Macroeconomic Determinants of European, Australian and Korean Stock Market
-유럽, 호주와 한국 주식시장에서의 거시경제요인들에 의한 영향분석-

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요 약

이 논문은 거시경제변수가 유럽, 호주, 한국의 주식시장 변동성에서 시간에 따른 변화(Time Variation)를 설명할 수 있는지에 관하여 조사하는데에 목적을 두고 있다. 그리고 이 논문은 미국에서 발표된 논문들의 결과와 달리 많은 경우에서 주식시장 변동성의 시간에 따른 변화가 과거의 화폐적 또는 실물적 거시경제 요소의 변화 가능성에서 통계적으로 유의하게 영향을 받는 지를 알 수 있었다. 따라서 자본 및 포트폴리오 배분에 대한 중요한 의미를 가지고 있다. 한국의 경우 경제회복에 따라 통화와 산업생산의 변동성 증가가 이뤄지면 주식시장의 성장에 중요한 역할을 할 수 있을 것이다. G7국가중에서 상대적으로 소규모국가인 이태리와 네덜란드에서도 위에서와 같은 결과들을 발견할 수 있었다. 한편 한국에서 특이한 점은 경제회복 이후에는 산업생산증가율의 증가가 통화량의 증가보다 더 주식시장에 중요한 영향을 줄 것 임을 알 수 있다.

1. Introduction

Enhanced understanding of the determinants of market volatility has many important implications for capital markets and corporate finance. For example, Bollerslev, Engle and Wooldrige (1988) find evidence that stock market volatility is priced in the US market and as a result affect the average cost of capital, allocation efficiency, and the overall health of the economy. Solnik (1993) and Harvey (1993) discuss the portfolio allocation implications when information including market volatility is predictable. Essentially, one can find portfolios which

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first-order stochstically dominate alternatives if one has a better forecast of what tomorrow's portfolio variance will be. Very recently, Shiller (1994) suggests a need to develop macroeconomic based derivative securities as a means of enhancing an individual's ability to swap risks which cannot be hedged in financial markets. The extent to which the current equity related financial derivatives are inadequate in performing this task depends to a large extent on the degree to which equity markets tracks the macroeconomy.

According, numerous papers have investigated the relationship of US stock market volatility with the macroeconomy. Schwert (1989) and Officer (1973) related market volatility to the volatility of nominal and real economic variables. Schwert (1989) finds some evidence that volatility is counter-cyclical with the business cycle, however, he does not report a strong systematic relationship between US market volatility and the volatility of the US economy.

Although the US results are not strong, intuitively, as the underlying environmental conditions change over time. I would except a corresponding evolution in various ecnomic indicators including the stock market.[1] Hence, an investigation of the extent to which European stock market volatility is related to macroeconomic fundamentals can be informative not just for European investors and policy-makers but also to shed new light on this important issue. I focus on evidence from the seven largest European equity markets. These markets, in descending order of market capitalisation, are UK, Germany, France, Italy, Switzerland, the Netherlands, and Belgium. These seven European markets accounted for approximately 90% of the capitalised value of all European equity markets in 1993. I also include the USA in our study for purposes of comparisons and calibration *vis-a-vis* the results of Schwert (1989).

In section 2 I document cross-sectional differences between the unconditional moments of European stock index returns and macroeconomic variables. In section 3 I address the time series properties of stock market return volatility. I report various diagnostics which justift modelling return volatility as a stationary autoregressive progress. In section 4 I report the relationship between macroeconomic variables and stock market volatility. Unlike the US stock market, I find several instances among European markets in which stock market volatility can be predicted based on past estimates of macroeconomic volatility. Next, I

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1 To date, the evidence for other global equity kets is very sparse. Kupiec (1991) provides some insights into the trends of market volatility for OECD countries while Kim and Singal (1993) find that emerging market volatility is directly related to the business cycle and liberalisation policies.

present impulse response analysis to assess the dynamic response of return volatility to unanticipated macroeconomic shocks. Conclusions follows.

2. Data and Descriptive Statistics

My sample includes local currency monthly data January 1990 to approximately June 1998, depending on the series. I use monthly rather than quarterly data in order to maximise the number of observations. The trade-off, however, is that many macroeconomic series such as GDP and trade balances are only available on a quarterly basis. Thus, the macroeconomic factors used in my study are industrial production, as a proxy for real activity, and money supply and inflation as proxies for monetary factors. All variables are expressed in terms of growth rates in order to focus on the relationship between stock market returns, rather than stock prices, and the macroeconomy.[2)]

In <Table 1>, I report the unconditional mean, variance, and kurtosis for each country's stock market return, production growth rate, money supply growth rate, and inflation rate in desending order of the magnitude of volatility. Casual observation of these results suggest a connection between cross-sectional variation in stock market return volatility, as measured by variance, and the volatility of macroeconomic factors. Panel (a) reveals that Italy is the most volatile stock market in my study. It also has the most volatile money supply growth rate, the third most volatile productivity growth rate. On the other hand, US stock market volatility is the lowest in our sample and likewise ranks at or near the bottom in most of my measures of macroeconomic volatility. As one might expect, Germany has the lowest degree of price variability. However, it is interesting to note that low Germany price volatility does not below average stock market volatility or money supply growth rate volatility.[3)]

2 This also avoids the problems associated with non-stationary variables with infinite second moments.

3 A detailed cross-sectional analysis is deferred to future research.

<Table 1> Unconditional central moments.

	Mean	Variance	Kurt.
(a) Returns			
1. Italy	1.095	50.157	4.589
2. Netherlands	0.998	25.452	5.609
3. France	1.076	35.311	4.555
4. Germany	0.922	30.001	4.904
5. Australia	1.055	49.350	4.897
6. Korea	0.725	53.632	1.900
7. USA	0.893	18.002	5.667
(b) Productivity growth rate			
1. Italy	0.371	6.187	7.012
2. Netherlands	0.364	5.712	6.825
3. France	0.311	8.599	59.929
4. Germany	0.308	5.222	13.101
5. Australia	0.435	1.056	0.823
6. Korea	0.512	6.099	3.434
7. USA	0.293	1.004	8.312
(c) Money supply growth rate			
1. Italy	1.341	13.031	15.706
2. Netherlands	0.812	5.911	6.378
3. France	0.918	6.085	28.932
4. Germany	0.933	7.912	6.332
5. Australia	1.877	1.788	1.111
6. Korea	1.361	1.807	0.623
7. USA	0.715	2.909	3.744
(a) Inflation rates			
1. Italy	0.819	0.522	4.701
2. Netherlands	0.519	0.618	13.009
3. France	0.716	0.348	3.587
4. Germany	0.488	0.332	3.877
5. Australia	0.565	0.250	2.044
6. Korea	0.506	0.318	2.828
7. USA	0.599	0.321	4.358

3. Economic Determinants of Return Volatility

Whether the above volatility predictions can be enhanced by expanding the information set to include macroeconomic factors is explored in this section. I also attempt to determine the direction of causality if any between stock market volatility and macroeconomic volatility. Both objectives can be achieved by esting a VAR system composed of estimated stock market and macroeconomic volatilities. Various hypotheses can be tested within this framework to determine: (i) which macroeconomic factors help explain stock market volatility, and (ii) make qualified statements on the direction of causality between the stock market volatility and macroeconomy.[4] The suggested VAR system is of following form,

$$Y_t = VD_t + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + U_t \qquad (1)$$

Where Y_t is a (4×1) matrix of the estimated variances of the variables in question, i.e. returns, inflation rates, productivity growth rates, and money supply growth rates. Y_t elements are assumed to be stationary variables. D_t are 12 monthly dummies and V and A_1
=VEC(B) are (12×4) and (4×4) coefficient matrices respectively. Ut are assumed to be a white noise process, i.e. $E_t(U_t)=0$, $E(U_tU_s)$ is nonsingular, Ut and Us are independent for s t, and either Ut is multivariate normal or alternatively all fourth moments exist and are bounded. Let B be the coefficient matrix such that B=(V, A1,⋯,Ap) and =VEC(B). Under these conditions, the least squares estimates are consistent and normally distributed, i.e.

$$\sqrt{T}(\hat{\beta}-\beta)\rightarrow N(0,\Gamma^{-1}\otimes\hat{\Sigma}_{ii}) \qquad (2)$$

where Γ is the cross-product matrix of the right-hand side variables of equation.[5]

4 I am unaware of a generally accepted means of testing for causality in a GARCH framework. Hence, I note this as another motivation for using VARs as a means of modelling and estimating volatility.

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$$R_t=\sum_{j=1}^{12}\alpha_j D_{jt}+\sum_{i=1}^{12}\beta_j R_{t-i}+e_t$$

R_t is variable in question and D_j are dummy variables which allow for differential monthly returns.

These conditions insure that tests on subsets of the parameter space can be made based on classical inference procedures with known distributional form.

I assess which past elements of Y_t are significant values of each individual elements of Y_t. Specially, I test whether the coefficient associated with each right-hand side variable of equation (6) and its correspondings lags are jointly insignificantly different from zero. Formally, let jk, I denote the jk element of A_i. Then the null hypothesis that lagged values of variable k are not significant predictors of the future volatility of variable j can be expressed as,

$$H_0: \alpha_{jk,1} = \alpha_{jk,2} = \cdots = \alpha_{jk,p} = 0 \tag{3}$$

This null hypothesis is identical to the test for Granger causality. The idea behind Granger causality being that cause must precede effect. Thus, if variable x causes variable y, it should also be the case that x should help y.[6] I test null hypothesis, as stated in equation (1), by forming Wald statistics of the following form,

$$\lambda_F = \hat{\beta}' C' [C((ZZ')\Gamma^{-1} \otimes \hat{\Sigma}_U]^{-1} C\hat{\beta} N^{-1} \tag{4}$$

where N are number of restrictions under the null and C is an $(N \times (K*K+12))$ matrix which restricts the parameter space under the null.[7]

Inferences for the VAR return volatility model consisting of four lagged values of inflation (Int), productivity growth rate (Prod), and money supply growth rate (Money) are reported in Table 3. To reiterate, a factor is said to 'Granger' cause volatility if its lagged values are jointly significant in the return equation of the VAR lagged values of returns are jointly insignificant in the factor's VAR equation. To assess significance, I report Wald statistics, and their corresponding

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$e_t^2 = a + b \cdot S_{t-1}^{+} e_{t-1} + \varepsilon_t$

6 I use the term 'Granger' causality in the above defined statistical sense. How it relates to a standard meaning of causality is problematic. For further discussion see Hamilton (1994). With this in mind, I view Granger causality as a means of informing the analyst of whether a set of variables contains useful information in formulating predictions about another set of variables.

7 Division by N is suggested by Lukepohl (1991) as a means of correcting for degrees of freedom lost when estimating Σ_U. This correction transforms the Wald statistic from its usual chi-squared distribution to an F-distribution with N, t-k degrees of freedom.

p-values for each right-hand side variable, for each of the four equations of the VAR. For example, reading across the first column of panel (a), only lagged returns are significant. Hence I find no evidence to suggest that macroeconomic factors are important sources of stock market return volatility in the USA. This is a rather troublesome result in that a priori I would expect return uncertainty to reflect fundamental uncertainty in the economy. However, as noted in the introduction, this result is consistent with those reported in Schwert (1989). I find similar for the UK, Switzerland, and Belgium.

For Germany and France, lagged money supply growth rates are found to 'Granger' cause stock market return volatility. Given, the extraordinary emphasis that German policy-makers place on stabilising monetary aggregates, it would seem only natural for the German stock market to mimic such concerns. France, on the other hand, while historically not known for exercising monetary constraint, has more recently placed increased emphasis on monetary stability in an effort to promote European monetary union. Perhaps to some extent our anlysis is capturing these efforts and concerns.[8)]

In contract, I find return volatility for Italy and the Netherlands to be more responsive to real economic uncertainty than monetary uncertainty. As noted in Table 1, these country's inflation volatilities are among the highest in my sample. This suggests that in countries in which monetary uncertainty is more of an every event, stock market volatility is less affected by changes in monetary volatility. I conjecture that this may reflect a relatively high degree of price indexing in these economies. It is well known that indexing wages and commodity to inflation reduces the sensitivity of an economy to monetary shocks while increasing its sensitivity to real shocks. My results are consistent with this view.

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8 This also suggests that our data might have been subjected to important structural changes that if explicitly modelled might have revealed a greater association between fundamentals and returns.

<Table 2> VAR estimation results*

Dep. Var.	Ret.	Infl.	Prod.	Money	BP(12)
(a) USA					
Ret.	3.5912 (0.011)	0.9062 (0.519)	1.0045 (0.4189)	0.5121 (0.9899)	11.51
Infl.	1.6421 (0.2903)	3.7080 (0.009)	0.6116 (0.7117)	1.3489 (0.3455)	11.03
Prod.	1.6597 (0.2777)	1.4011 (0.382)	3.2455 (0.199)	1.2072 (0.4681)	11.84
Money	1.3115 (0.4121)	1.0032 (0.354)	1.5005 (0.198)	13.8497 (0.0011)	23.58
(b) Germany					
Ret.	4.6623 (0.0001)	0.0888 (0.8841)	1.3349 (0.2532)	2.5443 (0.0367)	8.90
Infl.	0.6302 (0.6054)	1.4932 (0.1912)	1.0212 (0.3898)	0.7015 (0.6152)	7.35
Prod.	0.9833 (0.4004)	0.5758 (0.6543)	4.6018 (0.0001)	0.6081 (0.6582)	7.12
Money	2.2018 (0.0723)	0.3211 (0.9025)	0.4490 (0.5182)	1.6005 (0.1613)	52.75
(c) France					
Ret.	2.4283 (0.0499)	0.5888 (0.8003)	0.5112 (0.7005)	2.6222 (0.0378)	13.51
Infl.	0.7786 (0.5234)	8.2478 (0.0001)	0.5317 (0.6889)	0.0988 (0.8877)	7.21
Prod.	0.8281 (0.4344)	3.4225 (0.08910)	42.2295 (0.0000)	0.2344 (0.6767)	3.32
Money	3.5121 (0.032)	0.2154 (0.8754)	1.1932 (0.3411)	7.9341 (0.0001)	24.68
(d) Italy					
Ret.	4.7147 (0.0001)	0.8889 (0.4832)	2.7923 (0.0278)	1.7145 (0.1233)	6.34
Infl.	0.6780 (0.5734)	8.8237 (0.0001)	1.1003 (0.2561)	0.5117 (0.6902)	23.17
Prod.	1.2419 (0.0914)	1.1101 (0.3892)	7.5791 (0.0001)	1.7476 (0.1236)	4.94
Money	0.8976 (0.2345)	1.9545 (0.1898)	0.3412 (0.3335)	0.4618 (0.3985)	40.54
(e)Netherlands					
Ret.	1.2729 (0.0987)	1.2334 (0.2841)	2.3776 (0.0501)	0.2778 (0.8954)	6.88
Infl.	0.8211 (0.4555)	14.9191 (0.0001)	1.1145 (0.2889)	1.1112 (0.3789)	28.04
Prod.	1.9232 (0.0967)	1.6318 (0.0988)	1.3144 (0.2893)	0.9755 (0.4111)	13.77
Money	0.6799 (0.6366)	1.4878 (0.2845)	2.8443 (0.0178)	2.5061 (0.0387)	21.34

<Table 2> VAR estimation results *(Continued)*

Dep. Var.	Ret.	Infl.	Prod.	Money	BP(12)
(f) Australia					
Ret.	1.5601 (0.2526)	0.4881 (0.7446)	0.2446 (0.9069)	2.5413 (0.0995)	4.56
Infl.	2.1651 (0.1403)	2.7011 (0.0864)	0.0938 (0.9823)	0.1343 (0.9663)	8.85
Prod.	3.1855 (0.0574)	0.3390 (0.8461)	0.3324 (0.8756)	0.2289 (0.9164)	8.77
Money	3.3126 (0.0517)	0.3233 (0.8565)	0.3283 (0.8532)	3.1997 (0.0567)	19.97
(g) Korea					
Ret.	9.4955 (0.000)	1.1785 (0.3272)	0.4373 (0.8516)	0.8452 (0.5392)	8.23
Infl.	1.1383 (0.3489)	4.3132 (0.0008)	4.0206 (0.0015)	6.2281 (0.0000)	13.43
Prod.	3.0006 (0.000)	2.9141 (0.0132)	27.2446 (0.0000)	0.7975 (0.5749)	0.87
Money	2.0248 (0.0188)	2.1732 (0.0552)	0.8781 (0.5153)	14.5445 (0.0000)	21.15

Notes:* VAR consists of return volatility (Ret.), money growth volatility (Money), productivity growth volatility (Prod.), and estimated with four lags. I report the summation of the VAR coefficients with p-values of joint significant. BP(12) are Box Pierce statistics for serial correlation in the residuals based on 12 lags.

Money supply volatility was found to Granger cause return volatility for Germany and France while industrial growth rate volatility was found to Granger cause return volatility for Italy and the Netherlands in Table 2. Contrast to this, money supply volatility and industrial growth rate volatility were found to Granger cause return volatility for Australia and Korea. In all other cases, none of the macroeconomic factors were found to be significant. I investigate these relationships further by analyzing the parameter estimates of the return equation of each VAR.

The dynamic response of return volatility to a given unanticipated shock in a factor's variance can be traced through time by impulse response analysis. This is accomplished by first expressing equation (1) in terms of its equivalent pseudo moving average representation in the following manner,

$$Y_t = \mu + \Sigma_{i=0}^{\infty} \Phi_i \varepsilon_{t-i}, \quad \Phi_0 = I_4 \tag{5}$$

$$\Phi_i = \Sigma_{j=1}^{i} \Phi_{t-j} A_j, \quad i = 1.2.\cdots. \tag{6}$$

The φ_{jk} element of Φ_i represents the reaction of variable j to a one unit innovation in variable k, i periods ago. To account for contemporaneous innovations I orthogonalise innovations along normal lines as follows,

$$\Theta = \Phi_i P \tag{7}$$

where P denotes the Choleski decomposition of the residual variance covariance matrix Σ_{Π}. The element of Θ_i is interpreted as the response of variable j to an orthogonal innovation to variable k, i periods ago.[9]

In Figures 1 and 2 I show the impulse responses for return series for return series which were previously determined to be significantly affected by changes in money supply volatility: Germany and France. In both cases I observe a lag between the time of the shock and impact on return volatility of approximately two periods (two months). From period 2 to 4 I observe a sharp transitory increase in return volatility peaking at period 4 and diminishing to zero by lag 5. Hence, increases in money supply volatility have a significantly positive impact on market volatility which occurs approximately 2 months hence, peaks at month 5, and declines back to normal by around month 6.

In Figures 3 and 4 I show the impulse responses for the two return series which were previously determined to be significantly affected by changes in industrial production volatility: Italy and the Netherlands. For Italy, I find that increases in the volatility of industrial production has a significantly positive effect on returns that occurs approximately 2 periods after the shock, peaks in period 3, and returns to normal by period 8. For the Netherlands, I observe a sharp increase in return volatility followed by reversal in which market volatility fall below normal levels for period 3-6.

In Figures 5 and 6 I show the impulse responses for the two return series which

9 A noted criticism of impulse response analysis based on Cholesky decomposition is the sensitivity of the variable ordering. To investigate this possibly I tried all possible ordering and found my reported results to be quite robust.

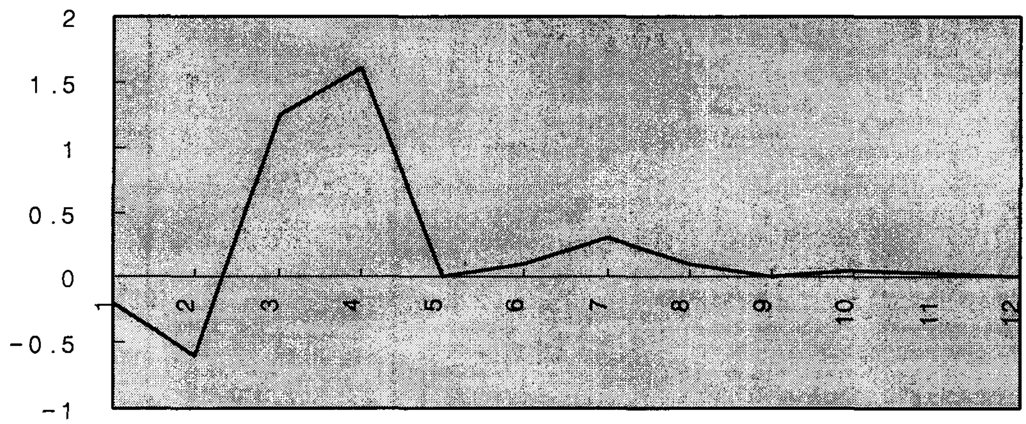
were previously determined to be significantly affected by changes in money supply and industrial production volatility shock: Australia. For Australia, I find that increases in the volatility of money supply has a significantly positive effect on returns that occurs approximately 2 periods after the shock, peaks in period 5, and returns to normal by period 7. Also I find that increases in the volatility of industrial production has a significantly positive effect on returns that occurs approximately 1 periods after the shock, peaks in period 3, and returns to normal by period 8.

In Figures 7 and 8 I show the impulse responses for the two return series which were previously determined to be significantly affected by changes in money supply and industrial production volatility shock: Korea. For Korea, I find that increases in the volatility of money supply has a significantly positive effect on returns that occurs approximately 3 periods after the shock, peaks in period 5, and returns to normal by period 8. Also I find that increases in the volatility of industrial production has a significantly positive effect on returns that occurs approximately 1 periods after the shock, peaks in period 4, and returns to normal by period 8.

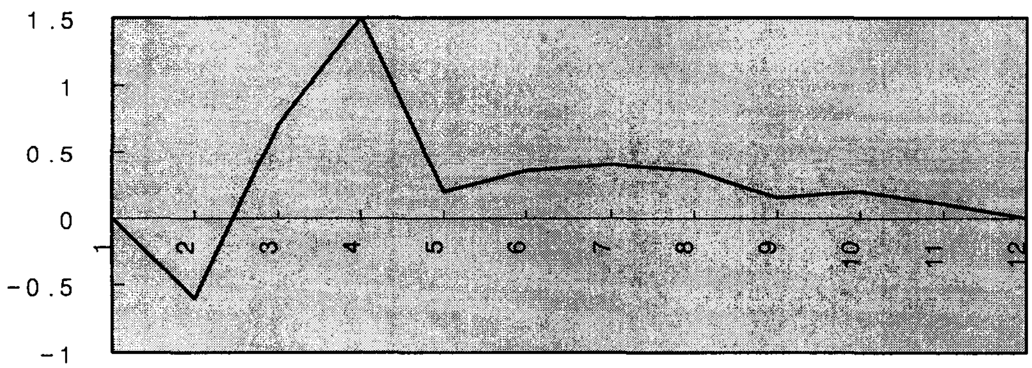
After the 1990 in Korea, I analyze as a monthly data of M2 supply volatility, inflation rate, industrial production volatility and stock return. In these results, I find that results are same as above findings. I find that increases in the volatility of M2 supply have a significantly positive effect on returns that occurs approximately 3 periods after the shock, peak in period 5, and returns to normal by period 8. And increases in the volatility of industrial production have a significantly positive effect on returns that occurs approximately 1 periods after the shock, peaks in period 4, and returns to normal by period 8. Also increases in the volatility of industrial production have an impact on stock return faster than those of M2 supply. That is follows.

Information of revenue of company instantly have an impact on stock return. Contrary to this, increases in the volatility of M2 supply have an impact on stock return through liquidity. In case of volatility of M2 supply, effects on stock return and increase of revenue of company through increase of sales on rising of price will be predicted to have more than one year. So increases in the volatility of M2 supply is relatively more slow than those of industrial production at impact on stock return.

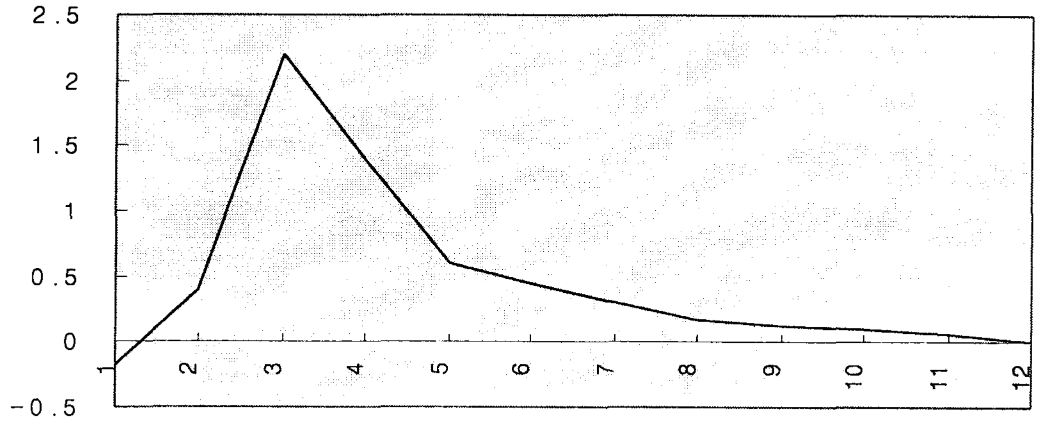
Therefore, increases in the volatility of M2 supply and industrial production through recovery of economy growth will do play a important role on increase of stock return. In Italy and the Netherlands, relatively small economy among the G7, these results are same. Therefore, after the recovery of economy growth, increases in the volatility of industrial production will have more important role about stock return between the two.



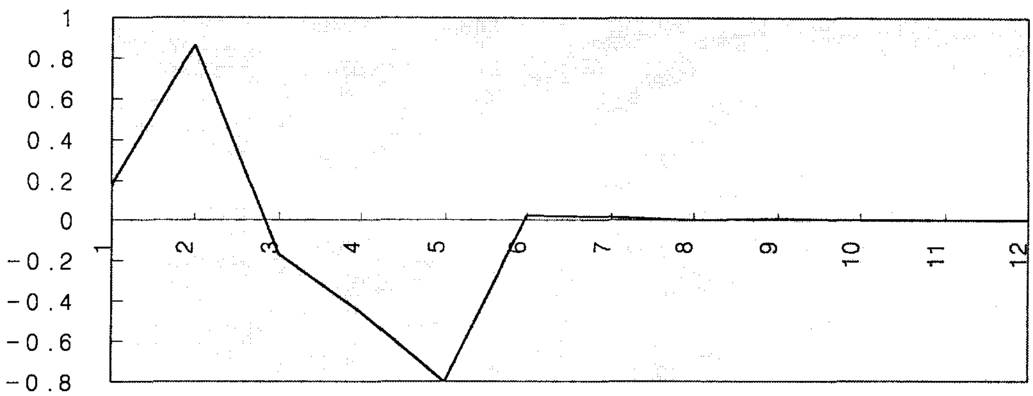
<Figure 1> Response of stock market return on money supply volatility shock in Germany



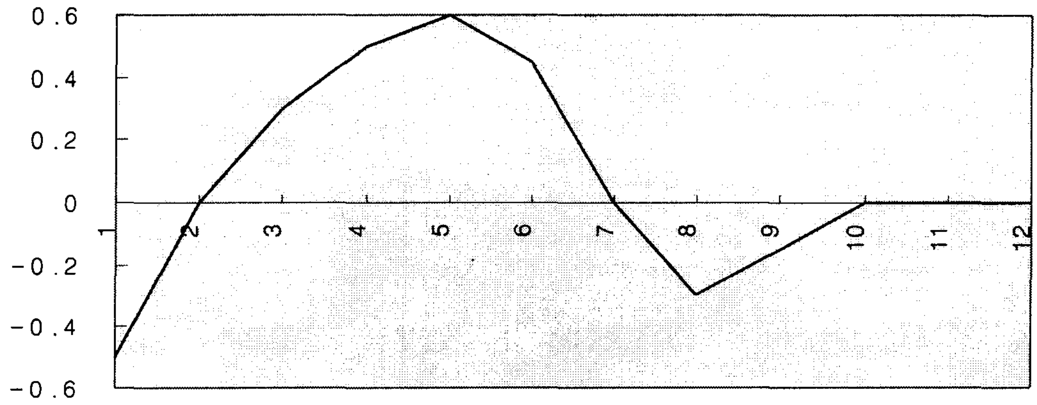
<Figure 2> Response of stock market return on money supply volatility shock in France



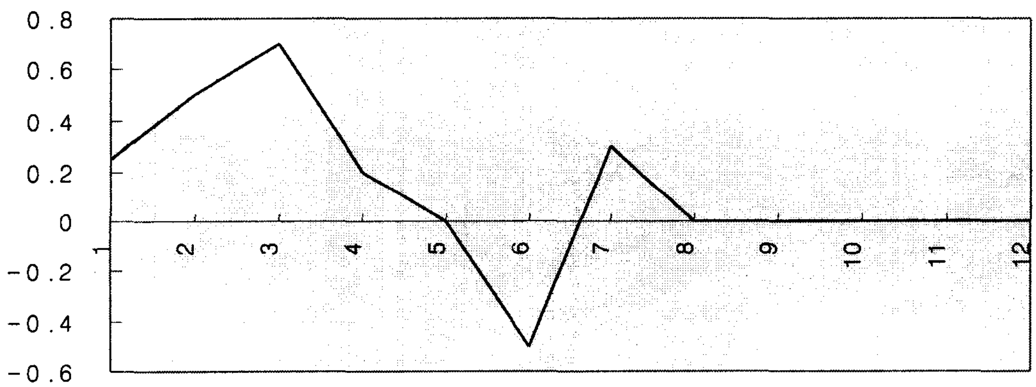
<Figure 3> Response of stock market return on industrial production volatility shock in Italy



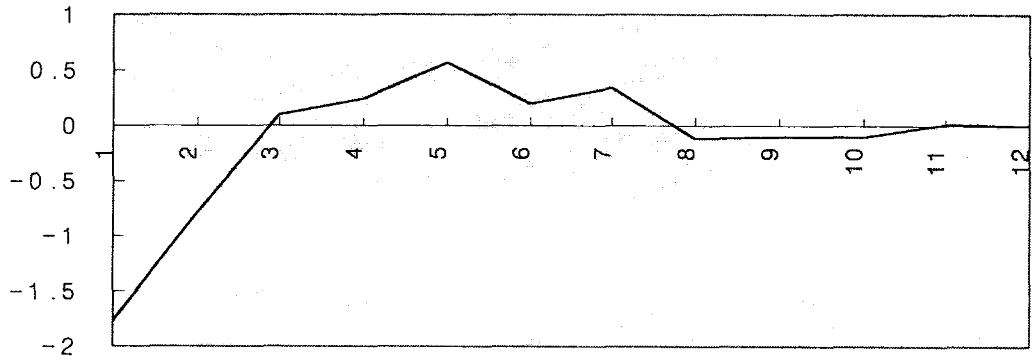
<Figure 4> Response of stock market return on industrial production volatility shock in the Netherlands



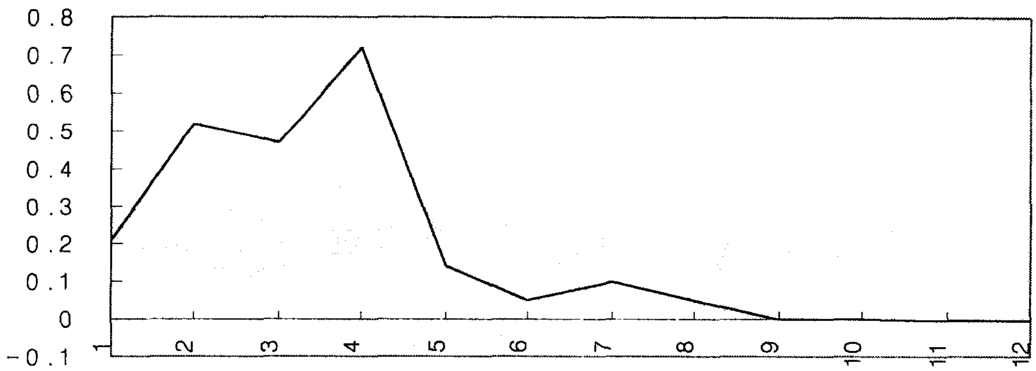
<Figure 5> Response of stock market return on money supply volatility shock in Austrailia



<Figure 6> Response of stock market return on industrial production volatility shock in Austrailia



<Figure 7> Response of stock market return on money supply volatility shock in Korea



<Figure 8> Response of stock market return on industrial production volatility shock in Korea

4. Conclusion

Estimates of stock market volatility are important for capital budgeting decisions and formulating optimal portfolios. If volatility estimates can be improved by incorporating macroeconomic data, it follows that the above mentioned allocation decisions can also be improved. The results presented in this paper suggest that for many European equity markets, return volatility predictions can be enhanced by incorporating information about the macroeconomy. A more formal test based on out of sample forecast is left for future research. In the case of Germany, France, Italy, and the Netherlands, I find that the relative importance of each factor varies substantially across countries. For Germany and France, monetary instability is a significant factor while for Italy and the Netherlands, industrial production is a significant factor. I argue that stated policy objectives and price indexing may contribute to these cross-sectional differences.

How return volatility is a affected by changes in significant factors is revealed by performing impulse response analysis. In general, I find that market volatility responds to economic shocks with 1 to 2 month lag. Futhermore, increased factor variance leads to an increase in market return volatility with the impact on market volatility being transitory in all cases lasting for 6 to 8 months.

I show the impulse responses for the two return series which were previously determined to be significantly affected by changes in money supply and industrial production volatility shock: Australia. For Australia, I find that increases in the volatility of money supply has a significantly positive effect on returns that occurs approximately 2 periods after the shock, peaks in period 5, and returns to normal by period 7. Also I find that increases in the volatility of industrial production has a significantly positive effect on returns that occurs approximately 1 periods after the shock, peaks in period 3, and returns to normal by period 8.

I show the impulse responses for the two return series which were previously determined to be significantly affected by changes in money supply and industrial production volatility shock: Korea. For Korea, I find that increases in the volatility of money supply has a significantly positive effect on returns that occurs approximately 3 periods after the shock, peaks in period 5, and returns to normal by period 8. Also I find that increases in the volatility of industrial production has a significantly positive effect on returns that occurs approximately 1 periods after the shock, peaks in period 4, and returns to normal by period 8.

After the 1990 in Korea, I analyze as a monthly data of M2 supply volatility, inflation rate, industrial production volatility and stock return. In these results, I find that results are same as above findings. I find that increases in the volatility of M2 supply have a significantly positive effect on returns that occurs approximately 3 periods after the shock, peak in period 5, and returns to normal by period 8. And increases in the volatility of industrial production have a significantly positive effect on returns that occurs approximately 1 periods after the shock, peaks in period 4, and returns to normal by period 8. Also increases in the volatility of industrial production have an impact on stock return faster than those of M2 supply. The gap of external interest rates and domestic interest rates closely has been affected both sides, as inflows and outflows of funds.

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