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Can Macroeconomic Volatility affect Stock Market Volatility? The case of 5 Central and Eastern European Countries

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ABSTRACT

This paper examines whether macroeconomic instability can influence stock market volatility in a sample of 5 emerging European countries. To account for the effects of fundamentals, modified ARCH/GARCH models are employed. The results are discordant from one country to another, but when a dynamic panel GMM is estimated, exchange rate volatility is found to be the sole significant explanatory variable.

Key words: Macroeconomic volatility, stock market volatility, panel estimation

JEL Classification: C58, E44, G15

1. Introduction

Volatility is one of the central pieces of finance and its measurement and forecast have been a trending research topic ever since the concept became synonymous with the risk of a financial instrument. When analyzing sources of stock market volatility, one ponders the news, capitalization or the number of listed companies, but rarely considers GDP, inflation or other variables accounting for an economy's fundamentals.

The results of existing studies are discordant: Schwert (1988) emphasizes the weak impact of macro variables on American stock market volatility, while Diebold and Yilmaz (2008) select a sample of both developed and emerging markets and discover a significant connection between GDP and stock returns. Prior to this, Fama (1977) stated that stock returns and inflation are negatively correlated, suggesting that stocks should be used as hedge against inflation. But the most noteworthy contribution is made by Engle, both through the creation of the conditional volatility models and the introduction of the GARCH-MIDAS and Spline-GARCH extensions. The latter divides volatility into a short-term and a long-term component and demonstrates that the stock market volatility trend is influenced by the fundamentals.

This paper focuses on a pool of 5 emerging markets from CEE (Czech Republic, Croatia, Poland, Romania and Hungary). The main variables are stock market indexes and macroeconomic variables i.e. industrial production, inflation, unemployment and exchange rates. The time span covers 14 years, from 2000 to 2013.

Methodology implies extracting volatility using variance with a rolling window of 12 observations and through ARCH/GARCH models. The next step was an analysis with modified conditional volatility models for each country, followed by dynamic panel estimation. The panel revealed that the sole significant determinant of the stock market volatility is exchange rate volatility and the relationship is a positive one.

The finding suggests that as fundamentals volatility is determinant for stock market variance, these variables should be modeled jointly. An extended approach like the incorporation of the macroeconomic variables in modeling the stock market volatility might enhance the existing methods which gauge and forecast market volatility based on stocks' historical data. Moreover, the paper has implications for investors, who might use the correlation between macroeconomic variance and market volatility to hedge properly and also for the policymakers who can quantify the residual impact their decisions have on stock market.

The paper is structured as follows: the first section consists of a brief literature review followed by a description of data and the methodology used. The final two sections exhibit the results for each country and for the entire panel and the subsequent conclusions.

2. Literature Review

At first, the link between the stock market and macro variables has been made through the effects of inflation on asset returns. In their paper, Fama and Schwert (1977) look up for assets which preserve their returns when purchasing power erodes. The authors presume that inflation alters the term structure of interest rates and consequently the valuation process. They develop a model where coefficients signal whether an asset is backed against expected or unexpected inflation or it provides full hedging. Using data from the American stock market, the authors found that treasury bills and government bonds safeguard their gain against expected inflation. Moreover, stock returns are negatively correlated with both expected and unexpected inflation.

A new approach is introduced by Shiller and Campbell (1988), who state that the dividends are the channel between the fundamentals and the financial markets: the difference between the expected and the realized quote (volatility) is influenced by future dividends and the expectations related to them. One should take into consideration that the event of a company paying dividends is conditioned by the economic cycle. Schwert (1988) advocates a more thorough explanation, referring to the Dividend Discounted Model and how the conditional variance of a stock price is given by conditional variance of cash flows and the yield curve. Hence, as the macro environment shifts from expansion to contraction, the margins of companies have the tendency to follow the cycle and this implies a comovement of fundamentals, dividends and stock price.

In the same paper, Schwert studied the nexus between macroeconomic uncertainty and stock returns in USA. He pooled data on industrial production, inflation and monetary base, but couldn't find a significant link to the stock market index dynamics. On the other hand, he highlighted the countercyclical behaviour of market volatility. The same procyclical performance of returns and countercyclical features of volatility have been emphasized by Corradi, Distaso and Mele (2012). Moreover, isolating each explanatory variable and reiterating the tests, they discovered that industrial production and inflation are the main notable sources of market instability. Albeit this finding, the authors advise that a rigorous analysis of market volatility can't be performed using merely fundamentals.

To obtain comparable results in Europe, Errunza and Hogan (1998) employed the same methodology used by Schwert in his study. They applied a two-step OLS to extract the market volatility and integrated the macro components in a VAR model. The results range from one country to another: in the UK the connection was inexistent, in Italy the industrial production variation was the only notable determinant, whereas in Germany the monetary base instability leaks into market volatility.

VAR methodology was employed by Zakaria and Shamsuddin (2012) to verify whether a connection between fundamentals volatility i.e. GDP, inflation, exchange rate, interest rate and monetary base exists in Malaysia. By determining volatility with GARCH models and estimating the Granger causality test, the paper reveals that inflation volatility conditions market volatility.

Taking into consideration the features of financial time series, standard deviation can sometimes be an inaccurate measurement of volatility. This issue led to the creation of ARCH models. Their inventor, Robert Engle, and Rangel (2008) introduced Spline-GARCH model which separates market volatility into two components, a short-term and a long-term one, and then demonstrate that the latter is highly correlated with the business cycle. Testing their hypothesis on a panel of 50 countries, the authors proved that inflation, GDP and short-term interest rates are significant determinants. Recessions and inflationary episodes lead to an increase of long-term market variability component. In addition to that, the authors observed volatility's propensity to be higher in emerging markets and to be negatively correlated with market capitalization and the number of listed companies.

In 2009, Engle, Ghysels and Sohn develop GARCH-MIDAS model and decided to test it on the same data Schwert used in his study. They discovered a correlation between the variability of the index, inflation, industrial production, monetary base and interest rate spread. Girardin and Joyeux (2013) employed a GARCH-MIDAS model to test the existing theory on the Chinese stock market and identified inflation and industrial production as valid explanatory variables.

Combining both Schwert and Engle methodology, Diebold and Yilmaz (2008) pool data from 40 emerging and developed countries consisting of GDP, consumption and inflation. Varying the frequency of observations (monthly, quarterly and annually) and controlling one variable at a time, they noticed a positive relation between the variables and also that it is unilateral: GDP volatility affects market variability, whereas market volatility does not alter GDP volatility.

3. The Dataset

The study spans over 14 years, from 2000 to 2013 and covers 5 countries: Czech Republic, Croatia, Romania, Poland and Hungary. In order to maximize the sample size and thus to increase the accuracy of the estimation, the monthly frequency of data has been preferred. Considering the existing literature and constrains regarding data availability, the following macro variables have been selected: industrial production (as proxy for GDP), the harmonized index of consumer prices (HICP) as measure of inflation, unemployment and exchange rate. Because the Eurozone is the main trading partner for our 5 countries, we decided to use the bilateral exchange rate with the euro. As for the stock market, the best available broad-based indexes were included: PX-GLOB, CROBEX, BET-C, WIG and BUX. The main data sources were Eurostat, ECB and national stock exchanges. An arithmetic mean was applied to convert the indices and the exchange rates from daily to monthly frequency.

Two issues concerning data series features emerged: the stationarity and the seasonal adjustment. We converted exchange rate and stock market indexes from prices into returns using the following formula

$$R_t = \ln(P_t) - \ln(P_{t-1}) \qquad (1)$$

Eurostat provides data as percentage change on previous month which are also seasonally adjusted, except for inflation. So these series were turned from fixed-based to chain-based price indexes (month-on-month percentage change) and, as it commonly used by Eurostat, Tramo/Seats method was subsequently employed to remove the seasonal variations.

Augmented Dickey-Fuller, Phillips Peron and IPS (for the panel estimation) tests applied to our sample reveal that the unit root was successfully removed and all series are stationary.

4. The Methodology

The best known method to capture volatility is through the standard deviation or variance of an asset return. But financial time series have some distinct characteristics which make conditional variance models more suitable. For example, they are leptokurtic, meaning that the distribution is more peaked in the center and has thicker tails than to the Gaussian curve. Moreover, they exhibit clusters, assuming that volatility is positively correlated with its proximate level and this leads to heteroskedasticity (the variance is not constant over time).

Let's assume that we can model a series using two equations: one for its conditional mean and another one for its conditional variance. We shall denote the volatility obtained by applying a rolling window on growth rates "unconditional variance", whereas the one extracted from the ARCH models "conditional variance".

Engle was the first who presumed that the variance can be defined as a function of errors and introduced the ARCH model:

$$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \alpha_2\varepsilon^2_{t-2} + \alpha_3\varepsilon^2_{t-3} + \ldots + \alpha_q\varepsilon^2_{t-q} \quad (2)$$

This model presumes that the conditional variance is a function of *q* lagged squared residuals from the mean equation. One can easily observe a pitfall, which is that a large number of lags have to be included in order to gauge the entire dynamic of variance.

In order to have a consistency between the left and the right side of the equation, a constraint is imposed: the coefficients must be positive ($\alpha_i \geq 0$)

Moreover, as it is desirable for volatility to follow a mean-reverting process, the sum of the coefficients should be less than 1 ($\sum_i^q \alpha_i < 1$.)

Bollerslev created the GARCH model, which assumes that the conditional volatility is given by both lagged squared errors (influence encapsulated α parameters) and by an autoregressive component of variance (β is associated with the persistence of volatility).

$$\sigma^2_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i\varepsilon^2_{t-i} + \sum_{j=1}^{p} \beta_j\, \sigma^2_{t-j} \quad (3)$$

The non-negativity constraint holds for the GARCH model, too. Also, the mean-reverting restraint becomes.

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1 \quad (4)$$

Both ARCH and GARCH models suggest that a former disturbance would influence the current variance. So it is preferable if the shocks of the present conditional variance fade away and don't continue to affect the future values of the variance. This restriction is possible if the property (3.3) holds. If the sum of the coefficients equals 1, the phenomenon of persistence of volatility appears, and it implies that we need to use an IGARCH (Integrated GARCH) model.

Stocks exhibit the leverage effect which is considered to be the main cause of the asymmetric volatility phenomenon, the feature that makes volatility more sensitive in market downswings than in market upswings. As ARCH/GARCH models use squared residuals, they don't account for the difference between a positive and a negative shock and incorporate them equally. GJR (named after its creators: Glosten, Jagannathan and Runkle) and Threshold-ARCH – TARCH model variance likewise, having extensions which take different values depending on the nature of shock.

For example, the equation below describes the variance of a GJR model. The coefficient I_{t-i} is equal to 1 when the shock is negative ($\varepsilon_{t-i} < 0$) and 0 otherwise.

$$\sigma^2_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i\varepsilon^2_{t-i} + \sum_{j=1}^{p} \beta_j\, \sigma^2_{t-j} + \sum_{i=1}^{q} \alpha_i\varepsilon^2_{t-i} * I_{t-I} \quad (5)$$

The EGARCH is another model suitable for asymmetrical shocks. It brings an important improvement because the usage of logarithm removes the drawback regarding the non-negativity constraint of the coefficients.

$$\ln\sigma^2_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(z_{t-i} + \gamma(|z_{t-i}| - E|z_{t-i}|)\right) + \sum_{j=1}^{p} \beta_j \ln(\sigma^2_{t-j}) \quad (6)$$

where z_t is a variable depending on the type of error distribution and the γ parameter measures the asymmetry (if $\gamma<0$ bad news increase volatility more than the good ones)

A panel analysis is suitable for our research because the dataset has both a temporal dimension given by the 168 monthly observations and a cross-sectional dimension defined by the sample of 5 countries. Moreover, the panel allows us to identify more complex correlations between variables and, by combining both its dimensions, it increases the degrees of freedom and the accuracy of our estimation.

4.1. Fixed-effects panel

Let 7be the equation for the fixed-effects model:

$$y_{it} = \beta x_{it} + \alpha_i + \varepsilon_{it} \quad (7)$$

Where y_{it} is the dependent variable, β is the coefficient of the independent variable, x_{it} is the independent variable, α_i is the specific intercept for each entity (time invariant), ε_{it} is the error term .

A fixed-effects model assumes each entity has its own distinct characteristics that may or may not condition the dependent variable. It is said that this bias exists because the individual errors are correlated with the independent variable. As each country is unique, it is mandatory for entities' time invariant features and error term not to be correlated among cross-sections. If this correlation exists, the random-effects model is more suitable.

4.2. Random-effects model

A random-effects model should be employed if one considers that the differences across entities have an impact on the dependent variable. One of the advantages of a random-effect model is that it allows time invariant features to exert a significant influence on the dependent variable without being integrated in the intercept.

Let8 be the equation of a random-effects model:

$$y_{it} = \beta x_{it} + \alpha + u_{it} + \varepsilon_{it} \quad (8)$$

where u_{it} is the within-entity error term and εit is the between-error term.

Even though the random-effects models are considered to be more efficient because they lose less degrees of freedom, one should test if the errors are correlated with the independent variables using the Hausman test. The null hypothesis is that they are not correlated and therefore the random-effects are more desirable than the fixed-effects.

4.3. The GMM approach

A fundamental assumption when estimating an econometric model is that the independent variables must not be correlated with the error term. The violation of this principle means the estimators will be biased. Therefore, if the Hausman test signals that our panel exhibits fixed effects, these should be eliminated. Furthermore, we will have to account for the additional cross-sectional heterogeneity: heteroskedasticity and error autocorrelation.

Arellano and Bond's GMM model offers a facile solution to deal with these problems. First of all, it introduces instrumental variables which are correlated with the independent variables and also uncorrelated with the errors, eliminating the dependence between regressor and error term.

Let 9 be the equation of a dynamic panel:

$$y_{it} = \beta_1 y_{i,t-1} + \beta_2 X_{it} + \varepsilon_{it} + \alpha_i \tag{9}$$

Where X_{it} pools the independent variables, ε is the error term and α_i account for the fixed-effects.

We can notice that α_i is time-invariant. By differentiating the equation, GMM eliminates the fixed-effects.

$$\Delta y_{it} = \beta_1 \Delta y_{i,t-1} + \beta_2 \Delta X_{it} + \Delta\varepsilon_{it} \tag{10}$$

As $(y_{i,t-2} - y_{i,t-3})$ are correlated with $(y_{i,t-1} - y_{i,t-2})$, but uncorrelated with $(\varepsilon_{it} - \varepsilon_{i,t-1})$, they can be used as instruments for $(y_{i,t-1} - y_{i,t-2})$. This justifies why lagged variables will be considered instruments. Identified and over-identified GMM will be estimated and the Sargan test will signal if the proper exogenous instruments have been selected.

5. Results

5.1. Individual estimation

Volatility was recovered using the two methods mentioned above: as the variance of returns by applying a rolling window of 12 observations and through the conditional variance models. Although we have shed light on the downsides of using the unconditional variance, we want to test whether the link holds during both estimations.

First of all, we have determined which model provides the best fit for each variable. The next step was to introduce in the variance equation of the indices the macroeconomic volatility as an exogenous variable.

For example, if a GARCH is estimated for the index, the new variance equation is

$$\sigma^2_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j} + \sigma^2_{\text{industrial prod}} + \sigma^2_{\text{inflation}} + \sigma^2_{\text{unempl}} + \sigma^2_{\text{exch. rate}} \qquad (11)$$

The process was an iterative one, which involved testing whether

(1) The new variable is statistically significant
(2) The properties of the model (error distribution, absence of ARCH residuals effects) and the constraints of its initial parameters are preserved.

In line with the existing literature, our initial assumption is that there should be a positive correlation between the variables because macroeconomic volatility increases the uncertainty related to stocks returns. For example, variance of unemployment and industrial production signals changes in economic activity which subsequently affects companies' margins, the dividends they pay and their stock prices. Also, nominal asset returns are uncertain when inflation is more volatile. Investors possessing foreign currencies might be reluctant to adjust their portfolios when the exchange rate is volatile and the following decrease of liquidity should loop into wider spreads and ultimately increase market volatility.

The outcomes acquired are displayed in the section A of the appendix.

First of all, one can notice that some results follow our initial assumptions and the results cited in the existing literature, that the correlation is positive, while others fail to support them. An example of positive relationship between the variables is Romania, where an increase of exchange rate volatility with one percent leads to a 0.0009 increase in stock market index volatility when ARCH model is used to obtain macroeconomic volatility, while the coefficient increases to 0.0011 when unconditional variance is employed. Meanwhile in Poland, if variance methodology is used, estimation results state that a 1% increase in exchange rate volatility reduces market volatility by -0.0006. The other variables are significant scarcely: the unemployment variance in Croatia is in a positive correlation with market volatility and when using conditional variance series, industrial production in Czech Republic and inflation in Hungary are both in a negative relation with market variability.

It is quite difficult to compare the results with the ones from the existing literature, mainly because they focus on long-term component rather than on the entire realized volatility. For example, using a GARCH-MIDAS for Chinese stock market, Girardin and Joyeux (2013) discovered that from 1996 to 2010 a 1% increase in volatility of inflation increases the long run volatility of returns by 0.023% for A-shares and 0.051% for B-shares. Engle (2009) used the same model for American stock market and revealed that from 1985 to 2004 a 1% increase in inflation volatility leads to a 0.1054% increase of long-run market volatility, whereas the coefficient is 1.4998% for industrial production.

For other variables such as the variance of inflation in Czech Republic of the unconditional volatility of unemployment in Poland, the additional macroeconomic alters the properties of the other parameters from the model, so we decided not to consider the variables as meaningful, although the t-test shows that they are significant.

An interesting fact is that inflation and industrial production were predominant significant variables in the existing literature, while the exchange rate had little to no explanatory power, often not being even taken into consideration. Our findings suggest that among these countries the results are reverted, exchange rate being a prevailing factor in explaining stock market volatility.

Secondly, we notice that the links do not hold across the two estimations. One can observe that the prevailing significant explanatory variable is the exchange rate volatility, but except for Romania, in every other country the significant regressor ranged from one assessment to another as one can see in the Table A.1 and A.2. So these two measures of volatility did not lead to consistent results.

Other papers suggest that fundamentals are either foreseeing or lagging the dynamics of market indexes.1So a second analysis has been performed: 6 lags and 6 leads have been selected and we tested whether a positive correlation will appear throughout this structure. Unfortunately, no clear pattern emerged.

The source of inconsistency with the prevailing literature could be the fact the countries from our sample are not members of the Eurozone, so they enjoy independent monetary policy and specific exchange rate regimes. The purposes of central banks' interventions in the foreign exchange markets, changes in the key interest rate and open market operations are to pursue each country's specific objectives regarding growth, inflation reduction and exchange rate stability. In addition to that, according to the Phillips curve, on the short-run a decreasing inflation leads to a higher rate of unemployment. All these suggest that the variables might be a distorted reflection of the fundamentals. Moreover, it's commonly known that emerging stock markets have a higher volatility and offer a greater expected return than the mature markets, so the stock markets might not be as tightly anchored to the underlying macroeconomic foundations as they are in the developed economies.

These distinct features of each country play a crucial role in understanding our findings and because of the inconsistency in results it was impossible to draw conclusions after this section. Therefore, panel estimation had to be used.

5.2 Panel estimation

Our previous analysis reveals that the distinct features of each country shape the results. In this chapter we will use an estimation method that will eliminate these features, fixed effects as we will henceforth call them.

As our objective was to estimate ARCH models that encompass the best of our data volatility, we ended up with heterogeneous panel series that are highly influenced by the characteristics of the conditional volatility models. So we decided to employ the unconditional variance series. Table B.1 sums up the results of the stationarity tests. The next step was to identify if the panel exhibits fixed or random

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[1]Conrad Christian., Loch Karin.,(2014), „*Anticipating Long-Term Stock Market Volatility*", Journal of Applied Econometrics

effects. We assumed that each country has distinct features such as the fiscal and monetary policy or the exchange rate regime that are critical in defining the behaviour of data, suggesting the presence of fixed-effects. Table B.2 illustrates the result of the Hausman test, which rejects the null hypothesis, supporting our assumption.

There is no precise guidance in choosing the appropriate lags as instruments. We have to bear in mind that the instruments should be correlated with the exogenous variables, but not with the errors. Choosing far lags might result in weak instruments, while closer lags might still exhibit correlation with the residuals. So the correlogram and the Ljung-Box test enabled the identification of lags which revealed a potential correlation, while meeting the initial constraints.

For the identified model, the following instruments have been employed: 4th lag of the exchange rate and the 3rd lag of the market index, unemployment, inflation and industrial production. As we have mentioned, we can choose as instrument either the lagged level or the lagged dynamic of a variable. As previous papers advocate that the level instruments are more stable, we decided to use them as suggested, maximizing their efficiency.

The identified estimation results are presented in the table B.3. They reveal that, at a confidence level of 95%, the exchange rate volatility is the only significant explanatory variable. Moreover, the relationship is a positive one, suggesting that a 1% increase of the exchange rate variability will eventually spill over into a 0.0008% rise of the stock market volatility.

For the over-identified panel, we decided to double the number of instruments, from 5 to 10: 2nd and 3rd lags of stock market and industrial production, 3rd and 4th lags of unemployment, lags 2 and 4 of the exchange rate and 3rd and 4th lags of inflation. Subsequently, the findings displayed in the table B.4 reinforce our primary results, that the FX volatility is the sole macroeconomic determinant of market volatility. The purpose of the over-identified model is to increase the efficiency of the parameters through the additional information incorporated, so doubling the instruments adjusted the coefficient from 0.0008198 to 0.0008167.

Even though the unemployment t-test probability decreased from the previous estimation, it is still out of what could be considered a safe confidence level.

The Sargan test value is 2.4566 (Prob J-stat is 78.30%) indicates that the instruments are exogenous.

6. Conclusions

There are numerous studies that highlight the link between the fundamentals uncertainty and the performance of the stock market. As macro-financial linkages in Central and Eastern Europe are largely unstudied, the objective of this paper was to shed light on whether this connection exists acrossa panel of 5 countries from this region.

First of all, volatility has been recovered using both variance of returns and ARCH models. Then we have modified the conditional models of market indexes, adding macro volatility as exogenous variables in the variance equation. The results reveal that a relationship between macro fundamentals and market indexes exists, but varied from one country to another and sometimes the correlation is negative rejecting our initial hypothesis. As a consequence, the panel estimation has been employed. The purpose of this estimation was to remove the distinct features of each state which biased our results, the so-called fixed effects. The identified and over-identified dynamic panel GMM models revealed that there is a positive relationship between exchange rate volatility and stock market volatility.

The explanation for this phenomenon is that, when the exchange rate is volatile, the investors owning foreign currencies may be reluctant to adjust their portfolios and delay the order placement, reducing the number of transactions which leads to wider spreads and increasing volatility.

The reflexivity between the fundamentals and the stock market is still an intriguing subject for further research, as one could emphasize whether the relationship between variables is bilateral or if it more pronounced during different stages of the business cycle.

References

Campbell, J. and Schiller, R., 1987. Stock Prices, Earnings and Expected Dividends, The Journal of Finance, Vol 43

Conrad C. and Loch K., 2014. Anticipating Long-Term Stock Market Volatility, SSRN ID 2154882, Journal of Applied Econometrics (Forthcoming)

Corradi, V. et al. , 2012, Macroeconomic Determinants of Stock Market Volatility and Volatility Risk-Premiums, Journal of Monetary Economics, No. 60

Diebold, F. and Yilmaz, K. 2008, Macroeconomic volatility and stock market volatility, worldwide", NBER Working Paper No. 14269

Engle, R. and Rangel, G.J., 2008, The Spline-GARCH Model for Low Frequency Volatility and Its Global Macroeconomic Causes, Review of Financial Studies, Vol. 21

Engle, R. et al, 2009, Stock Market Volatility and Macroeconomic Fundamentals, Review of Economics and Statistics – MIT Press Journals, Vol. 95

Errunza, V.and Hogan, K., 1998, Macroeconomic determinants of European stock market volatility, European Financial Management, Vol. 4

Fama, E.F. and Schwert, G.W., 1977, Asset returns and inflation, Journal of Financial Economics, North-Holland Publishing Company, Vol 5

Girardin, E. and Joyeux, R., 2013, Macro Fundamentals as a Source of Stock Market Volatility in China: A GARCH-MIDAS Approach", Economic Modelling - The International Journal of Theoretical and Applied Papers on Economic Modelling, Vol 34

Nana, G. et al, 2013, GARCH-extended models: theoretical properties and applications, Department of Financial Mathematics, FraunhoferInstitut fur Techno und Wirtschaftsmathematik

Roodman, D., 2009, A Note on the Theme of Too Many Instruments, Oxford Bulletin of Economics and Statistics, Vol 71

Schwert, G.W., 1988, Why does stock market volatility change over time?, The Journal of Finance, Vol XLIV, No 5

Zakaria, Z. and Shamsuddin, S, 2012, Empirical Evidence on the Relationship between Stock Market Volatility and Macroeconomics Volatility in Malaysia, Journal of Business Studies Quarterly , Vol. 4, No. 2

Appendix

A. Results of the individual estimation

Table A.1 Results with macro volatility extracted through variance

Country	Variable	Coefficient	Prob (t-Statistic)
Czech Republic	Exchange rate	-0.0002	0.8034
	Inflation	0.0137	0.0287*
	Industrial production	-0.0008	0.3922
	Unemployment	0.0476	0.3423
Croatia	Exchange rate	-0.0003	0.6197
	Inflation	0.0028	0.5913
	Industrial production	-0.0003	0.6197
	Unemployment	0.0103	0.0156**
Poland	Exchange rate	-0.0006	0.0000**
	Inflation	-0.0194	0.4159
	Industrial production	0.0001	0.2613
	Unemployment	0.0026	0.0002*
Romania	Exchange rate	0.0011	0.0015**
	Inflation	0.0005	0.7759
	Industrial production	0.0007	0.5352
	Unemployment	-0.0001	0.9388
Hungary	Exchange rate	-0.0001	0.8375
	Inflation	-0.0045	0.3147
	Industrial production	0.0006	0.5553
	Unemployment	-0.1243	0.0023*

The coefficients of macroeconomic variables have to be multiplied by 10^{-4} to interpret them as percentage changes

** - introduction of the variable is incompatible with model constraints*

*** - coefficients are statistically significantat a confidence level of 95%*

**** - coefficients are statistically significant at a confidence level of 90%*

Table A.2 Results with macro volatility recovered by ARCH models

Country	Significant variables	Coefficient	Prob (t-Statistic)
Czech Republic	Exchange rate	0.0001	0.0567**
	Inflation	0.0079	0.2343
	Industrial production	-0.0004	0.0926***
	Unemployment	-0.0063	0.6600
Croatia	Exchange rate	0.0002	0.7693
	Inflation	-0.0165	0.2908
	Industrial production	0.0006	0.0252*
	Unemployment	-0.0016	0.9089
Poland	Exchange rate	0.0007	0.8991
	Inflation	0.0031	0.8218
	Industrial production	0.0008	0.2549
	Unemployment	0.0007	0.1974
Romania	Exchange rate	0.0009	0.0393**
	Inflation	-0.0044	0.2727
	Industrial production	-0.0001	0.2857
	Unemployment	0.0213	0.3460
Hungary	Exchange rate	0.0007	0.8551
	Inflation	-0.0055	0.0019**
	Industrial production	0.0001	0.5042
	Unemployment	-0.0366	0.3516

The coefficients of macroeconomic variables have to be multiplied by 10^{-4} to interpret them as percentage changes

B. Panel results

Table B.1 Stationarity tests

Variable	ADF (Prob F-statistic)	PP (Prob F-statistic)	IPS (Prob F-statistic)
Inflation	0.0005	0.0002	0.0002
Unemployment	0.0061	0.0441	0.0282
Exchange Rate	0.0002	0.0083	0.0001
Industrial Production	0.0005	0.0010	0.0002
Market Index	0.0057	0.0131	0.0017

Table B.2 The results of Hausman test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	70.760798	4	0.0000

Table B.3 Identified dynamic panel GMM

Variable	Coefficient	Prob(t-statistic)
Unemployment	-0.0015	0.9593
Inflation	0.0052	0.5624
Exchange rate	0.0008	0.0381**
Industrial Production	0.0001	0.8739

Table B.4 Over-identified dynamic panel GMM

Variable	Coefficient	Prob(t-statistic)
Unemployment	-0.0028	0.3338
Inflation	-0.0067	0.7808
Exchange rate	0.0008	0.0064**
Industrial Production	-0.0001	0.7753