or negative FX market pressure (a tranquil regime) to a state characterised by higher FX pressures (a crisis regime). In other words, there are jumps in the mean and –depending on the setting– changes in volatility of the time-series across different regimes. The assumption that the values of the pressure variable come from two different distributions is our motivation for examining the European Monetary System (EMS). Our model captures the stages of the EMS accurately: the ‘old’ EMS when several realignments took place, the ‘new’ EMS when there were no adjustments of the bands and the final stage characterised by extreme FX pressure that culminated in the abandonment of the mechanism.

1The terms “regime” and “state of the world” are used interchangeably throughout the text.
Adopting this modelling technique has the advantage that it enables us to calculate the probabilities of a shift between the two regimes as well as their duration. Hence, we obtain a measure of how much crisis-prone the EMS was. Moreover, the regime switching vector autoregression of EMS participants allows us to answer the question of whether correlations between countries differ across regimes. We also use the Dungey et al. (2005b) multivariate version of the Forbes and Rigobon (2002) formula to test explicitly for changes in market linkages. We find evidence that volatility transmission is ‘over and above’ what would be justified by the transmission mechanism prevailing during tranquil periods. Subject to some caveats, which we discuss in a later section, this constitutes evidence of ‘contagion’ effects.\footnote{The definition of contagion has been the subject of debate in the literature. We discuss this in more detail in section 3.3.}

Our approach is simple and intuitive and does not require the breakdown of the sample into crisis and no crisis periods in an \textit{ad hoc} manner. In other words, crisis periods are endogenously determined. Moreover, in contrast to most other studies, which use stock returns and bond spreads, the use of a pressure index enables us to focus on volatility transmission in the FX market. The following section reviews in some detail currency crisis models that have used the regime-switching specification. Section 3 details our data, methodology and estimation results. Section 4 concludes the paper.

\section{The Literature}

This paper provides a link between the literature on currency crisis and the literature on contagion through correlation analysis implemented in a regime-switching framework. Hamilton’s framework (1989), which has recently found ample use in the crisis literature, is appropriate to model contagion through the analysis of state-dependent correlations. We choose to analyse EMS, as it has the interesting characteristic of featuring both a quiet period and an eventful, extremely volatile period. As shown in later sections, the model picks these up accurately.
The idea of having discrete random changes in regime modelled as a Markov chain is straightforward. An $N$-state Markov chain can be described by $P\{r_t = k | r_{t-1} = j, r_{t-2} = i, \ldots\} = P\{r_t = k | r_{t-1} = j\} = p_{jk}$, where $r_t$ is a random variable taking values 1, 2, ..., $N$. This process implies that $r_t$ depends only on the most recent value $r_{t-1}$; in other words, previous states do not affect the current state. Several crisis incidents have been recently examined in a literature that uses this assumption, including the cases of the EMS, Latin America and Asia. In what follows, we summarise in chronological order this evolving strand of the literature.

An early effort to explain the EMS crisis using a regime switching methodology is by Piard (1998) who studies the experience with the French franc and the Italian lira between 1978 and 1993. She models transition probabilities as time-varying and uses several variables to capture the effect of fundamentals. These include the debt to GDP ratio, real exchange rate, trade balance, inflation, M2 to reserves ratio, output growth, unemployment, and the Mark/Dollar exchange rate. The dependent variable is a foreign exchange market pressure index.

In the case of the French franc, Piard finds that unemployment, the trade balance and the real exchange rate are associated with regime switches. In the case of the lira, the –not surprising– result is that the debt to GDP ratio affects significantly the transition probabilities. There is also weaker evidence on the role of lagged inflation and growth rate differentials with Germany. The effects of these variables are ‘asymmetric’, in the sense that the association between the exogenous variables and the MPI differs across the two states of the world (tranquil and crisis). Overall, the finding of the importance of French unemployment and Italian fiscal imbalances is consistent with other studies (e.g. see Drazen and Masson, 1994 for the former and Amato and Tronzano, 2000 for the latter). It is also one of the mainstream explanations for these countries’ foreign exchange pressures and eventual realignments, alongside political factors and problems of competitiveness.

Jeanne and Masson (2000) use a two-state MSM with fixed transition probabil-

\footnote{See Krolzig (1997), chapters 1 and 2 and Hamilton (1994), chapter 22, for a detailed statistical review of Markov chains and their use in regime switching models.}
ities for the French franc; the dependent variable here is a measure of realignment expectations. The sample consists of monthly observations for the period 1987-93. They interpret the regime shifts as shifts between different states of private sector expectations in the context of a second generation model. The chosen specification explains a measure of exchange rate expectations (the one-month interest differential between Euro-franc and Euro-DM instruments after correcting for expected movement toward the center of the band using a drift-adjustment method), via changes in the unemployment rate, the trade balance, and the real exchange rate. The equation includes a regime-dependent intercept and a time trend. Estimation of the model delivers estimated coefficients that have the expected signs and are significant at the 10% level, except for the real exchange rate. The intercept assumes different values in the two states, which are found to be persistent.

In a similar fashion, Amato and Tronzano (2000) examine the credibility of the Italian fixed exchange rate using data for the period 1990-95. The dependent variable is the one-month nominal interest rate differential between Italy and Germany. They model the transition probabilities as both time-varying and fixed, and use a variety of debt and fiscal indicators including the share of short-term debt, the share of foreign debt, the debt to GDP ratio, government deficit, etc. The fixed model produces a low-mean credible state and a high mean non-credible state. The indicators have the expected signs and are significant. In addition, the credible regime is more persistent than the non-credible one. The time-varying methodology produces similar results. The deficit and debt fiscal indicators have the expected effects and are significant. The debt management considerations are equally interesting: increases in the share of long-term and foreign currency debt lower the conditional probability of the not credible state, in contrast to increases in the share of short-term debt.

Martinez-Peria (2002) uses the Diebold et al. (1994) methodology to capture the effects of certain fundamentals on the probability of transition from a tranquil to a crisis state. She uses monthly data on exchange rates for Belgium, Denmark, France, Ireland, Italy, Spain, and the UK to estimate the following models for the EMS: an
autoregressive (AR) specification involving exchange rates, and a vector autoregres-
sive (VAR) specification involving exchange rates, an interest rate differential with
Germany, and reserves. The variables included in the matrix of exogenous variables
are: domestic credit growth, the imports/exports ratio, the unemployment rate, the
fiscal deficit and interest rates. The variables are expressed as differences from the
corresponding German variable.

The results from the AR model indicate that the interest rate differential and
the government surplus as a percentage of GDP are correctly signed and significant.
In the VAR model no variable is individually significant, but the test of joint in-
significance is rejected. The model is re-estimated for the period 1988-93 including
survey data on expected exchange rates, but again the estimated coefficients are in-
dividually insignificant. The author argues that realignment expectations were fairly
constant throughout 1988-1993, and that there were few regime switches during that
period.

Fratzscher (2002) uses a three-state fixed transition probabilities model and con-
centrates on the role of contagion in currency crises. His sample consists of monthly
observations from 1986 to 1998 on 24 emerging economies. He uses a market pres-
sure index and estimates an autoregressive model of order 1 with varying intercepts
and heteroscedastic errors. The specification includes two measures of contagion: a
‘real’ measure depicting trade links and a financial measure capturing links through
capital market returns. The model allows for switching intercepts and changes in
the error variance.

The regressions are run separately for each country and there is no single factor
that appears to be significant in all cases. However, there is evidence that foreign
debt, domestic credit and the real exchange rate are relevant in several cases. The
author finds that including the contagion variables in the specification for most
countries in the sample eliminates the regime shifts and hence a linear model would

\[ \text{These are Argentina, Bolivia, Brazil, Chile, Colombia, Mexico, Peru, Venezuela, China, India,}
\text{Indonesia, Korea, Malaysia, Pakistan, Philippines, Sri Lanka, Thailand, Czech Republic, Hungary,}
\text{Jordan, Poland, Russia, South Africa, and Turkey.} \]
be sufficient in modelling crises.

The role of contagion in Indonesia’s currency crisis is explored in Cerra and Saxena (2002). They estimate both the fixed and time-varying versions of a two-state Markov switching model using monthly data from 1986-1997. Their list of exogenous variables includes private claims to GDP (capturing the lending activity of the banking system), foreign liabilities to GDP (measuring the sensitivity of the banking system to capital inflow reversals), and a political confidence index. Similarly to other studies the original list of indicators is richer but they filter it through OLS and Probit estimations. Only these variables whose estimated coefficients are found to be significant in the regressions are included in the MS model.

The fixed version of the model is of order 1 and has a switching mean, and includes the exogenous indicators mentioned above. The authors find that the no-crisis state is highly persistent. They also report a significant negative coefficient on political confidence. The time-varying version is used to identify contagion effects from Thailand and Korea to Indonesia. It is shown that this specification picks crises more quickly, but also predicts crises that never happened. The main finding here is that mounting speculative pressure on the Korean and Thai currencies lead to increased probability of switching from a non-crisis to a crisis state in Indonesia. Hence, there is evidence of contagion.

In a study of the Asian crisis, Abiad (2003) uses monthly data for Indonesia, Korea, Malaysia, the Philippines and Thailand and focuses primarily on the forecasting/signalling ability of the model. The estimation period is 1972-99 and the chosen methodology is a two-state Markov switching model with time-varying transition probabilities. The author categorises the exogenous variables in three groups: macroeconomic indicators, capital flows indicators and financial fragility indicators. He uses a general-to-specific approach to narrow down the set of variables used in each country. The first stage regressions confirms the role of real overvaluation (i.e. the overvaluation of the real exchange rate), as this is the only correctly signed and significant variable across all countries. The ratio of M2 to deposits, real
GDP growth, domestic credit growth, export growth, stock market performance were among the indicators used in the country specifications. As the study belongs primarily to the early warning system literature, the significance of the estimated parameters is not discussed extensively. It is found, however, that the model does an “adequate” job in predicting currency crises.

Summarising, the use of Markov switching models in the currency crises literature has increased over the last few years. The obvious advantage in comparison to Logit and Probit methodologies, which have been more popular, is that they allow for a continuous dependent variable and there is no need for an arbitrary choice of cutoff points in order to create a discrete variable and define what constitutes a crisis. The non-linear nature of the MS model is also appealing, as it is intuitive to assume that there are time series (such as an FX market pressure index) whose values come from different distributions if the state of the world has switched.

3 The Empirics

3.1 Data Description and Construction of Variables

The majority of the studies, reviewed in the previous section, focus on the use of Markov switching models in the search for plausible explanations of currency crises. In other words, they identify the effects of specific variables on the probability of switching from a tranquil to a crisis regime. This paper’s objective is different; we abstract from discussing the role of fundamentals and focus on detecting patterns of correlation across tranquil and crisis states of the world in order to extract the classification of periods into crisis and non-crisis ones. We use this classification to implement the multivariate version of the Forbes and Rigobon (2002) test (henceforth FRM), proposed in Dungey et al. (2005a).

We have deliberately adopted a straightforward MS-VAR framework without fundamentals, as from the investor’s point of view what really matters is how the markets behave in different regimes. For example, two more or less uncorrelated
markets that tend to synchronise during bad times will not offer diversification benefits in times of crisis. Also, what matters, from the paper’s point of view, is to have an appropriate classification of regimes. The success of the adopted specification in identifying correctly most realignments as crisis periods is strong indication that the classification can be used in conducting the FRM test.\(^5\)

The Markov-switching framework requires the specification of the number of the states of the world. In the absence of a statistical measure for the optimal number of regimes, we confine ourselves to examining a ‘tranquil’ state (in which our FX pressure measure –described below– assumes a zero or negative mean value) and a ‘crisis’ state (in which the pressure variable has a positive mean).\(^6\) The Markov-switching model is ideal for our purposes as it allows us to estimate the error correlations for different countries across the two regimes.

The FX pressure measure we use is a market pressure indicator (MPI), which is widely used in the currency crisis literature, but is rather neglected in tests of contagion, where stock and bond returns have been more popular. Of course, stock returns have a higher frequency and the data is readily available. Since the focus of this study is the foreign exchange market, we opt for a pressure indicator. The index consists of time series on the nominal exchange rate depreciation against the DM \((XR)\), the change in the interest rate differential with Germany \((IRD)\), and the change in foreign exchange reserves \((RES)\) –in US Dollars.

A market pressure index is a superior measure to simple nominal exchange rates, as it captures all pressure in the foreign exchange market, including unsuccessful speculative attacks. For example, the monetary authorities might be able to fend off an attack by raising their policy rate or by buying domestic currency (and thus

\(^5\)On a more practical note, the literature has been unable to identify variables that constitute shock transmission channels beyond doubt. Trade and bank lending have played a role in several crisis episodes but cannot explain the transmission of shocks across the board. Most papers seem to use variables in an almost ‘experimental’ way. It is also a possibility that market sentiment may drive changes in correlations. For example King et al. (1995) argue that “changes in correlations across markets are driven primarily by unobservable variables”.

\(^6\)Of course, one can assume more regimes if this is consistent with the data generating process. We feel that assuming two regimes in this case is appropriate.
spending their international reserves). This activity would not register in the exchange rate series, but it is evident in the MPI, which is, formally, expressed as:

\[ \text{MPI} = \alpha XR + \beta IRD - \gamma RES. \]

For the \( XR \) and \( RES \) series percentage changes were created by taking the first difference of the natural logarithms. For \( IRD \) we take the first difference since the series is already expressed in percentage points. An increase in the value of the index signifies pressures in the FX market, since a higher nominal exchange rate implies a depreciation of the domestic currency and higher interest differentials and reduced reserves show the implementation of defending policies by the central bank. The minus sign in the equation above ensures that a reduction in reserves translates into an increase in the value of the index. The weights \( \alpha, \beta \) and \( \gamma \) are determined by applying the following formula:

\[
w_i = \left( \frac{1}{\text{StDev}_i} \right) / \left( \frac{1}{\text{StDev}_{XR}} + \frac{1}{\text{StDev}_{IRD}} + \frac{1}{\text{StDev}_{RES}} \right)
\]

where \( w_i = \alpha, \beta, \gamma \), and \( i = XR, IRD, RES \). \( \text{StDev} \) stands for the standard deviation.

The countries in our sample are Belgium, Denmark, France, Ireland, Italy and the Netherlands. Spain, Portugal and the UK joined the exchange rate mechanism much later—and with a wider margin of 6% compared to 2.5% for the other members—and, hence, are not included. In addition, we do not consider countries that had
Figure 1: Plots of Market Pressure Indexes

pegged to the Ecu, e.g. Finland and Sweden. With the exception of the first five observations of the Irish interest rate and three observations of the French interest rate data comes from the International Financial Statistics of the IMF. The missing data were taken from the OECD’s Main Economic Indicators. The data are monthly and cover the period January 1978 to December 1993.

Table 1 reports descriptive statistics for all six countries. It can be seen that, unlike the other countries, the Netherlands index has a negative mean implying that on average the country did not face severe FX market pressures. The standard deviation of the index is also the lowest in the sample. For this reason the Netherlands is not included in our estimations. Ireland has the highest mean of all the countries and the most volatile MPI as shown by its standard deviation. However, from the plots in Figure 1 it can be seen that the rest of the series were also quite volatile.

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7Daily data would prevent us from forming a market pressure index.
8We do however check all our results by including the Netherlands in the sample. These estimations are not reported but do not alter our conclusions.
with intense pressures mounting during 1992. The distributions are not normal –
they are leptokurtic and positively skewed. Jarque-Bera tests reject normality in all
cases. All series are stationary around zero.

3.2 MS-VAR Estimation Results

In the analysis that follows, the variance and, hence, the correlations between the
MPIs of the five countries in the dataset are allowed to vary across regimes. This
permits us to test whether the crisis state is associated with increased correlations,
a fact that, if true, implies the presence of common shocks or interdependence. If,
in addition, the unconditional correlations significantly increase in the crisis state
this could be taken as indication of contagion, assuming that we are correct in our
presumption about the source country.

We begin our analysis with the simplest task of identifying common regime shifts,
i.e. checking whether the indexes respond to common international shocks. This
can be implemented by an MS-VAR with regime shifts in the mean of the MPI. At
this stage we assume homoscedastic errors and $u_t \sim NID(0, \Sigma)$. The multivariate
setting can be formally expressed as:

$$\omega_t = \mu(r_t) + \sum_{j=1}^{p} A_j(\omega_{t-j} - \mu(r_{t-j})) + u_t,$$

where $\omega_t = [MPI_{t}^{BEL}, MPI_{t}^{DEN}, MPI_{t}^{FRA}, MPI_{t}^{IRL}, MPI_{t}^{ITA}]'$,
$\mu$ is a regime-dependent mean, the regime vector $r_t = [r_t, r_{t-1}, \ldots, r_{t-p}]'$, ma-
trices $A$ contain estimates of the coefficients of the $p^{th}$-order autoregression, and $u_t$
is a gaussian error term. The criteria for lag selection do not deliver a unanimous
verdict. The likelihood ratio test suggests five lags, the final prediction error and the
Akaike statistic (AIC) give two, and the Hannan Quin and Schwarz criteria suggest
a random walk with a drift specification. Given that the AIC is the most powerful
test our preferred model features two lags.\footnote{We also estimate our models with 0, 1, 3, 4, 5 and 6 lags to calibrate the impact of the lag

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equation (1) has a representation of the form:  

\[ \omega_t = \mu(r_t) + \sum_{j=0}^{\infty} A_j^1 u_{t-j}. \]  

(2)

It is assumed then that the process can be seen as the sum of common system shocks (\(\mu(r_t)\)) and country-specific shocks (\(\sum_{j=0}^{\infty} A_j^1 u_{t-j}\)).

The first panel of Table 2 reports the mean of regime 1 (\(\mu_1\)) and the mean of regime 2 (\(\mu_2\)) as well as the shift in the mean across the two regimes. Regime 1 is the tranquil state, where there are either negative pressures on the MPI (implying appreciating domestic currency or a decrease in the interest rate differential or accumulation of reserves or a combination of these) or no pressures at all, in which case the mean is close to zero. A switch to a crisis state is associated with positive means indicating mounting FX pressures. The difference between the means is in all cases positive, with Ireland’s shift being the most dramatic.

The transition probabilities estimated using two lags indicate that both regimes are quite stable. The probability of switching from a tranquil to a crisis state is 19.9%, whereas the probability of a switch from crisis to tranquility is 24.3%. The non-varying contemporaneous correlations (as we have assumed homoscedastic errors variances do not change across states of the world) are not negligible. The highest correlation is between France and Italy (43.2%) and the lowest between France and Denmark (12.1%). Correlations between the rest of the countries are reported in Table 4, where we compare the sensitivity of correlations to different model assumptions.

The assumption implicitly made in the analysis is that the mean jumps instantly to its new level across regimes. We can relax this assumption, to allow for a smoother

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10See Krolzig (1997).
Table 2: Homoscedastic MSM(2)-VAR(2) and MSI(2)-VAR(2)

<table>
<thead>
<tr>
<th>Country</th>
<th>BEL</th>
<th>DEN</th>
<th>FRA</th>
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</thead>
<tbody>
<tr>
<td>$\mu_1$</td>
<td>-0.072</td>
<td>-0.321</td>
<td>-0.2</td>
<td>-0.365</td>
<td>-0.168</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>0.206</td>
<td>0.524</td>
<td>0.293</td>
<td>0.686</td>
<td>0.335</td>
</tr>
<tr>
<td>$\mu_2 - \mu_1$</td>
<td>0.278</td>
<td>0.845</td>
<td>0.493</td>
<td>1.051</td>
<td>0.503</td>
</tr>
<tr>
<td>$\nu_1$</td>
<td>-0.053</td>
<td>-0.157</td>
<td>-0.036</td>
<td>-0.249</td>
<td>-0.115</td>
</tr>
<tr>
<td>$\nu_2$</td>
<td>0.474</td>
<td>1.199</td>
<td>0.273</td>
<td>1.876</td>
<td>0.882</td>
</tr>
<tr>
<td>$\nu_2 - \nu_1$</td>
<td>0.527</td>
<td>1.356</td>
<td>0.309</td>
<td>2.125</td>
<td>0.997</td>
</tr>
</tbody>
</table>

Notes: Non-linear Markov-switching estimations with regime-dependent means (panel 1) or intercepts (panel 2) and homoscedastic errors. Order of VAR: 2. Number of regimes: 2. MSM: switching mean – see equation 1 in text. MSI: switching intercept – see equation 3. Results were obtained using H-M. Krolzig’s MSVAR package for Ox.

transition to the new level. The specification now becomes

$$\omega_t = \nu(r_t) + \sum_{j=1}^{p} A_j(\omega_{t-j}) + u_t,$$

with a representation, again with one lag, of the form

$$\omega_t = \sum_{j=0}^{\infty} A^1_j \nu(r_{t-j}) + \sum_{j=0}^{\infty} A^1_j u_{t-j}. \quad (4)$$

It can be seen that shocks here feed into $\omega_t$ through the matrix of estimated coefficients. Results are reported in the second panel of Table 2. In comparison to the model with a one-off shift in the mean, the magnitudes seem to have changed in several cases, mostly upwards. A characteristic of this model is that the crisis regime has now become much less persistent. The probability of switching to calm when in a crisis has now increased to 52.3%. The correlations have also changed in some cases but always remain positive. The particularly high correlation between France and Italy remains.

We have seen that all countries in our sample face simultaneous positive FX pressures when the regime switches from tranquil to crisis. This is hardly surprising given the amount of intra-trade between the EMS countries. What is more interesting is to see whether these switches also affect the contemporaneous correlations of the cross-country MPIs. To perform this estimation we need to relax the assump-
Table 3: Heteroscedastic MSM(2)-VAR(2) and MSI(2)-VAR(2)

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<tbody>
<tr>
<td>( \mu_1 )</td>
<td>-0.010</td>
<td>-0.042</td>
<td>-0.093</td>
<td>-0.081</td>
<td>-0.021</td>
</tr>
<tr>
<td>( \mu_2 )</td>
<td>0.31</td>
<td>0.399</td>
<td>0.491</td>
<td>0.576</td>
<td>0.399</td>
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<tr>
<td>( \mu_2 - \mu_1 )</td>
<td>0.32</td>
<td>0.441</td>
<td>0.584</td>
<td>0.657</td>
<td>0.42</td>
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<tr>
<td>( SE_1 )</td>
<td>0.397</td>
<td>0.867</td>
<td>0.445</td>
<td>0.835</td>
<td>0.521</td>
</tr>
<tr>
<td>( SE_2 )</td>
<td>1.45</td>
<td>1.046</td>
<td>1.27</td>
<td>2.579</td>
<td>1.413</td>
</tr>
<tr>
<td>( \nu_1 )</td>
<td>-0.012</td>
<td>-0.024</td>
<td>-0.083</td>
<td>-0.092</td>
<td>-0.029</td>
</tr>
<tr>
<td>( \nu_2 )</td>
<td>0.239</td>
<td>0.355</td>
<td>0.431</td>
<td>0.741</td>
<td>0.339</td>
</tr>
<tr>
<td>( \nu_2 - \nu_1 )</td>
<td>0.251</td>
<td>0.379</td>
<td>0.514</td>
<td>0.833</td>
<td>0.368</td>
</tr>
<tr>
<td>( SE_1 )</td>
<td>0.399</td>
<td>0.875</td>
<td>0.45</td>
<td>0.86</td>
<td>0.524</td>
</tr>
<tr>
<td>( SE_2 )</td>
<td>1.486</td>
<td>1.056</td>
<td>1.306</td>
<td>2.607</td>
<td>1.44</td>
</tr>
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Notes: Non-linear Markov-switching estimations with regime-dependent means (panel 1) or intercepts (panel 2) and heteroscedastic errors. SE: standard error. Order of VAR: 2. Results were obtained using H-M. Krolzig’s MSVAR package for Ox.

The specification of homoscedasticity. This is justified since a likelihood ratio test rejects the restrictions imposed by the homoscedastic model. As the variances and covariances vary across regimes we calculate two sets of correlations: one for the tranquil state and one for the crisis state. These correlations are, however, conditional on the increased volatility associated with crisis incidents and should not be used directly to make inferences on contagion.

The MSIH(2)-VAR(2) specification delivers a \( p_{11} \) (i.e. remaining in a non-crisis regime) transition probability of 87.1% whereas the \( p_{22} \) (i.e. remaining in a crisis regime) transition probability is 52.6%. The respective values for the MSMH(2)-VAR(2) are 86.2% and 52%. Both specifications deliver a similar duration for regime 1 (7.8 and 7.3 months respectively). Table 3 reports the changes in means caused by regime shifts in this heteroscedastic setting. Regime 2 is associated with higher volatility as measured by the standard errors reported.

Table 4 reports contemporaneous correlations for both regimes and models. It also shows correlations for a simple non-switching VAR, and the homoscedastic mean-switching and intercept-switching VARs. Focusing for a moment on these last three, it can be seen that some correlations seem to be fairly robust to different specifications. For example, the coefficient for Italy and France is around 45% in
### Table 4: Heteroscedastic MS-VAR – Correlations

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<td>0.36</td>
<td>0.22</td>
<td>0.15</td>
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</table>

**Notes:** For the heteroscedastic mean-switching (MSMH) and intercept-switching (MSIH) specifications, numbers below the main diagonal are regime 1 correlations whereas numbers above the main diagonal are regime 2 correlations. Order of all VARs: 2. Results were obtained using H-M. Krolzig’s MSVAR package for Ox.

All three models. Other correlations also appear quite stable, e.g. Belgium and Denmark, and Ireland and Belgium even though the magnitude of the correlation coefficient is not as high as for Italy and France. For some countries, though, the size of the correlations depends on the specification. In general, it tends to be lower in the MSI model. For example, for the simple VAR the coefficient for Italy and
Belgium is 21%, whereas for the MSI it is just 8%. The first three panels of the table report results for homoscedastic specifications, in other words the variance is assumed not to change across regimes. We place more confidence in estimates of the correlation coefficients derived from heteroscedastic specifications, reported in the last two panels of Table 4.

In seven out of ten cases there is an increase in the size of the correlation coefficient during regime 2. This result holds irrespectively of whether we estimate a mean-switching or an intercept-switching model. The magnitudes are also very similar. The most dramatic increases are observed between Belgium and Denmark (approximately 180%) and France and Italy (approximately 160%). In some cases, e.g. between France and Denmark, the correlations disappear in regime 2 or even become negative. Overall, there is evidence of increased correlation in FX pressures in the EMS during crisis periods. Taking fewer lags or an extra one does not alter this finding. Increasing the memory of the VAR beyond three lags, though, produces slightly different correlations.

Figure 2 reports the filtered probabilities of a switch to regime 2 for the duration of the EMS. Our chosen specification captures all phases of the mechanism: the volatile first stage (sometimes called the ‘old’ EMS) when there were 11 realignments, the ‘new’ or ‘hard’ EMS between 1987 and 1992 when no realignments took place and the final stage of speculative attacks that induced Britain and Italy to abandon the mechanism and eventually led to its demise. Comparing the crisis dating depicted in the figure with the actual incidence of realignments provides us with very encouraging results: 8 out of the 11 realignments are classified as crisis regimes.\footnote{The three that are not captured are the first two early devaluations of the Danish Krona and the Italian lira devaluation in 22 July 1985.} The crisis probabilities are presented in Appendix A.
3.3 Contagion

Up to this point, the paper has not offered an explicit contagion test; by using a regime-switching estimation to analyse FX movements in the exchange rate mechanism of the EMS it has shown that there is evidence that some, but not all, of the EMS participants faced simultaneous FX pressure during volatile crisis states, i.e. they exhibit increased MPI correlations in the crisis state. During calm periods exchange rates are normally driven by fundamentals, whereas during crisis periods investor confidence/psychology takes over. Changes in market sentiment may not be related to a country’s fundamentals, in which case they constitute the source of contagion.

The timing or geographical proximity of crisis incidents do not necessarily imply the presence of contagion effects. For example, the reason behind currency pressures could be a common shock that induces deterioration of the fundamental macroeconomic indicators in the affected economies. If the shock is unobservable it would
be easy to mistaken the effects of the disturbance for contagion. Therefore, one has to disentangle the role of common factors (international shocks or monsoonal effects) from the international transmission of country-specific shocks. The latter can be further classified as the effect of spillovers, if the transmission is through well-established fundamental links, or as contagion, if the transmission is ‘over and above’ what would be justified by such links.

Under this line of thinking, if a shock in country A (which is not common to country B) induces an increase in volatility in country B (controlling for the two countries’ fundamental links), the crisis can be classified as displaying contagion effects. There are two complications here: first, the source of the shock (the ‘origin’ country) needs to be known in advance; second, we need to adjust the correlations for the fact that they are a positive function of volatility.

Regarding the first issue, we examine the role of Denmark and Italy as the origin countries. As Eichengreen (2000) suggests, the rejection of the Maastricht Treaty by the Danish voters in June the 2nd, 1991 and the competitiveness problems that Italy had accumulated over the years may have led to the demise of the ERM. The tests that follow provide substantial evidence that Denmark exported its volatility to other EMS countries. The evidence for Italy is less conclusive.

Regarding the second issue, if the cross-market correlation was high before-crisis then any shock to country A could have implications for country B. This would be described as interdependence but not as contagion (see Forbes and Rigobon, 2002). Hence, we need to correct for the effects of heteroscedasticity. If this point is not addressed, then the increased volatility in one market—a characteristic of a crisis state—could lead to increased correlations with another market even though the underlying transmission mechanism of shocks has not changed.\footnote{Using this definition, Favero and Giavazzi (2000) find evidence of contagion in the EMS.}

The ‘unconditional’ (corrected) correlations, as suggested by FR are given by:
\[
\rho_U = \frac{\rho_C}{\sqrt{1 + \frac{\sigma_c - \sigma_{nc}}{\sigma_{nc}}(1 - \rho_C^2)}}. \tag{5}
\]

where \(\rho_U\) is the unconditional correlation, \(\rho_C\) is the conditional correlation and \(\sigma\) is the standard deviation of the shock-originating country’s MPI (\(c\) denotes the crisis regime and \(nc\) the non-crisis regime). Dungey et al. (2005a)\(^{14}\) show that this test can be extended into a multivariate regression framework by estimating a system of equations, where for country \(A\) (the first equation of the system) we would have

\[
\left( \frac{\omega_{A,t}}{\sigma_{nc,A}} \right) = \phi_A' \Lambda + \chi_A' (\Lambda \otimes \delta_t) + \nu_{At}, \tag{6}
\]

where \(\omega\) stands for the market pressure index, \(A\) is the destination country, \(t\) denotes time, \(\sigma_{nc}\) is the standard deviation of the non-crisis observations, \(\phi\) and \(\chi\) are \((N - 1) \times 1\) vectors of coefficients, matrix \(\Lambda\) contains stacked MPI observations (explained below) scaled by the non-crisis standard deviations \(\Lambda = \left[ \left( \frac{\omega_{1,t}}{\sigma_{nc,1}} \right) \ldots \left( \frac{\omega_{N-1,t}}{\sigma_{nc,N-1}} \right) \right]\), \(\delta_t\) is a dummy variable whose value is 1 for the crisis observations and 0 for the non-crisis observations and \(\nu_t\) is an error term. The coefficient estimates contained in \(\chi_A\) can be thought of as the effects of the corresponding regressors in the crisis state on country \(A\)’s pressure index. If there is no change in these effects when the system is in a crisis state these coefficients should be zero and contagion is not present.

The first equation in our system is for Belgium, and, including an intercept and a dummy, can be written as

\(^{14}\)Dungey et al. (2005a) provide a useful summary of contagion tests. Other recent tests include Corsetti et al. (2003).
\[
\frac{(\omega_{\text{BEL},t})}{\sigma_{\text{nc,BEL}}} = \phi_{\text{BEL}}^0 + \phi_{\text{BEL}}^1 \delta_t + \phi_{\text{BEL},\text{DEN}} \frac{(\omega_{\text{DEN},t})}{\sigma_{\text{nc,DEN}}} + \phi_{\text{BEL},\text{FRA}} \frac{(\omega_{\text{FRA},t})}{\sigma_{\text{nc,FRA}}} + \phi_{\text{BEL},\text{IRL}} \frac{(\omega_{\text{IRL},t})}{\sigma_{\text{nc,IRL}}} + \phi_{\text{BEL},\text{ITA}} \frac{(\omega_{\text{ITA},t})}{\sigma_{\text{nc,ITA}}}
\]

\[
+ \chi_{\text{BEL,DEN}} \frac{(\omega_{\text{DEN},t})}{\sigma_{\text{nc,DEN}}} \delta_t + \chi_{\text{BEL,FRA}} \frac{(\omega_{\text{FRA},t})}{\sigma_{\text{nc,FRA}}} \delta_t + \chi_{\text{BEL,IRL}} \frac{(\omega_{\text{IRL},t})}{\sigma_{\text{nc,IRL}}} \delta_t + \chi_{\text{BEL,ITA}} \frac{(\omega_{\text{ITA},t})}{\sigma_{\text{nc,ITA}}} \delta_t + \nu_{\text{BEL},t};
\]

the second equation, for Denmark, is

\[
\frac{(\omega_{\text{DEN},t})}{\sigma_{\text{nc,DEN}}} = \phi_{\text{DEN}}^0 + \phi_{\text{DEN}}^1 \delta_t + \phi_{\text{DEN,BEL}} \frac{(\omega_{\text{BEL},t})}{\sigma_{\text{nc,BEL}}} + \phi_{\text{DEN,FRA}} \frac{(\omega_{\text{FRA},t})}{\sigma_{\text{nc,FRA}}} + \phi_{\text{DEN,IRL}} \frac{(\omega_{\text{IRL},t})}{\sigma_{\text{nc,IRL}}} + \phi_{\text{DEN,ITA}} \frac{(\omega_{\text{ITA},t})}{\sigma_{\text{nc,ITA}}}
\]

\[
+ \chi_{\text{DEN,BEL}} \frac{(\omega_{\text{BEL},t})}{\sigma_{\text{nc,BEL}}} \delta_t + \chi_{\text{DEN,FRA}} \frac{(\omega_{\text{FRA},t})}{\sigma_{\text{nc,FRA}}} \delta_t + \chi_{\text{DEN,IRL}} \frac{(\omega_{\text{IRL},t})}{\sigma_{\text{nc,IRL}}} \delta_t + \chi_{\text{DEN,ITA}} \frac{(\omega_{\text{ITA},t})}{\sigma_{\text{nc,ITA}}} \delta_t + \nu_{\text{DEN},t},
\]

etc.

The vector of observations \( \omega \) contains the non-crisis observations endogenously selected by the MS-VAR stacked upon the crisis observations. As mentioned before, both sets of non-crisis and crisis observations are scaled by the standard deviation of the non-crisis observations. As shown in Dungey et al. (2005b) the multivariate version of the FR test in this regression framework is better placed to detect contagion. In addition, whereas the standard errors of (5) are based on a small sample asymptotic adjustment, the standard errors of (6) are least squares errors.

We estimate the system of five equations as seemingly unrelated regressions (SUR), a method that controls for heteroscedasticity and contemporaneous correlation. The results, reported in Table 5, are consistent with the change in correlations across states in Table 4. As mentioned before, we focus our attention on Denmark,
whose rejection of the Maastricht Treaty has often been blamed for triggering pessimistic market expectations that eventually led to the end of the ERM. Italy’s competitiveness problems have also been blamed for the instability in the EMS.

The application of the FRM test shows that Denmark has been indeed affecting other countries’ FX markets. Specifically, pressures in Denmark’s FX market appears to trigger pressures in Belgium and Ireland. It is noteworthy that the opposite is not true, i.e. pressures in Belgium or Ireland do not have a significant effect on Denmark’s MPI movements. The correlation with France under a crisis regime is negative. Both countries appear to be influencing each other, but Denmark’s effect
is greater in magnitude. Denmark’s MPI does not seem to affect Italy’s pressure index. It is, however, affected by it, moving in the opposite direction during a crisis state. Italy also affects France—and is affected to a lesser extent by it. Wald tests of parameter significance confirm the above conclusions.

The analysis presented here has implications for portfolio diversification. Risk-averse investors would like to hold assets whose returns are negatively correlated in a crisis state. Assuming that MPIS move largely because of movements in currencies, this property is exhibited between the Italian lira and the Danish krone (for a shock originating in Italy) and the Danish krone and the French frank (for shocks originating in any of the two countries). As an example, an investor who diversified between krone and franks would limit losses in a crisis state. If, on the other hand, he/she had holdings in krone and Belgian franks there would be no benefit from diversification, as in a crisis state the two currencies would be almost perfectly positively correlated.

4 Concluding Remarks

This paper has used a Markov switching model with fixed transition probabilities to study FX market pressures and contagion in the ERM. Using a market pressure indicator for five participant countries and allowing for regime switching and heteroscedastic errors, we find that most FX market correlations increase during the crisis state.

The features of the model are attractive for this kind of analysis. The use of a continuous crisis variable means that we do not need to choose an arbitrary cut-off point in order to define a crisis. The Markov model allows for a tranquil and a crisis state and assigns probabilities that the system was in one or the other at a given month. The chosen specification does well in defining the EMS’s realignments as crisis states.

We use this endogenous determination of crisis states to implement the Dungey et al. (2005a) multivariate version of the Forbes and Rigobon (2002) test to detect
contagion in the EMS. We consider Denmark and Italy as the source countries (Denmark for rejecting the Maastricht Treaty and Italy because of accumulated competitiveness problems) and find that the former indeed exported its volatility to countries like Ireland and Belgium. Contagion effects appear to exist between Italy and Denmark as well.

A Cycle Dating

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Notes: Regime probabilities are from a MSIH(2)-VAR(2) model. (*) indicates when an actual realignment took place.

REFERENCES


