Euro and Convergence of the Dynamic Structure Of the Stock Markets

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Abstract

This paper examines the impact of the euro's launch on the dynamic structure of the stock markets for EU's member countries. Using a GARCH model for daily stock index for the period January 1995 - June 2004, we find evidence of convergence of the dynamic structure of the stock markets for France, Germany, Spain and Italy. In particular, both the short-term impact and the long-term persistence parameters are much closer among the four countries after the euro than before the euro. The half-lives of volatility shocks among the four countries varies from 10 to 77 days in the pre-euro period, while in the post-euro period, they all lie within a narrow band ranging from 34 to 43 days. Thus, the unification of the currency has helped induce the integration of the stock markets. We further apply a smooth transition regression (STR) model to identify the nature of the structural changes among these stock indices. Our results suggest that all four indices started the adjustment process more than one year before the date of euro's launch.

Keywords: Euro, GARCH Model, Volatility, Information Transmission, STR model

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1. Introduction

On January 1, 1999, an epochal event took place in the arena of international finance：Eleven European countries have replaced their national currencies and introduced a single European currency, the euro. The euro has been introduced at the end of a long convergence process beginning in 1979 with the creation of the European Monetary System (EMS). The euro-11 includes Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain. Bills and coins of the national currencies still remain in circulation as sub-denominations of the euro until January 1, 2002, when they will be exchange against new euro coins and bills. Four member countries of the European Union －Denmark, Greece, Sweden, and the United Kingdom－did not join the first wave. After 2001, Greece joined the euro area when it could meet the objective criteria. Czech will enter the euro club after 2004.

On January 1, 2002, coins and bills of twelve national currencies will finally be exchange for euro coins and bills. For the success or failure of single European currency much depends on the size of the effects described below. Do the gains from reduced transaction costs, the disappearance of exchange rate instability, and greater price transparency outweigh the losses from the cost of introducing the new currency and possible macroeconomics adjustment costs？ There are many positive arguments for euro. For instance, the euro will be the strongest currencies in the world, along with the US Dollar and the Japanese Yen. It will soon become the 2nd-most important reserve currency after the US dollar. According to the view of capital market, the Euro area will integrate the national financial market, leading to higher efficiency in the allocation of capital in Europe. However, there are many arguments against euro, too. After the introduction of Euro, businesses and consumers will have to convert their bills into new ones, and convert all wages and prices into euro. This will involve some costs as corporations and financial institutions need to update computer software for accounting purposes, update price lists, and so on. Another reason is about money devaluing power. If economical conditions are under recession, individual country cannot stimulate its economy by devaluing its currency and increasing exports due to the currency unify as a single symbol.

After the euro is introduced, it changes the dynamic balance of the stock markets in European countries. Has the strong growth in portfolio or/and foreign direct investment flows affected the international transmission of shocks to the euro area? Single currency can reduce the foreign exchange rate risk than before. As to the stock markets more stable or not must be testing. This paper uses data on several stock indices located in euro area and edited by individual countries, so that we can identify the volatility shocks after the Euro is introduced. Volatility transmission is a phenomenon of information flows. After the foreign exchange risk is eliminated between the Euro countries. It is more interesting to explore the issue that the risk premiums of the stock markets during individual member countries have changed or not.

We have considered the evolution of the volatility of daily stock returns for four EMU member countries, namely France, Germany, Spain and Italy over the period 1 January 1995 - 30 June 2004. The test for equality of unconditional variances is carried out in terms of a simple GARCH(1,1) model. To test for the presence of a volatility shift, a dummy variable assuming the value of one starting from 1 January 1999 has been included in the conditional variance equation for GARCH model. After this introduction the paper is organized as follows. In Section 2 we discuss related literature connecting stock markets and volatilities. In Section 3 we introduce theoretical models, dissect the effect of the introduction of the euro by means of a GARCH model with a dummy variable. Section 4 offers discussions on the data and methodology as well as the findings on the stock market integration over time. We also illustrate the empirical results. Section 5, the suitable smooth transition regression model is fitted for discussion in detail. Finally, concluding remarks are presented in Section 6.

2. Literature Review

After a series of monetary innovation in European area, the euro was introduced as single currency for the EMU on 1 January 1999, following an economic, monetary and financial convergence process that had spanned over two decades from the initial creation of the European Monetary System (EMS). Theoretically, it is reasonable for investors to view a single currency zone as a single area of financial opportunity. To a large extent, financial market integration is driven by market forces but constrained by regulatory barriers and the level of integration is neither uniform across market segments nor across time. Morana and Beltratti (2002) attempt to explain why European stock markets have changed with the introduction of the euro, they attribute changes in stock market volatility to the unification of interest rates and stabilization of macroeconomic fundamentals and not to the elimination of exchange rate risk. Billio and Pelizzon (2003) point out the fact that the volatilities in stock markets in European's countries are higher, they also find the volatility spillovers from both the world index and the Germany market have increased after EMU for the most European stock markets. Kim, Moshirian and Wu (2005) find that there has been a clear regime shift in European stock market integration with the introduction of the EMU. In addition they have found that the contribution of currency stability to stock market integration is only significant for the smaller EMU members with historically different economic structures. Most models used in finance suppose that investors should be rewarded for taking additional risk by obtaining a higher return. One way to describe this concept is to let the return of a security be partly determined by its risk. Poterba and Summers (1986) who recommend that the higher volatility for assets should react directly to expectations of risk premium movement in the future. Therefore the unconditional variance of stock return should depend on variances and covariances of such fundamentals. It follows that both first and second moments of returns should be affected by the introduction of the euro to the extent that these phenomena affect fundamentals and expectations thereof. Engle, Lilien and Robins (1987) suggested an ARCH-M specification, since GARCH models are now more popular than ARCH, it is more common to estimate a GARCH-M model. One properties of this model is square root of the conditional variance of asset returns enters into the conditional mean equation. Bollerslev, Engle and Wooldridge (1988) performs multivariate GARCH-M model into the discussion of stock market dynamic and infers the more risk a security, the higher expected return is required. French, Schwert and Stambangh (1987) employ GARCH-M model to analyze the relationship between stock returns and risk premium which listed in NYSE. They test the risk premium hypothesis in terms of volatility and analogous hypothesis is supported. Similar inference is appeared in Chou (1988), too. Ross (1989) considers the variance for the change of asset prices can be viewed as the speed of information transmission under the condition of arbitrage free. It seems implicitly that volatility will magnify while information transmission is speedup. In the past decade, multiple classes of GARCH models have been the technique of choice for research into financial links across stock markets. One of the main reasons is due to the high degree of persistence in the conditional means and variances of asset prices at high frequency levels. It is also well accepted in the empirical finance literature that the volatility of rising and falling financial markets differ and that negative shocks have a greater impact than positive shocks. Hence, variants of these models have been used to accommodate the possibilities of asymmetries in the variance of returns. For the distinguish variations in stock market integration over time, researchers have performed regressions on different sub-periods to gain insight into long-term changes in stock market integration dynamics.

The change in regime should not be regarded as predictable but as a random event. Conventionally, the parameters estimated are constant under traditional econometric methodology. However, once the data generating process appear structure changed, then the traditional approach must be modified in avoiding the empirical results are misleading. The effect of these risk shifts should be taken into account when the target of the research is to discuss the stock market volatility. For this purpose, the dynamics of the volatility process for the major European stock markets are discussed with a Smooth Transition Regression (STR) approach seems reasonable. Indeed, recent studies by Sarantis (1999) shows that STR can describe the influence on the structure change for the stock market.

3. Econometric Methodology

Our aim is to examine whether the introduction of euro has induced information transmission dynamic change in stock market by making inferences from the behavior of daily conditional volatility of stock index returns and related parameters based on feasible model.

Asset prices depend on the information currently available in a market. Ross (1988) assumes that there exists an economy that is devoid of arbitrage and proceeds to provide a condition under which the no-arbitrage situation will be sustained. In Ross (1988), Theorem 2 implies that the variance of price change will equal to the rate of information flow. The implication of this is that the volatility of the asset price will increase as the rate of information flow increases. Any change in the rate of information flow will change the volatility of the price of the stock market. If this is not the case, arbitrage opportunities will be available. It follows that if euro increase the flow of information, then in the absence of arbitrage opportunities the volatility of the stock market must change. Therefore, unless information remains constant, volatility must be time varying, even on a daily basis. Whether or not this actually happens is ultimately an empirical question.

To analyze the impact of euro on stock market volatility, a variant of the GARCH type models are employed, which allows for variant response of volatility to news. It is a natural way to capture the time varying nature of volatility is to model the conditional variance as a GARCH process. GARCH models the conditional variance of the error term as a linear function of the lagged squared residuals and the lagged residual conditional variance. To see how this model arises consider the simple GARCH(1,1) specification

$$
\begin{aligned}
&R_t = \varepsilon_t \\
&h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (1)\\
&\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)
\end{aligned}
$$

where h_t is the conditional volatility at time t, α_0 is a coefficient that relates the past value of the squared residuals,(ε_{t-1}^2), to current volatility, and β_1 is a coefficient that relates current volatility to past period of volatility. The Greek letter Ω_{t-1} denotes the information set. The advantage of a GARCH model is that it captures the tendency in financial data for volatility clustering. In analyzing the behavior pre-euro and post-euro it is necessary to isolate influences not due to euro so that the impact of euro can be assessed more readily. Having isolated market-wide movements, the impact of euro is then captured by the introduction of a dummy variable. Such a model is represented by the following modification.

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_t \qquad (2)$$

where D_t is a dummy variable taking on the value 0 pre-euro and 1 post-euro. If the euro dummy is statistically significant, then euro has an impact on the volatility of the stock market. For a phenomenon to be identified is integrated GARCH (I-GARCH) that the parameters α_1 and β_1 in equation (1) and/or (2) must together sum to unity. This implies the presence of an approximate unit root in the autoregressive polynomial. With I-GARCH the model specification is characterized by non-stationary variables, such that any shock to the variance of a process is permanent.

There are several stages to the analysis undertaken in this article. First, the question of whether euro has increased or decreased the level of volatility is analyzed by equation (1) and (2) with a dummy variable that takes on the value 0, pre-euro and 1, post-euro. The modified equation is estimated for the stock market associated with the whole period. A significant positive coefficient suggests euro has increased stock market volatility, whereas a negative value suggests the opposite. The second point to note in comparing results for before and after the onset of euro is that the onset of euro has not led to a change in the nature of volatility. The large increase in α_0 post-euro together with the changes in α_1 and β_1 indicate that there has been an increase in the unconditional variance. The unconditional variance is given by $\frac{\alpha_0}{1-\alpha_1-\beta_1}$. Judging from unconditional variance, one can infer whether is consistent with more information being transmitted to the stock market as a result of the onset of euro. Similarly, the value of α_1 has increased post-euro, suggesting an increase in volatility. Just as α_1 reflects the impact of recent news, and β_1 can be thought of as reflecting the impact of "old news". The coefficient β_1 states the impact of price changes relating to days prior to the previous day and thus to news which arrived before yesterday. The increase in the rate of information flows to be anticipated from the onset of euro is expected to lead to a reduction in uncertainty regarding previous news. This will lead to a fall in the persistence of information.

In finance, the return of a security may depend on its volatility. To model such a phenomenon, one may consider the GARCH-mean (GARCH-M) model. Also see Engle, Lilien and Robins (1987). A GARCH-M model can be written as

$$
\begin{aligned}
R_t &= a_0 + \delta\sqrt{h_{t-1}} + \varepsilon_t \\
h_t &= \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (3) \\
\varepsilon_t|\Omega_{t-1} &\sim N(0, h_t)
\end{aligned}
$$

where a_0 and δ are constants. The parameter δ is called the risk premium parameter. A positive δ indicate that the return is positively related to its volatility. The risk premium is an increasing function of the conditional variance. In other words, the larger the conditional variance of returns is, the greater the compensation for an agent to hold the long-term assets. GARCH-M model is used to discuss the relationship between expected return and risk premium, parameter δ can response the degree of adjustment for return due to risk premium. From GARCH-M model implies that there are serial correlations in the return series. The serial correlations are introduced by those variables in the volatility process. The existence of risk premium is another reason that some historical stock returns have serial correlations (also see Tsay (2005)). We perform GARCH-M model to the event of euro for empirical data later.

4. Data and Empirical Results

4.1 Data Description and Statistics

In this article, daily closing prices on stock market indexes are used for the countries shown in Table 1 for pre-euro and for post-euro. Data closing price indices for the period 1 January 1995 to 30 June 2004 are adopted. Logarithmic returns are constructed from these series. All data are from Yahoo Finance, the web site is located at (http://finance.yahoo.com/) offered by Reuters.

Table 1

Data Description and Statistics (daily returns)

Pre-euro(1 January 1995 to 31 December 1998: sample size 944)						
	Mean	St.D	Skewness	Kurtosis	Maximum	Minimum
France CAC	0.081	1.350	0.133	7.758	9.757	-6.185
Germany DAX	0.093	1.355	-0.394	6.902	8.116	-6.450
Spain IBEX 35	0.122	1.374	-0.555	7.048	6.468	-7.327
Italy MIBTEL	0.091	1.454	-0.027	5.713	7.861	-6.634
Post-euro(1 January 1999 to 30 June 2004: sample size 1339)						
France CAC	-0.023	1.653	-0.071	5.195	7.002	-8.543
Germany DAX	-0.016	1.887	-0.195	6.173	7.553	-13.919
Spain IBEX 35	-0.015	1.555	-0.049	4.456	6.028	-7.909
Italy MIBTEL	-0.082	1.358	-0.527	9.841	6.832	-12.737

Note:

1. This table reports the basic descriptive statistics for the logarithmic stock returns before and after the introduction of the euro.
2. Return is defined as $100 \times [\log(p_t)-\log(p_{t-1})]$

Table 1 contains summary statistics on stock markets for four euro-countries. The first sub-sample period (1 January 1995 to 31 December 1998) indicates the phase before euro is introduced. The second sub-sample (1 January 1999 to 30 June 2004) is the extended post-euro phase. A break down of the full sample period contributes to our understanding of the long-term dynamics of the stock market integration process. In table 1, we note that the sign of returns from individual countries all appear positive during the pre-euro period but invert to negative average returns for the post-euro period. This could simply be attributed to the law of averages in that the idiosyncratic differences in information transmission are more predictable for the value-weighted average of the whole European zone. As is evident in Table 1, volatility in returns tends to be larger for Italy than other countries in the pre-euro stage, but smaller after the euro is introduced. As to the indicator for skewness, only in France, during the pre-euro period skew to the right. Others are all own positive skewness. In addition, no matter what countries for pre- and post-euro periods, the coefficient of kurtosis always more than three. Namely, the fat tails for return's distribution is existed. It is seems that GARCH model can capture these patterns and can be fitted into these data. In Figure 1 we have plotted the time series of the returns for France, Germany, Spain and Italy. The Figure 1 shows that regardless pre- or post-euro period, volatility clustering is evident. This is consistent with the conjecture that inferred from GARCH model. It appears that such model used here is reasonable.

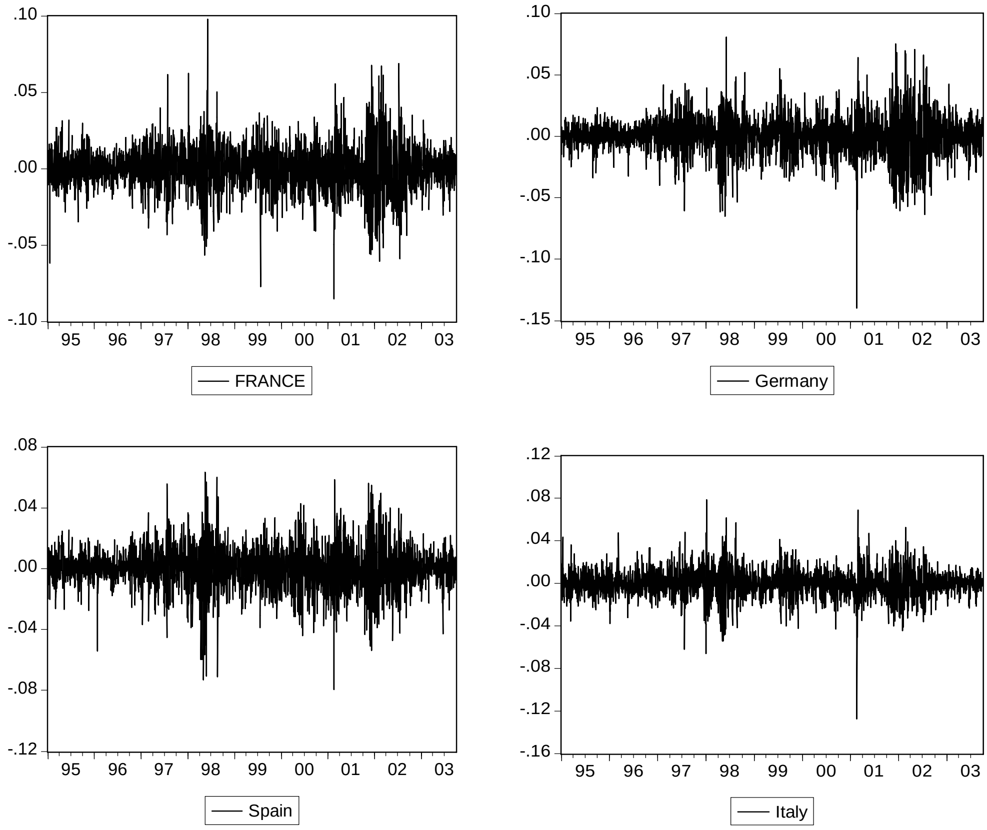

Figure 1: Daily returns series for France, Spain, Germany and Italy

(1 January 1995 to 30 June 2003)

For the requirement of econometric approach, we perform the test for GARCH effects as below. The results are simply reported in Table 2. As can be noticed from the Table 2, in none of the cases, the value of the test statistic is greater than the critical value from the χ^2 distribution with conventional significant level 5%. So we could reject the null hypothesis. The evidence therefore apparently to suggest that there is GARCH effect for the series of every stock market based on our sample.

Table 2: The GARCH Effects Test

k	France	Germany	Spain	Italy
1	9.425**	8.721**	7.754**	10.563**
2	20.958**	17.123**	12.829**	22.749**
3	21.362**	24.822**	14.523**	23.372**
4	22.328**	29.876**	16.214**	24.152**
5	25.027**	30.148**	18.262**	27.444**
6	27.501**	32.330**	19.093**	29.406**
7	31.435**	34.810**	29.059**	38.056**
8	36.709**	38.391**	33.940**	40.065**
9	42.752**	39.122**	34.312**	42.910**
10	44.636**	41.028**	36.664**	51.730**
11	47.850**	42.706**	46.106**	52.118**
12	48.821**	44.656**	57.029**	54.184**

Note : 1.** symbols significant level 5% 。

2. Numeric is test statistic TR^2 (the number of observations multiplied by the coefficient of multiple correlation) for LM(k) test. The TR^2 is distributed as a χ^2 (k), where T is sample size, R^2 is the coefficient of determination by postulated linear regression, and k is the own lags to test for ARCH of order k. The mean equation is as below: $R_t = a_0 + a_1 R_{t-1} + \varepsilon_t$ 。

3. Sample period is from 1 January 1995 to 30 June 2004.

4.2 Empirical Results for Simple GARCH(1,1)

Checking the relationship between information transmission and volatility dynamic for euro, data is dividend into two sub-periods, namely, pre- and post-euro period. It is worth to noticing the changes for coefficients based on GARCH model from pre-euro period to post-euro period. Empirical results are demonstrated as Table 3:

Table 3 GARCH(1,1) Model for pre-euro and post-euro period

$$R_t = \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$
$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

	Country	UVAR	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\alpha}_1 + \hat{\beta}_1$	$Q(12)$	$Q^2(12)$
Sample period: 1995/1/1-1998/12/31								
Pre-euro	France	2.000	0.022*	0.067***	0.922***	0.989	11.147	8.625
			(1.931)	(5.960)	(60.890)		[0.516]	[0.735]
	Germany	2.333	0.021***	0.090***	0.901***	0.991	11.686	5.428
			(3.504)	(5.583)	(53.681)		[0.471]	[0.942]
	Spain	1.815	0.049***	0.119***	0.854***	0.973	29.991	10.339
			(3.217)	(5.002)	(28.806)		[0.185]	[0.586]
	Italy	2.029	0.138***	0.154***	0.778***	0.932	30.576	13.586
			(3.585)	(6.257)	(21.589)		[0.166]	[0.328]
Sample period: 1999/1/1-2004/6/30								
Post-euro	France	2.688	0.043***	0.084***	0.900***	0.984	11.639	5.576
			(2.966)	(7.779)	(68.144)		[0.475]	[0.936]
	Germany	3.421	0.065***	0.100***	0.881***	0.981	14.282	12.938
			(2.971)	(10.268)	(58.240)		[0.283]	[0.374]
	Spain	2.150	0.043***	0.090***	0.890***	0.980	10.253	10.575
			(2.997)	(5.916)	(49.330)		[0.594]	[0.566]
	Italy	2.211	0.042***	0.126***	0.855***	0.981	14.472	9.790
			(3.709)	(12.112)	(51.263)		[0.272]	[0.634]

Notes:

1.*,**and *** symbol the significant level at 10%, 5% and 1%, respectively.

2. The t-statistics is arranged in ( ), and the number in [ ] is p-value. Q symbols Ljung-Box(1978) Q-statistics. Q^2 is Ljung-Box Q^{2-} statistics.

3.UVAR denotes unconditional variance that can be calculated by the formula $\alpha_0 /(1-\alpha_1-\beta_1)$ from GARCH model.

Essentially, the GARCH(1,1) model uses three parameters to characterize the evolution of the volatility process. The parameter α_0 indicates an inherent uncertainty level. The parameter α_1 is the coefficient of the lagged residual squared. It signifies the importance of the recent innovations or "news" in the market. The parameter β_1 is the coefficient of the lagged conditional variance. It controls the dependence of future volatility on "old news" because it relates to the previous day's conditional variance which is by itself a function of information prior to the previous day. A higher α_1 also indicates that the news is transmitted faster to the future variances. On the other hand, a higher β_1 indicates a higher persistence of volatility shocks and a slower speed of information. We test the information transmission hypothesis by testing the changes in these coefficients before and after the euro trading. From Table 3, α_1 is higher than pre-euro appears in France and Germany. Similar to α_1 for information transmission, coefficient β_1 is lower than pre-euro period. Evident from the evidence by France and Germany derived from GARCH(1,1) model, the hypothesis of information transmission is supported for the time being. As to Spain and Italy, after euro is introduced, the efficiency of information transmission had not improved apparently. One of the possible reasons is that for matching the regulation requirement. Italy and Spain have decreased their annual inflation rate by several percentage points in a short time. The short-term nominal interest rate in Italy has decreased from 11% to 3% in only two years. Economic convergence has therefore left concrete signs in the macroeconomic structure. The introduction of the euro should be associated with a reduction of volatility of macroeconomic fundamentals of the historically unstable European economics like Spain and Italy, due to convergence of the stochastic process of fundamentals to that of the more stable northern European economies (Similar inference also can see Morana and Beltratti (2002) and Flannery and Protopapadakis (2002)). However, judging from the long term unconditional variance, these four euro members all reflect a phenomenon of increase.

After the euro is introduced, we find $\alpha_1 + \beta_1$ for the post-euro periods for France and Germany in Table 3 is decreasing, even not strongly. The evidence shows that the volatility process for the post-euro periods is less affected by large shocks whose effect will diminish at a faster speed than of the pre-euro periods for France and Germany. However, analogous inference has not appeared from Italy and Spain. Using the parameters of the volatility process, we also compute some statistics to help indicate the difference between different dynamic processes. Specifically, we adopt the method by Chou (1988) to calculate the half-lives of volatility shocks for these different structures. The half-lives of volatility shocks are 63, 77, 25, and 10 days for pre-euro periods and 43, 36, 34 and 36 days for post-euro periods for France, Germany, Spain and Italy, respectively. Comparing with pre-euro periods, the half-lives of volatility shocks in the post-euro periods have decreased for France and Germany, while the opposite changes have occurred for Spain and Italy. Thus, the adjustment of volatility dynamics seems to indicate a movement to an integration of the four markets.

4.3 Empirical Results for Modified GARCH(1,1)

Dummy variables allow us to construct models in which some or all regression model parameters change for some observations in the sample. They are often called dichotomous or binary variables as they take just two values, usually 1 or 0, to indicate the presence or absence of a characteristic. That is, a dummy variable D_t is

$$D_t = \begin{cases} 0, pre-euro \\ 1, post-euro \end{cases}$$

We perform the modified GARCH(1,1) model with dummy variable embedded in the volatility and the empirical results illustrated as Table 4.

Table 4: The modified GARCH(1,1) model with dummy variable

$$R_t = \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_t$$
$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

Sample period	Country	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\lambda}$	$Q(12)$	$Q^2(12)$
Full sample	France	0.027***	0.075***	0.912***	0.006	16.496	5.867
1995/1/1-2004/6/30		(3.292)	(9.832)	(96.605)	(0.919)	[0.170]	[0.923]
	Germany	0.026***	0.096***	0.891***	0.026	11.488	9.178
		(4.661)	(11.999)	(87.832)	(1.404)	[0.488]	[0.688]
	Spain	0.034***	0.096***	0.888***	0.007	14.127	10.483
		(4.471)	(8.089)	(63.240)	(1.000)	[0.293]	[0.574]
	Italy	0.075***	0.134***	0.838***	0.020	25.053	9.855
		(4.550)	(13.140)	(52.997)	(1.316)	[0.115]	[0.629]

Notes:

1. *, ** and *** symbol under the significant level 10%, 5% and 1% is significant.
2. The number in ( ) is t-statistics, and the number in [ ] denote p value.
3. Q symbol Q statistics derived by Ljung-Box(1978) and the Q^2 is the value for Ljung-Box Q^2 statistics.

No matter what any stock market in our sample, judging from the estimate of coefficient $\hat{\lambda}$ for dummy variable D_t are all insignificant from zero based on conventional statistical inference in Table 4. One reasonable conjecture is that the news about euro-introduction is known before 1 January 1999 and had reacted by the participants in the stock markets. Due to the date for the event of euro introduction can be classified as public information, it seems reasonable to make such an influence and remark by the efficient market hypothesis.

4.4 Empirical Results for GARCH-in-Mean

We now extend our economic model of stock return for euro's introduction so that the expected return depends positively on the perceived riskiness of the stock return. Suppose that the riskiness can be adequately represented by the conditional own square root variance of the forecast errors of returns. This structure of expected returns can be represented by the GARCH in mean model. The GARCH in mean results from this specification are shown in Table 5. From a statistical perspective, the model is adequate in explaining the variations in the pre-euro sub-period. However, insignificant of explanatory variables with risk premium during the post-euro sub-period suggests that the influence of risk premium factor on stock market is declining. But the effects still maintain positive for the relationship between expected return and risk premium.

Table 5: GARCH(1,1)-M Model

$$R_t = a_0 + \delta\sqrt{h_t} + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$
$$\varepsilon_t|\Omega_{t\text{-}1} \sim N(0, h_t)$$

Sample period	Country	$\hat{a}_0$	$\hat{\delta}$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$Q(12)$	$Q^2(12)$
Pre-euro (1995/1/1-1998/12/31)								
Pre-euro	France	0.078	0.159***	0.019*	0.065***	0.925***	10.859	7.458
		(0.542)	(2.881)	(1.901)	(6.181)	(69.757)	[0.541]	[0.826]
	Germany	0.033	0.088***	0.026***	0.106***	0.883***	11.120	4.164
		(0.853)	(3.471)	(3.733)	(5.865)	(49.235)	[0.519]	[0.980]
	Spain	0.109	0.029***	0.055***	0.129***	0.842***	20.283	7.580
		(0.942)	(3.907)	(3.384)	(5.086)	(27.136)	[0.062]	[0.817]
	Italy	0.030	0.108**	0.132***	0.152***	0.782***	25.528	14.588
		(0.178)	(2.448)	(3.544)	(6.195)	(22.394)	[0.103]	[0.265]
Post-euro (1999/1/1-2004/6/30)								
Post-euro	France	-0.094	0.092	0.039***	0.080***	0.905***	12.037	5.819
		(-0.688)	(0.929)	(2.772)	(7.712)	(70.349)	[0.443]	[0.925]
	Germany	-0.179	0.143	0.062***	0.099***	0.883***	14.139	13.161
		(-1.230)	(1.497)	(2.852)	(10.108)	(58.728)	[0.292]	[0.357]
	Spain	-0.038	0.053	0.035***	0.085***	0.900***	10.194	12.278
		(-0.288)	(0.535)	(2.735)	(6.103)	(54.802)	[0.599]	[0.424]
	Italy	-0.196	0.126	0.041***	0.127***	0.855***	15.282	10.633
		(-1.396)	(1.577)	(3.403)	(11.526)	(51.220)	[0.226]	[0.561]

Notes:

1. *, ** and *** symbol under the significant level 10%, 5% and 1% is significant.

2. The numbers in ( ) are t-statistics, and the numbers in [ ] denote p values.

3. Q and Q^2 are Ljung-Box(1978) Q statistics for normalized residuals and squared normalized residuals.

5. Smooth Transition Regression (STR) Model

The parameters in the empirical model might alter due to interventions by monetary institutions or government's policies. Hence the conditional mean in the equation may change from one level to another level. The thresholds are the discontinuity points of the conditional mean function. Conventional GARCH type family cannot capture such a phenomenon. In response to this criticism, STR model have been proposed which can depict part outline for structural shifts, also see Teräsvirta (1994) and the reference therein. The STR models provide a more realistic representation of aggregate behaviors in economies while a single structural break model does not. The STR model is more useful in describing the characteristic of smooth transferring than threshold auto-regression (TAR) model and Markov regime-switch model. The later two models are feasible in describing the abrupt structure change, see Sarantis (1999). Thus, we pick up the stock markets data for euro members and fit them into the STR model. The purpose here is to check the latent possibility for smooth transferring in model's parameters. A time series y_t is said to follow a STR(T) model if it satisfies

$$y_t = x_t'\pi_1 + x_t'\pi_2 F(z_t) + u_t \qquad t = 1,.........,T \tag{4}$$

where $x_t = (1, y_{t-1},..., y_{t-p}, x_{1t},..., x_{qt})'$ is a vector with $m \times 1$, $m = 1 + p + q$, as to the $\pi_1 = (\pi_{11},...,\pi_{1m})$ and $\pi_2 = (\pi_{21},...,\pi_{2m})$ both are parameter vector with $m \times 1$, μ_t is an error term with the assumptions $E(u_t) = 0$, $E(x_t u_t) = 0$ and $E(z_t u_t) = 0$. The symbol $F(z_t)$ is a smooth transition function allowing the model to switch smoothly between regimes. In practice, $F(.)$ often assumes one of three forms – namely, logistic, exponential, or a cumulative distribution function. Above all, the two former types are more popular than the last. The variable z_t denotes transferring variable, z_t offers a suitable platform for the transition between $E\left(y_t \middle| x_t\right) = x_t{}'\pi_1$ and $E\left(y_t \middle| x_t\right) = x_t{}'(\pi_1 + \pi_2)$. In the beginning, when the parameter is unchanged, namely $F(Z_t) = 0$. The STR can demonstrate as $E\left(y_t \middle| x_t\right) = x_t{}'\pi_1$ for the time being. When structure switching is happening, then the function value for $F(Z_t)$ is altered from zero and approaching to unity and the structure converge to the structure of $E\left(y_t \middle| x_t\right) = x_t{}'(\pi_1 + \pi_2)$. According to the terminology from econometrical literature, the LSTR is called. Another type for STR is called ESTR. The major distinction between LSTR model and ESTR is purely in transferring process. If the initial value for $F(Z_t)$ is equal to unity and transferring to zero, then coming back to unity. This type of structure is called ESTR. The function forms for LSTR and ESTR can be illustrated as follows:

LSTR:

$$F(t) = F(t,\gamma) = (1 + \exp\{-\gamma(t^k + \alpha_1 t^{k-1} + \ldots + \alpha_{k-1} t + \alpha_k)\})^{-1} - 1/2\,, \quad k = 1,3 \qquad (5)$$

ESTR:

$$F(t) = F(t,\gamma) = 1 - \exp\{-\gamma(t-\alpha)^2\} \qquad , \quad k = 2 \qquad (6)$$

where t denotes the time trend, and can be viewed as the transition function. α symbols the critical value for structure change and γ can describe the structure transferring speed. It can be easily shown that F(t)$\rightarrow 0$ when $\gamma \rightarrow 0$. In this case, equation (4) becomes a usual linear model. When $\gamma \rightarrow \infty$, there is a single structural break in the parameters. When k=1,3, the first order Taylor approximation of $F(t;\gamma)$ at $\gamma = 0$ is

$$F(t;\gamma) \approx F(t;0) + F'(t;0)\gamma = a_1\gamma(t^k + \alpha_1 t^{k-1} + \ldots + \alpha_k) \qquad (7)$$

Substitute this equation into equation (4) to yield

$$y_t = x_t^{'}\pi_1 + a_1\gamma x_t^{'}\pi_2(t^k + \alpha_1 t^{k-1} + \ldots + \alpha_k) + u_t \qquad (8)$$

When k=2, the second order Taylor approximation of $F(t;\gamma)$ is

$$F(t;\gamma) \approx F(t;0) + \frac{1}{2}F''(t;0)(t-\alpha)^2 = a_2\gamma(t-\alpha)^2 \quad (9)$$

Then equation (4) with k=2 can be expressed as

$$y_t = x_t'\pi_1 + a_2\gamma x_t'\pi_2(t-\alpha)^2 + u_t \quad (10)$$

Equation (8) and (10) can be rearranged to a re-parameterized model.

$$y_t = \Phi_{10} + x_t\Phi_1 + \sum_{j=1}^{k}\lambda_j t^j + \sum_{j=1}^{k}(x_t t^j)'\varphi_j + u_t \quad (11)$$

The null hypothesis $H_0 : \gamma = 0$ become

$$H_0 : \lambda_j = 0, \varphi_j = 0, \quad \text{j=1,…,k.} \quad (12)$$

The variable Z_t can be generalized to include additional state variables that are thought to influence the structure by economical theory. Let $Z_t = x_{t-d}$, where d is called the time lag parameter, then equation (4) can treat as smooth transition autoregressive model (STAR). If economic theory does not indicate the appropriate specification of x_{t-d} or it is difficult to do so, the STAR model with $Z_t = t$ will be a suitable candidate for modeling the dynamic behavior of the underlying data generating process. In particular, most empirical studies show that one can apply STAR models to financial time series analysis with $Z_t = t$, and build into a STR framework. In other words, the concept of time trend is incorporated into transition function. Implying such model owns the property of smooth transferring with time. Meanwhile, one can test whether the coefficients change or not in the STR model around distinct time phases. If the estimates for parameters are changed in statistics, then we can infer that the data dynamic structure is changed. For example, if the transition function $\mathrm{F(t)}$ is equal to zero, for $\mathrm{t} \le \mathrm{t}_0$ and $\mathrm{F(t)}$ is equal to unity, for $\mathrm{t} > \mathrm{t}_0$, then the data can be called as a pattern with single break point.

One econometric procedure to test for smooth transition structure in the presence of a structural break involves using Lagrange Multiplier (LM) type testing suggested by Lin and Teräsvirta (1994). LM type test has an asymptotic χ^2 distribution under the null hypothesis H_0: $\gamma = 0$ in equation (5) and (6). By using similar steps to derive the LM test, there are two steps to obtain the test statistic. First regress y_t on x_t to obtain the residual sum of squares, SSR_0. Second, construct an auxiliary regression for the residuals from the first step on x_t and $x_t t^j$ to get the residual sum of squares, SSR_j, j=1,2,…,k. LM test statistics can separate into three types, i.e. LM_1, LM_2 and LM_3. The problem is to determine whether an observed series is suitable modeled by LM_1, LM_2 or LM_3. The implementation of Lin and Teräsvirta (1994) technique is straightforward:

Step 1: Estimate the regression for variable on variable , and collect the sum of square residuals (SSR_0).

Step 2: Using the residuals which collected from step 1 with x_t series and $x_t t^j$ series , then perform another estimates for auxiliary regression. The sum of square residuals (SSR_j) is collected.

Step 3: Construct the LM statistics as bellows:

(13)

where T is the sample size and LM_j follows a Chi-square distribution with degrees of freedom k×m. Here, the LM_1, LM_2 and LM_3 are extracted for our analysis.

We analyzed STR model with four euro countries, and the concrete model is listed below.

$$\Delta y_t = a_1 + \sum_{i=1}^{n} b_i \Delta y_{t-i} + \left[c_1 + \sum_{j=1}^{k} d_i \Delta y_{t-j} \right] F(Z_t) + \varepsilon_t \qquad (14)$$

Where represents logarithmic stock index for each sample markets, is the first difference for stock index for euro countries. The function is a transition function and is transition variable. Test criteria used here to determine appropriate lag lengths is AIC. , , and are all parameters to be estimated. If the estimated parameters with smoothing change, then we can obtain a few insights from equation (14). Surely, the timing for real structure break point within their stock markets can be found for euro countries. Lin and Terasvirta (1994) suggest a sequence of nested tests to choose the appropriate k as follows. (i) If the null hypothesis in equation (12) is rejected, take equation (11) as the maintained model and first test

$$H_{03} : \lambda_3 = 0, \varphi_3 = 0 \quad (15)$$

against its complement. Then test

$$H_{02} : \lambda_2 = 0, \varphi_2 = 0 \,|\, \lambda_3 = 0, \varphi_3 = 0 \quad (16)$$

and finally test

$$H_{01} : \lambda_1 = 0, \varphi_1 = 0 \,|\, \lambda_2 = 0, \varphi_2 = 0, \lambda_3 = 0, \varphi_3 = 0 \quad (17)$$

But it is not necessary to run this test again since it is the same test against equation (14) for k=1. After deriving those specification tests, compare the p values and select the smallest one to choose k to estimate the nonlinear model in equation (4) by nonlinear least squares method.

Table 6: LM test and STR Model Specification Test

		LM type test			Specification test		
	Time lag	LM_1	LM_2	LM_3	H_{03}	H_{02}	H_{01}
France	2	14.969	18.491	25.499	11.740	18.484	25.499
		(0.061)	(0.046)	(0.025)	(0.059)	(0.017)	(0.025)
Germany	1	13.803	18.168	28.485	16.080	24.693	28.485
		(0.084)	(0.047)	(0.022)	(0.046)	(0.018)	(0.022)
Spain	2	9.160	14.427	22.390	12.968	18.828	22.390
		(0.093)	(0.069)	(0.036)	(0.050)	(0.016)	(0.036)

Italy	1	12.223	18.4883	28.220	16.692	26.015	28.220
		(0.088)	(0.032)	(0.014)	(0.052)	(0.001)	(0.014)

Note: p-value is posted in each bracket for LM type test and LM type test. Time lag length is determined by minimum AIC criterion under linear regression.

Judging from LM type tests, the null of constant parameters are strongly rejected by the data. In addition, through a specification test that we can find regardless which country, the p-value is minimization under H_{02} statistics. Hence, it is proper for performing the STR model embedded in k=2 for stock market data based on our framework. The outcome of the empirical STR model is reported in Table 7.

Table 7: The Results for STR model

$$\Delta y_t = a_1 + \sum_{i=1}^{n} b_i \Delta y_{t-i} + \left[c_1 + \sum_{j=1}^{k} d_i \Delta y_{t-j} \right] F(Z_t) + \varepsilon_t \quad \forall i = j$$

$$F(t) = F(t;\gamma) = 1 - \exp\left\{-\gamma(t-\alpha)^2\right\}$$

	France	Germany	Spain	Italy
$\hat{a}_1$	-0.002*	0.001*	0.002**	0.006**
	(-1.686)	(1.763)	(2.446)	(2.523)
$\hat{b}_1$	0.076	0.056	0.122**	0.042
	(1.162)	(1.250)	(2.324)	(0.242)
$\hat{b}_2$	-0.186**	—	0.088*	—
	(-2.573)		(1.875)	
	0.003**	-0.002*	-0.002**	-0.006**
	(2.154)	(-1.896)	(-2.358)	(-2.463)
$\hat{d}_1$	-0.074	-0.091*	-0.148**	-0.032
	(-1.015)	(-1.655)	(-2.422)	(-0.179)
$\hat{d}_2$	0.182***	—	0.071	—
	(2.393)		(1.188)	
$\hat{\gamma}$	0.271	0.031	2.903	5.986
	(1.289)	(0.874)	(1.096)	(1.125)
$\hat{\alpha}$	15.201***	7.059***	48.294**	7.329***
	(31.144)	(4.160)	(3.152)	(58.770)
Logl	6289.381	6072.106	6368.614	6501.506
AIC	-5.515	-5.324	-5.584	-5.700

SBC	-5.497	-5.308	-5.564	-5.685
Q(12)	-0.201	0.109	-0.019	-0.127
	[0.111]	[0.079]	[0.297]	[0.122]
$Q^2(12)$	-0.100***	0.178***	0.087***	0.109***
	[0.000]	[0.000]	[0.000]	[0.000]
JB	883.237***	464.301***	500.316***	350.846***
	[0.000]	[0.000]	[0.000]	[0.000]

Note: *, ** and *** symbol significant in statistics under the significance level 10%, 5% and 1%, respectively. The number in (.) is t-statistics and in [.] is p-value. Logl denote maximum likelihood value, Q expresses the Ljung-Box(1978) Q-statistics, Q^2 is Ljung-Box Q^2-statistics and JB is Jarque-Bera statistics for normality. The time lag length is determined by AIC and SBC criterion. We can find the proper time lag length for independent variable is 2, 1, 2 and 1 corresponding to France, Germany, Spain and Italy, respectively.

From Table 7, γ represent the transferring speed for parameter change. Even γ is not significant by conventional statistics views in STR model for each country, but there are evident distinction among these countries. The estimated value of γ is 5.986 for Italy and 2.903 for Spain. However, the estimated value for γ is 0.271 and 0.031 in France and in Germany, respectively. We can infer that the event of euro's introduction makes variant impact in terms of the speed for market structural switch. For comparing the transfer speed, we depict their transition function in Figure 2. Each plot for transition function is shown U-shape with time axis. Their transferring speed are distinct each other. Specially, in France and Germany, the transferring speed is moderate. Inversely, the tempo is more violent in Spain and Italy.

As to the aspect of transition timing, one can indicate the transition time point from figure 2 roughly. In Spain, the structural change happened in May, 1996. The three others seem observed around September, 1997. Apparently, the news for euro has been reacted in each stock market before 1 January, 1999. In other words, there are not special impacts to each member country at 1 January, 1999. Thus, before euro is introduced formally, the volatility is increased in each euro member country. Similar to we stated at section 4 in this paper, the risk premium for investing stock market is significant before euro.

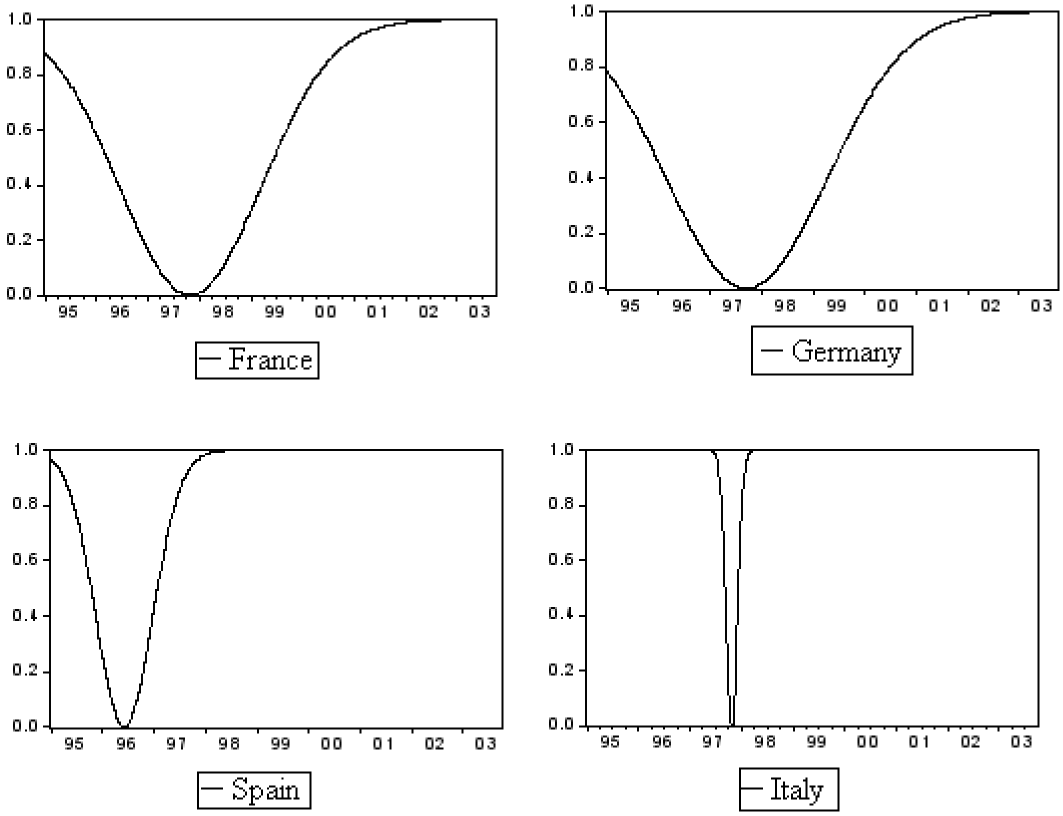

Figure 2: Smooth Transition Function Plots for France, Germany, Spain and Italy

6. Conclusions

In this paper we have analyzed the volatility structure of four major European stock markets. The purpose of this paper is to test the changes in dynamic structure brought about by the introduction of the euro. For this purpose we have compared the dynamics of the conditional volatility process estimated by several models, a simple GARCH model, a simple GARCH with dummy variable model, a GARCH-in-mean model and a STR model characterized by structural change. We have found that the implications of these models are very interesting and different. The GARCH model finds evidence of convergence after the euro's introduction in the dynamic structure of the volatility process. The half-lives of volatility shocks among the four countries varies from 10 to 77 days in the pre-euro period, while in the post-euro period, they all lie within a narrow band ranging from 34 to 43 days. The STR model also suggests the existence of structural change during the sample period of our study. In particular, we have found that a STR model is a suitable characterization of the data and that can detect significantly different patterns among the four European markets. As far as the transition process is concerned, there are signals of an early reaction happened in the Spain stock market. The timing for transition point is triggered about one to two year or so early before the introduction of euro.

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