ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

DYNAMICS OF EMERGING EQUITY MARKETS VOLATILITIES AND FORECASTING PEFORMANCE OF EXISTING MODELS

Ph. D. THESIS

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

GELİŞMEKTE OLAN PİYASALARDA OYNAKLIK YAPISININ İNCELENEREK VAROLAN MODELLERLE TAHMİN BAŞARISININ TEST EDİLMESİ

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ŞUBAT 2013

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Date of Submission : 31 September 2012
Date of Defense : 14 February 2013

FOREWORD

This dissertation where written during the time-period from spring 2007 until summer 2012, under the supervision of Professor Oktay Taş, Istanbul Technical University, Management Engineering Programme. The intent of the dissertaion is to examine underlying dynamics of the volatitily of emerging stock markets and forecasting performances of the existing models in these markets.

I want to thank my supervisor Oktay Taş of being great help during the development of this dissertaion, BAP program in Istanbul Technical University and of being so supportive with the necessary hardware and software, TÜBİTAK for the support that they provide me to fund my spendings with the scholarship program for domestic Phd students, and last but definitely not least Higher Education Council for making my studying abroad possible by funding my visit at UPENN in Pennslyvania during 11 months.

I also want to thank Professor Kevin Sheppard of providing many matlab codes in the field of financial econometrics in his web page, which spares me a lot of time to accomplish such an extensive study, eventhough I could not find a chance to meet him personally.

September 2012 Zeynep İLTÜZER

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ABBREVIATIONS

RW	**:** Random Walk
HM	**:** Historical Mean
MA	**:** Moving Average
EWMA	**:** Exponentially Weighted Moving Average
AR	**:** Autoregressive Model
ARCH	**:** Autoregressive Conditional Heteroskedasticity
GARCH	**:** Generalized Autoregressive Conditional Heteroskedasticity
GRJGARCH	**:** Glosten Jagannathan and Runkle GARCH
EGARCH	**:** Exponential GARCH
APARCH	**:** Asymmetric Power ARCH
NAGARCH	**:** Nonlinear Asymmetric GARCH
FIGARCH	**:** Fractionally Integrates GARCH
SV	**:** Stochasitic Volatility
MSE	**:** Mean Square Error
RMSE	**:** Root Mean Square Error
MAE	**:** Mean Absolute Error
MAPE	**:** Mean Absolute Percentage Error
MME-U	**:** Mean Mixed Error-Under
MME-O	**:** Mean Mixed Error-Over
MLAE	**:** Mean Logarithm Of Absolute Error
RC	**:** Reality Check
SPA	**:** Superior Predictive Ability
MCS	**:** Model Confidence Set
MMSE	**:** Minimum Mean Square Estimator
MMSLE	**:** Minimum Mean Square Linear Estimator
GMM	**:** Generalized Method Of Moments
MCMC	**:** Markov Chain Monte Carlo
QML	**:** Quasi Maximum Likelihood
CAPM	**:** Capital Asset Pricing Model
BEKK	**:** Baba, Engle, Kraft and Kroner
MGARCH	**:** Multivariate GARCH
CCF	**:** Cross Correlation Function
LR	**:** Likelihood Ratio
AR	**:** Autoregressive Model
LB	**:** Ljung-Box diaognastics
CPI	**:** Consumer Price Index
IP	**:** Industrial Production
M1	**:** Money Supply
INT	**:** Short Term Interest Rate
ISE	**:** Istanbul Stock Exchange
PX	**:** Prague Stock Exchange

IBOV	**:** Brazil Bovespa Index
SENSEX	**:** Bombay Stock Exchange Sensitive Index
CNB	**:** Czech National Bank
IFC	**:**The International Finance Corporation
SP	**:** Standard and Poors

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DYNAMICS OF EMERGING EQUITY MARKETS VOLATILITIES AND FORECASTING PERFORMANCE OF EXISTING MODELS

SUMMARY

Volatility is one of the most researched, argued topic in the finance literature due to the fact that its role in asset and portfolio decisions and especially in derivative markets. The focus of these studies are primarily to model volatility mathematically. Secondly, it is to find out the underlying dynamics of volatility, which will eventually serve for modelling the volatility. When this huge literature is over viewed, the most important point is that it is very hard to obtain a general conclusion about the performance of the existing models due to many subjective decisions that have to be taken during the forecasting process, which means all emprical results are only valid in their context. For instance, it is not possible to say, GARCH model is better than EWMA. Hence, first chapter of this dissertation aims to fill this gap in the literature by analyzing forecasting performances of the models for 19 emerging markets on 8 different forecast horizons with 11 volatility models comprising both naive nonparametric models such as Random Walk or Moving Average and sophisticated models such as GARCH models or Stochastic Volatilitiy model. Such an extensive coverage and the methodology applying the recent developments in econometrics, namely Reality Check, Superior Predictive Ability and Model Confidence Set, provides to eliminate fragilities in forecasting and to draw some common conclusions about the performances of the models for emerging markets. In the most general terms, the results show that as the forecast horizon increase, there is a movement from sophisticated models to naive models in terms of best performing model. Although this is the motivation of the first part of the study, it also serves to understand if the efforts put by the researchers so far in modelling volatilty really pays off, since there is a considerable amount of time and resources are dedicated to this area. The results show that all the efforts to come up with a better model in which the assumption of basic GARCH model are improved does not compensate. No matter what the forecast horizon is, the performances of the GARCH family models are not so different from each other despite of the increasing complexity of the models and computational burden of estimating the models. This is an important indication for the future researchers in the area that the key for developing more succesfull models requires a new approach which does not based on GARCH model approach. At this point, the importance of the studies aiming at finding out the underlying dynamics of the volatility comes to attention due to the limited improvement in the forecasting performance with econometric modelling. Hence, in the second chapter of the study, the aim is to figure out whether the volatility of stock markets are driven by some macro economical dynamics or not. Although the studies under this topic suffers from data availability and sound methodology to model and test the relation between volatility and a certain economical variable, BEKK, one of the Multivariate GARCH models, provides a convinent way to capture both time

variant dynamics of the volatility and simultaneous relations between variables. In the second chapter, the bidirectional causal relations in Granger sense between macro economic volatilitiy and stock market volatility for some emerging markets are analyzed and the results show that there exists causal relations between stock market volatility and macro economic volatility, and they are specific to countries dynamics, which means for every market, macro economic, regional and structural variables need to be analyzed in order to explain the volatitiy of the stock market in terms of underlying dynamics. However, the data issues such as availability and low frequency of macro economic variables make it very difficult to perform such an extensive analysis. Still, the results support that the volatility modelling should depend on some structural underlying dynamics not only time series properities.

GELİŞMEKTE OLAN PİYASALARDA OYNAKLIK YAPISININ İNCELENEREK VAROLAN MODELLERLE TAHMİN BAŞARISININ TEST EDİLMESİ

ÖZET

Finansal piyasalarda oynaklığın tahmini ve tahminlerin değerlendirilmesi, gerçekleşen oynaklığın nasıl ölçüleceği, yapılan tahminler sonucu elde edilen hata terimlerinin nasıl değerlendirileceği, hangi modellerin çalışmaya dahil edileceği, tahmin ufkunun ne olacağı gibi pek çok konuda öznel seçimler yapılmasını gerektirmektedir. Oynaklığın tahmini üzerine çok geniş bir literatür olmasına rağmen, bu tür öznel seçimlerin varlığı, çalışmalardan genel bir çıkarım yapılmasını mümkün kılmamaktadır. Modellerin tahmin başarıları üzerine yorum yapmak bir yana, sadece bir piyasa için bile tek bir modelin üstün performansından bahsedilememektedir. Kısaca, oynaklık modellerinin performanslarını analiz eden çalışmalardan elde edilen sonuçlar, tahminlerin elde edilmesi ve değerlendirilmesi süreçlerindeki farklılar nedeniyle sadece oluşturulduğu çerçevede geçerli olmaktadır. Bu nedenle, bu alanda pek çok yayın yapılmasına rağmen "Oynaklık tahmininde GARCH modeli EWMA' dan daha başarılıdır" ya da "Oynaklık tahmininde Stokastik Oynaklık modeli GARCH modelinden daha başarılıdır" şeklinde genel sonuçlar çıkarılamamaktadır. Bu durumda, hem araştırmacılar hem de yatırımcılar, oynaklık hesaplamaları için, kendi tercihlerine göre bir model seçmektedirler ki, bu tercih büyük çoğunlukla çok yaygın bir şekilde kullanılan GARCH modellerinden biri olmaktadır. GARCH modeller ailesinin kullanımı o kadar yaygındır ki göreli başarısı neredeyse artık sorgulanmamaktadır. Oysaki "Oynaklık tahmininde GARCH modeli EWMA 'dan daha başarılıdır" şeklinde bir genelleme yapılıp yapılamayacağını araştırmak için pek çok piyasanın oynaklık tahmini aynı yöntem ile incelenip değerlendirilmelidir. Bu noktada araştırmanın yöntemi, yukarıda bahsedilen öznel kararların etkileri göz önünde bulundurularak oluşturulmalıdır. Örneğin, hangi modellerin başarılarının değerlendirileceği bunlardan biridir. Literatürdeki çoğu çalışma, performansları karşılaştırılacak modelleri seçerken, geliştirilmiş modellerin kısıtlı bir bölümünü çalışma kapsamına almaktadır. Bu durum, çalışma kapsamı dışında kalan modellerin performansları değerlendirilemeye alınamadığıdan sonuçların sadece değerlendirmeye alınan modeller içinde geçerli olmasına sebep olmaktadır. Sadece GARCH ailesi modellerinin performanslarının karşılaştırıldığı çalışmalar bu duruma örnek teşkil etmektedir. Özetle, oynaklık tahmin literatüründe, tahmin metodolojisinin çeşitli aşamalarında alınan öznel kararlar nedeniyle, varolan modellerin tahmin performansı ile ilgili genel bir sonuç çıkarılamaması problem teşkil etmektedir. Sonuç olarak yapılan her çalışma kendi kapsamı içinde geçerli hale gelmek, geliştirilen modellerin performansları hakkında genel bir karşılaştırma ve değerlendirme yapılamamaktadır. Çalışmanın ilk bölümünde, gelişmekte olan piyasalar için varolan modellerin performansları hakkında bir genelleme yapılabiliyor mu sorusunun cevabı aranarak sözkonusu

probleme bir cevabının olup olmadığı araştıılmıştır. Elde edilen sonuçlar, gelişmekte olan piyasalardaki yatırımcıların, oynaklık tahmini için model seçimlerini yaparken, yaygın olarak kullanılan hangi model ise onu seçmekten öteye geçmelerini sağlayıp, seçimlerini bilimsel bir çerçeveye oturacaktır. Ayrıca çalışmanın üzerine kurulduğu genel çerçeve sayesinde, modellerin gerçekleşen değerden yüksek veya düşük tahmin üretme eğilimleri belirlenebilmektedir. Bu ise, söz konusu yatırımcıların seçtikleri modelden elde edilen tahmininin, karar ve uygulama süreçlerinde yaratacağı olası avantaj ve dezavantajların farkında olunmasını sağlayacaktır. Bu amaçla çalışmanın ilk bölümünde, 19 gelişmekte olan ülkenin hisse senedi piyasa oynaklığı, 8 farklı tahmin ufkunda, Rassal Yürüyüş veya Hareketli Ortalama gibi basit tahmin yöntemlerinden GARCH modelleri ve Stokastik Oynaklık gibi matematiksel olarak sofistike modelleri de kapsayacak şekilde 11 oynaklık modeli kullanılarak tahminleri gerçekleştirilmiştir. Çalışmanın metodolojisi oluşturulurken, oynaklığın tahmini ve tahminlerin değerlendirilmesi sürecinde alınan pek çok öznel kararın sonuçlar üzerindeki etkisini ortaya çıkaracak şekilde oluşturulmuştur. Bu öznel seçimlerden ilki oynaklığın varyans mı yoksa standart sapma ile mi ölçüleceğinin belirlenmesi gelmektedir. Literatüre de her araştırmacı nedenini belirtmeden kendi öznel tercihini yapmaktadır. Bu noktadan sonra yapılan ikinci seçim, oynaklık getiri gibi direk olarak gözlemlenen bir değişken olmadığı için gerçekleşen oynaklığın hangi yöntem ile hesaplanacağını konusundadır. Bu konuda literatürde, günlük getirilerin karesi, ortalamadan arındırılmış günlük getirilerin karesi, ardışık korelasyondan arındırılmış getirilerin karesi gibi değişik yaklaşımlar bulunmaktadır. Değişik yaklaşımların varlığı temelde getirilerin, ortalamadan (koşullu veya sabit) arındırılıp arındırılmaması gerekliliği konusunda araştırmacının eğilimine dayanmaktadır.

İkinci olarak, model parametrelerinin hesaplaması için örneklem seçiminin nasıl gerçekleştirileceği çalışmalar arasında önemli bir fark yaratmaktadır. İki yöntem mevcuttur. Yöntemlerden birinde, örneklem kümesi dinamik bir yapıda ötelenerek güncellenerek, model parametreleri her tahmin için yeniden hesaplanırken, diğer yöntemde ise sabit bir örneklem kümesi kullanılarak, tüm tahminler için kullanılacak olan parametreler hesaplanır. Bu konuda literatürde, dinamik yapının tercih edildiği yöntemlerin ekonomide zaman içinde görülen yapısal değişimlerin etkilerini daha iyi yansıttığını, statik yaklaşımın sebep olduğu bu sapmanın model performansı üzerindeki etkisini de sınırlamış olacağını belirtilmekle beraber seçim araştırmacıların insiyatifindedir.

Modellerin değerlendirmesi süreci içinde oldukça önemli diğer bir nokta ise model performanslarının nasıl karşılaştırılacağıdır. Bu konu tahminlerin elde edilmesi kadar önemli olmasına rağmen araştırmacılar tarafından gereken özen gösterilmemiştir. Sonuçlar doğrudan doğruya hata istatistiklerin sıralamasına göre belirlenmiş, çoğu durumda elde edilen hata istatistiklerin birbirine çok yakın olması ve ortaya çıkan sıralamanın istatistiksel olarak anlamlı olup olmadığı şüphesi sonuçların güvenirliğini azaltan bir faktör olmuştur. Son yıllarda geliştirilmiş olan Gerçeklik Kontolü (GK), Üstün Tahmin Becerisi (ÜTB) ve Model Güven Kümesi (MGK) yöntemleri ile hata istatistiklerindeki anlamlı farklılıklar belirlenip modellerin performanslarının birbirinden farklılaşmasının istatistiki olarak anlamlı olup olmadığını test etme imkânı bulunmaktadır. Bu çalışmada GK, ÜTB ve MGK yöntemleri kullanılarak model performanslarının karşılaştırılması istatistiksel olarak analiz edilmiştir. Bu yöntemler sonuçların genelleştirilebilmesine olanak sağlamaktadır. Model performanslarının karşılaştırılmasında hangi hata istatistiklerinin seçileceği konusu da araştımanın insiyatifine bağlı olduğundan yapılan seçimlerin model performanslarının belirlenmesindeki etkisi ve elde edilen sonuçların uygulamacılar açısından önemi göz önünde bulundurulmalıdır. Çalışmaya hem simetrik hata istatistikleri MSE, RMSE, MAE, MAPE hem de asimetrik hata istatistikleri MME-U, MME-O, MLAE, LINEX dahil edilmiştir. Finansal piyasalar için hem simetrik hem de asimetrik hata istatistiklerinin kullanımı anlamlıdır. Modelin gerçekleşen değerden düşük veya yüksek olarak tahminler üretmesi özellikle türev ürün piyasa oyuncuları için önem arz etmektedir. Örneğin kısa pozisyon alan bir yatırımcı için oynaklık tahmini için kullanılan modelin genellikle gerçek değerin altında tahminler üreten bir model olduğunu bilmesi, modelin ürettiği oynaklık sonucu oluşan fiyat beklentisini bu bilgiye dayanarak revize edebilir ya da bu doğrultuda değerlendirmeler yapabilme imkanı bulabilir. Bu bağlamda asimetrik hata terimleri modelin performansını değerlendirmekten çok modelin ürettiği hataların gerçekleşen değerin altında veya üstünde değerler üretme eğilimini incelemek için çalışmaya dahil edilmiştir. Dolayısıyla modellerin başarısı simetrik hata istatistiklerine göre değerlendirilmiştir.

Çalışmaya dahil edilen modeller oynaklık literatüründeki modellerin temsili bir kümesi olarak seçilmiştir. Basit modeller adı altında toplanılan Rassal yürüyüş, Tarihsel Ortalama, Hareketli Ortalama, EWMA literatür de oynaklık tahmininde kullanılan temel parametrik olmayan yöntemlerdir. Son yıllarda stokastik oynaklık modelinin kullanıldığı ve geliştirildiği çalışmaların öne çıkmasına rağmen, GARCH ailesi modelleri oynaklık literatürüne hakim durumdadır. Finansal varlıkların gösterdiği kaldıraç etkisi, doğrusal olmama, uzun hafıza gibi belli karakteristik özellikleri yansıtabilmek için, farklı yazarlar tarafından temel GARCH modelinin değişik versiyonları diyebileceğimiz yeni modeller oluşturulmuştur. GARCH ailesi modellerinin hepsi çalışmanın kapsamı düşünüldüğünde dahil edilemeyecek kadar çoktur. Bu noktada temel GARCH modelinin yanında, yukarıda saydığımız karakteristik özellikleri içeren modeller seçilerek temsili bir GARCH modeller ailesi kümesi oluşturulmuştur. Ve son olarak da Stokastik oynaklık modeli seçilmiştir.

En genel anlamda sonuçlar göstermiştir ki tahmin ufku arttıkça, tahmin başarısında, sofistike modellerden basit modellere doğru bir geçiş olduğu görülmüştür. Çalışma ayrıca oynaklık modellerinin geliştirilmesi için harcanan onca zaman ve çabaya değen bir gelişme sağlanıp sağlanmadığını anlamaya yardımcı olmaktadır. Sonuçlar göstermiştir ki, GARCH modelinin varsayımlarını esnekleştirerek geliştirilen pek çok model aslında harcanan çabaların karşılığını ödememektedir. Tahmin ufku ne olursa olsun modellerin artan kompleksitesine ve hesaplanma yüklerine rağmen, GARCH ailesi modellerinin başarısı birbirinden çok da farklılaşmamaktadır. Bu, oynaklık alanında gelecekte yapılacak araştırmaların daha başarılı olmasının anahtarının GARCH modelleme yaklaşımı dışında yeni bir yaklaşım tarzına ihtiyaç olduğunu açıkça göstermektedir. Bu noktada, oynaklığın mekanik olarak modellenmesiyle elde edilen kısıtlı ilerleme, oynaklığın altında yatan ekonomik ve yapısal dinamiklerin belirlenmesini amaçlayan çalışmalara dikkati çekmektedir. Tahvil ve bono piyasaları ile hisse senedi piyasaları arasındaki oynaklık geçişinin, gelişmiş piyasalar ile gelişmekte olan ülkelerin hisse senedi piyasaları arasındaki oynaklık geçişinin, gelişmekte olan ülkelerin birbirleri arasındaki oynaklık geçişinin, ülkelerin makro ekonomik göstergeleri ile hisse senedi piyasa oynaklığı arasındaki ilişkilerin incelendiği çalışmalar bu amaca hizmet etmektedir. Bu çerçevede, bu çalışmanın ikinci bölümde, gelişmekte olan ülkelerin hisse senedi piyasa oynaklığının daha etkin bir biçimde modellenmesi ve tahminine katkı sağlanıp sağlanamayacağı konusunda fikir sahibi olmak için, hisse senedi piyasa oynaklıklarının belli makro ekonomik dinamiklerden etkilenip etkilenmediği analiz edilmiştir. Gelişmiş ülkeler için yapılan çalışmalar incelendiğinde, çalışmaların çoğunun söz konusu ilişkiyi nedensellik boyutundan çok belli bir korelasyonun varlığı çerçevesinde incelemiş oldukları görülmektedir. Ayrıca çalışmalarda, incelemeye alınan makroekonomik değişkenler çoğunlukla ortak olmasına rağmen, her piyasa için farklı değişkenlerin hisse senedi piyasası oynaklığı ile ilişkili olduğu bulunmuştur.

Konu teorik açıdan değerlendirildiğinde, temel fiyatlama prensibi olan gelecekteki nakit akışlarının bugünkü beklenen değeri olduğu göz önünde bulundurulduğunda, bir ülkedeki makroekonomik şartların, iskonto oranları ve nakit akışları üzerindeki etkileri nedeniyle hisse senedi piyasalarının risk seviyesini yani oynaklığını etkileyeceği sonucu çıkmaktadır. Her ne kadar, temel fiyatlama prensibi açısından bakıldığında makroekonomik oynaklığın hisse senedi oynaklığının nedenlerinden olması gerektiği sonucu çıksa da, literatürde karşı görüşe sahip olanlar da bulunmaktadır. Karşıt görüşü savunanlar, ülkelerin makroekonomik koşullarında görülen değişimlerin ve bunun yarattığı beklentilerin, makroekonomik değişkenlere yansımadan önce, bu yeni bilginin, hisse senedi piyasalarında eş anlı olarak fiyatlara yansımış olduğunu ileri sürmekte ve hisse senedi piyasa oynaklığının ülkenin makroekonomik riskinin göstergesi olduğunu savunmaktadır. Bu noktada, gelişmiş ülkelerin hisse senedi piyasaları ile makroekonomik oynaklık arasındaki ilişki son 30 yıldır araştırılıyor olmasına rağmen, gelişmekte olan ülkeler için bu tür incelemeler yapılmamıştır. Gelişmiş ülkeler için yapılan çalışma sonuçları ve teorik çerçeve göz önünde bulundurulduğunda, gelişmekte olan ülkelerin hisse senedi piyasalarının oynaklığı ile makroekonomik oynaklık arasındaki ilişki incelenmeyi beklemektedir. Ekonometri alanında görülen son dönemlerdeki gelişmeler, araştırmacılara değişkenlerin oynaklığı arasındaki ilişkileri, zaman içinde değişkenlik gösteren bir yapıda ve nedensellik boyutunda analiz etme imkanı vermektedir. Bu gelişmelerin yardımıyla, çalışmanın ikinci bölümünde gelişmekte olan ülkelerin hisse senedi piyasalarının oynaklığı ile makro ekonomik oynaklığı arasında bir ilişki olup olmadığını BEKK-MGARCH(1,1) modeli yardımıyla Granger Nedenselliği çerçevesinde değerlendirmektir. Çalışma makroekonomik değişkenler olarak enflasyon, sanayi üretim indeksi, para arzı ve kısa dönem faiz oranlarını alarak Türkiye, Çek Cumhuriyeti, Brezilya ve Hindistan için söz konusu incelemeyi gerçekleştirmiştir. Bu tür çalışmaların önündeki en büyük engel veri eksikliği veya veri uzunluğunun yetersizliği olduğu için, ülke seçimleri, veri ulaşılabilirliğine dayanmaktadır. En genel anlamda, sonuçların incelenen ülkeye özgün olmakla beraber, makro ekonomik göstergelerdeki dalgalanmalar ile hisse senedi piyasası risk seviyesi arasındaki ilişkiyi desteklediği görülmüştür. Bu da göstermiştir ki, oynaklığı, altta yatan dinamiklerle tanımlayabilmek için, her hisse senedi piyasası için ilgili ülkedeki makro ekonomik, yapısal ve bölgesel pek çok değişkenin analize dahil edilmesi gerekmektedir. Fakat, yeterli geçmişe sahip olmama, frekanslarının düşük olması gibi veri problemleri bu çapta bir analizin gerçekleştirilmesinin önündeki en önemli engellerdendir. Yine de sonuçlar, oynaklık modellerinin sadece zaman serisi analizine değil belli yapısal dinamiklere de bağlı olarak geliştirmesi gerektiğini desteklemektedir.

1. INTRODUCTION

It is not wrong to say that the volatility is the most researched, argued topic in the finance literature due to the fact that its role in asset and portfolio decisions and especially in derivative markets. Empirically and theoretically many researches have been conducted and it does not look like that the interest in this field is getting fade mostly because the proposed models have not evolved the state where researchers are content with the results. Research topics in volatility can be summarized in three group: Those proposing new or modified models based on time series properties of financial time series, for instance all developments in GARCH family models, realized volatility, stochastic volatility etc.; secondly those applying or evaluating these proposed models in different financial markets, i.e all empirical works either those aiming at describing the volatility of markets by proposed models or those aiming at evaluating the performance of models in markets, and finally those aiming at finding the underlying dynamics of volatility, i.e all researches dealt with the spill overs, transmission, macroeconomic variables etc. When literature is overviewed the most important point that I have reached is that it is very hard to obtain a general conclusion about the performances of the existing models due to many subjective decisions that have to be taken. Therefore, results from the studies become specific to the setting that the authors chose, and one can find himself asking these kind of questions: Can the results be valid for the X country? or What if would the volatility, which is an unobserved variable, be measured in different ways? or What if would other models be included in the study? Or are the results still be valid for different forecast horizons? What if would different error statistics be used for the evaluation? And many more questions can be raised. Therefore, in order to figure out models performances for different markets and for different horizons and draw a generals conclusion, a study should: i) measure the volatility in the same way for all the markets in question, ii) involve the different forecast horizons from short term to long term, iii) involve different error statistics in order to see if the results are changing according to error statistics, iv) involve all the models existing in the literature. Only when these points are taking into account and a large set of markets included in the study, one can obtain some general sense of the performances of models. Hence, the first chapter of this dissertation aims to fill this gap in the literature by analyzing forecasting performances of the models for 19 countries with 8 different forecast horizons. To the best of our knowledge, there is no such comprehensive study in the field, which provides to draw some common conclusions about the performances of volatility models.

Another important gap especially for emerging markets in the literature is in the third group. To figure out the underlying dynamics of emerging equity markets is mostly confined to the examination of the volatility transmission between different countries. However, the interaction between macroeconomic volatility and stock market volatility has been an important consideration for developed markets; and it is important to examine the existence of a relation and, if there is one, the direction of the relation, which leads us to the concept of causality. However, how to perform the analysis is tricky since the volatility is a latent variable and it is hard to examine the causality between two latent variable. For the cases of developed markets, there are a few studies, and almost all of them follow a different approach all have different prons and cons. Fortunately, the recent developments in econometrics provide a convenient way to do this, i.e MGARCH models and bootstrapped testing. The second chapter of this dissertation covers the analysis of the bidirectional causal relations between macroeconomic volatility and stock market volatility for some emerging markets with the multivariate GARCH model. Since the chapters in the dissertation focus on different gaps in the literature, more comprehensive introduction for each chapter are provided in the very beginnings of the chapters.

2. MODELLING AND FORECASTING VOLATILIY

Forecasting volatility and its evaluation require varied subjective decisions in different dimensions. How should volatility be measured, i.e. variance or standard deviation? Which approach should be used for the proxy of observed volatility estimation? How should forecasts be evaluated? What should be the forecast horizon? The choices based on these questions affect the results of researches, which eventually create handicaps for volatility forecasting literature to compare and evaluate the results of the previous studies. Hence, to find out whether there really is a model that performs better than the alternatives for a certain horizon for the majority of emerging stock markets, they need to be evaluated all together with the same methodology in a way that the effects of these subjective decisions are minimized on the forecasting performances.

Firstly, there are two different approaches to measure volatility in the literature: variance and standard deviation. West and Cho (1995), Akgiray (1989), Yu (2002) and Gospodinov et. al (2006) used variances as a volatility measure while Walsh and Tsou (1998), Bluhm and Yu (2000) preferred standard deviations. Secondly, the researcher has to decide how to measure observed volatility since it is a latent variable. General approaches are daily squared returns (Merton, 1980; Klaassen, 1998), mean adjusted daily squared returns (Blair et. al, 2001, So et. al, 1999), daily squared return adjusted for serial correlation (Akgiray, 1989; Pagan and Schwert, 1990), the absolute change in returns (Bali, 2000; Dunis et. al, 2000). The existence of different approaches is mainly based on the question of whether the returns are adjusted for mean (conditional or constant) or not. The advocates of the use of squared returns adjusted for mean and serial dependence put forward that empirically proved high autocorrelation in returns should be controlled while the opponents claim that the statistical properties of the sample mean make it very inaccurate estimate of true mean, therefore taking deviations around zero instead of sample mean increases the forecast accuracy.

Another important decision is how to use the sample to estimate model parameters. Does it have a dynamic structure in which the sample is updated for every forecast or a static structure in which the sample is fixed for all forecasts. At this point, methodologies including dynamic approach provide a better reflection of the structural changes in the economy to the parameters of the model and prevent biases depending on the static approach on the model performances.

The comparison is quite important in the process of evaluation of performances. Although this stage is as important as forecasting; it is not treated as carefully as forecasting in the literature in which the conclusions are basically drawn from the rank obtained by the error statistics. However, error statistics of the competing models are most of the time so close that the question if the performances of the models are really distinguishes arises. On the other hand, the question of which error statistic should be used is another issue for the comparisons. Most commonly used error statistics are those with the symmetric property. Later on, the asymmetric error statistics started to be used in order to address different exposure to risks coming from the positions, long or short, of investors in markets. Although symmetric error statistic is more appropriate to evaluate model performances, it has a second priority when it comes to the significance of the rank obtained by the error statistics. The recent developments in econometrics, namely Reality Check (RC), Superior Predictive Ability (SPA) and Model Confidence Set (MCS), provide a solution for this problem. These procedures help the evaluation of the error statistics in a way that researchers can be sure the statistical significance of the ranks implied by the error statistics, which eventually put the comparison in a more sound ground.

As for the forecast horizon, the relevant forecast horizon varies by the purpose of the agents. Short forecast horizons are relevant for trading purposes and VaR estimations of financial institutions while the longer horizons are also relevant in derivative markets. While a certain model performs very well in a specific forecast horizon, it may not be the same for the other horizons. Since the purpose of the study is to evaluate the model performances in a general context, the results are evaluated for eight different forecast horizons varying between 1-day and 240-day.

Finally, which models are included in the evaluation process is also critical since the performances are relatively evaluated. The more comprehensive the model set is, the more certain one is about the performances of the models. With this perspective, the study covers Random Walk, Historical Mean, Moving Average, EWMA as simple nonparametric models and GARCH family models and Stochastic Volatility model as parametric models. Lately, the researches applying and/or developing Stochastic Volatility model is more popular and mostly focusing on the parameter estimation methods, however, GARCH family models are still dominant in the literature. The GARCH model is improved by the different researches with different approaches in order to incorporate empirically proved patterns in volatility in the financial stock markets, such as leverage effect, nonlinearity, long-memory. When the coverage of this study is considered, the inclusion of all developed GARCH family models is simply not logical. Therefore, good representative set of GARCH family models are formed in order to cover the models addressing at least one of the above mentioned volatility patterns.

All of the above mentioned points complicate any attempt to compare and generalize results in volatility forecasting literature. This paper aims to complement the literature in two ways. Firstly, to the best of our knowledge, this is the most comprehensive study for emerging stock markets in terms of firstly, the number of countries (i.e. 19 stock exchanges), secondly, the variety of the forecast horizons (short-, mid- and long-term) and thirdly the model coverage (11 models). The comprehensiveness in different dimensions provides one to draw general conclusions in forecasting performances of the models for emerging stock markets. Secondly, this study is distinguished from the others by the way in which forecast results are compared.

2.1 Volatiliy Models

2.1.1 Simple(Naive) models

2.1.1.1 Random Walk(RW)

According to RW, the best forecast of the tomorrow volatility is today volatility, Mathematicaly;

$$\hat{\sigma}_{t+1}^2 = \sigma_t^2 \tag{2.1}$$

where $\hat{\sigma}_{t+1}^2$ is the volatility forecast, σ_t^2 is the observed volatility, $t = w, w + s, w + 2s, \ldots$ and w is sample size , s is the forward shifting step in the rolling scheme.

2.1.1.2 Historical Mean(HM)

This is basically the mean of all observations before the relevant forecast is performed. That is, the sample size grows as additional observations are added.

$$\hat{\sigma}_{t+1}^2 = \frac{1}{t}\sum_{i=1}^{t} \sigma_i^2 \qquad \textbf{(2.2)}$$

where $\hat{\sigma}_{t+1}^2$ is the volatility forecast, σ_t^2 is the observed volatility, $t = w, w + s, w + 2s, \ldots$ and w is sample size , s is the forward shifting step in the rolling scheme.

2.1.1.3 Moving Average (MA)

According to HM, all past observations are used for the forecast. However, MA only takes into account past n observations, which is a subjective choice. MA can be considered as a recent historical mean of the variable. In the paper n is chosen as 240, which can be thought as one-year historical mean:

$$\hat{\sigma}_{t+1}^2 = \frac{1}{n}\sum_{i=k}^{k+n-1} \sigma_i^2 \qquad \textbf{(2.3)}$$

where $\hat{\sigma}_{t+1}^2$ is the volatility forecast, σ_t^2 is the observed volatility, $t = w, w + s, w + 2s, \ldots$ and w is sample size , s is the forward shifting step in the rolling scheme and $k = w - n + 1, w - n + s + 1, w - n + 2s + 1, \ldots$.

2.1.1.4 Exponentially Weighted Moving Average (EWMA)

As opposed to MA, EWMA gives exponentially decreasing weights to n past observations when past observations gets older. The intuition behind incorporation of deay in weights is that recent observations have much more importance in forecasting future volatility than older observations. As in MA, n is chosen as 240.

$$\hat{\sigma}_{t+1}^2 = \frac{\sum_{i=0}^{n-1} \lambda^i \sigma_{t-i}^2}{\sum_{i=1}^{n} \lambda^i} \qquad \textbf{(2.4)}$$

where $\hat{\sigma}_{t+1}^2$ is the volatility forecast, σ_t^2 is the observed volatility, $t = w, w + s, w + 2s, \ldots$ and w is sample size , s is the forward shifting step in the rolling scheme and λ is the smoothing constant and estimated by minimizing the sum of in-sample squared errors.

h-day volatility forecasts of the above nonparametric models are estimated by simple scaling rule ,which is $\hat{\sigma}_{t+1}\sqrt{h}$.

2.1.2 GARCH family models

It is not wrong to say that the current interest in volatility modeling and forecasting started with the seminal papers Bollerlsev (1986) and Engle (1982) in which GARCH and ARCH models were proposed respectively. After these seminal papers, variety of versions taking into account different characteristics of financial time series such as leverage effect, long memory, nonlinearity have been developed from GARCH modeling perspective. Therefore, the literature on conditional volatility models is enormous, and GARCH, GJR-GARCH, EGARCH, APARCH, NAGARCH and FIGARCH are chosen for the analysis since it is not simply practical to simultaneously study the every model when the scope and methodology is taking into account in the dissertation. However, selected models can be considered as a good representative set of GARCH family models since the model set includes those focusing on different patterns in volatility such as asymmetry, nonlinearity and long memory.

Let define R_t as the return process of a financial security.

$$\begin{gathered} R_t = \mu_t + \varepsilon_t \\ \varepsilon_t = \sigma_t z_t , \qquad z_t \sim N(0,1) \end{gathered} \tag{2.5}$$

where μ_t and σ_t are the conditional mean and the conditional variance of the return process, respectively. The conditional mean can be modeled by an ARMA process or taken as constant, which is equal to unconditional mean in this case $R_t = \mu + \varepsilon_t$. GARCH family models provide different formulations for the conditional variance, σ_t, of the process. The main idea behind the GARCH family models is that the conditional variance is a deterministic function of the past variances and shocks of the return processes. In this section, these GARCH family models are introduced.

2.1.2.1 Generalized Autoregressive Conditional Heteroscedasticity

GARCH model introduced in Bollerlsev (1986) captures the volatility clustering first noted by Engle (1982). GARCH(p,q) are defined by equation 2.6 in which the parameters are estimated by the maximum likelihood

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2.6}$$

where ε_{t-i} is the past innovation and α_i models the effect of the past innovations and σ_{t-j}^2 is the past contional volatility and β_j models the effect of past volatility on current volatility. The magnitude of βs indicates that how persistent is the volatility process, while high α values indicates that the volatility of the financial asset substantially affected by the shocks in the markets. The unconditional variance of the process is

$$\sigma^2 = \frac{\omega}{1-\sum_{i=1}^{p}\alpha_i-\sum_{j=1}^{q}\beta_j} \tag{2.7}$$

The model has to satisfy following constraints on the coefficients in order to provide the positiveness of the conditional variances and stationarity of the process:

(i) $\omega > 0, \alpha_i > 0, \beta_i > 0$

(ii) $\sum_{i=1}^{\max(p,q)} \alpha_i + \beta_i \leq 1$

Some additional constraints can be added for further moments.

2.1.2.2 Exponential GARCH (EGARCH)

GARCH model has some deficiency in modelling the effects of the positive and negative news on conditional volatility since it is emprically proven that negative news has bigger impact on the volatility process relative to positive news. Addressing this issue, however, requires additional constraints on the parameters, which eventually makes the optimization process harder in most situations. In order to provide a convienent modelling approach in which asymmetric effects can be parametrized without increasing the complexity of the estimation process, Nelson (1991) proposed EGARCH(p,q) by modeling conditional variance in logarithmic form:

$$ln\sigma_t^2 = \omega + \sum_{j=1}^{q}\beta_j \ln\sigma_{t-j}^2 + \sum_{i=1}^{p}\left[\theta_i\epsilon_{t-i} + \gamma_t\left(|\epsilon_{t-i}| - E(\epsilon_{t-i})\right)\right] \tag{2.8}$$

where $\epsilon_t = \frac{\varepsilon_t}{\sigma_t}$. When the distribution of the return innovations, ε, is assumed to be normal then $E(\epsilon_{t-i})$ equals $\sqrt{\frac{\pi}{2}}$, and it equals $\frac{v-2}{\pi}\frac{\Gamma((v-1)/2)}{\Gamma(v/2)}$ for student-t distribution The process is covariance stationarity if and only if $\sum_{j=1}^{q}\beta_j < 1$.

The parameters γ and θ together capture the asymmetric effects of positive and negative news exponentially. For instance, if $\gamma > 0$ and $\theta = 0$, then the logarithm of conditional variance increases when the magnitude of ϵ_t is greater then its expected value. Now let suppose that $\gamma = 0$ and $\theta < 0$, in this case the logarithm of conditional variance increases when the return innovations are negative.

2.1.2.3 Glosten, Jagannathan and Runkle GARCH (GRJ-GARCH)

Glosten et al. (1993) models the asymmetric effects by introducing a dummy variable into Bollerlsev (1986) GARCH specification, which takes value 1 when the return innovations are negative:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i I_{t-1} \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad \textbf{(2.9)}$$

where I_{t-1} when $\varepsilon_{t-1} < 0$, otherwise, $I_{t-1} = 0$. In this way, $\gamma + \alpha$ captures the effect of negative news on volatility, while the parameter α alone captures the effect of positive news. In parallel with GARCH model, approximately the same constraints are imposed with a little modifications, which are:

(i) $\omega > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$ and $\gamma_i \geq 0$

(ii) $\alpha_i + \gamma_i = 0$

(iii) $\sum_{i=1}^{p} \alpha_i + 0.5 \sum_{i=1}^{p} \gamma_i + \sum_{i=1}^{p} \beta_i < 1$

2.1.2.4 Asymmetric Power ARCH (APARCH)

Ding et al. (1993) empirically examined the autocorrelation structure of power of absolute returns, i.e $|r_t|^d$, and they reported that all the power transformations of the absolute returns have significant positive autocorrelations at least up to lag 100, which supports the claim that stock market returns have long-term memory. The closer d gets 1, the bigger the autocorrelation gets and it gets smaller when d goes away from 1. Based on this pattern, they developed a new model which captures the long memory in autocorrelation in different power transformations of absolute returns not just those absolute return as in ARCH and squared absolute returns as in GARCH. This modelling approach includes several other GARCH models as special cases.

$$\sigma_t^d = \omega + \alpha(|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^d + \beta \sigma_{t-1}^d \quad \textbf{(2.10)}$$

where $\omega > 0, \alpha_i \geq 0$, $\beta_i \geq 0$ and $-1 \leq \gamma_i \leq 1$.

2.1.2.5 Nonlinear Asymmetric GARCH (NAGARCH)

Engle and Ng (1993) recommends an approach, which they call news impact curve, in order to measure how news is incorporated into volatility estimates. In order to better estimate and match news impact curves to the data, they introduce several new candidates for modeling time-varying volatility, one of which is NAGARCH formulted as follows:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \left(\varepsilon_{t-i} + \gamma_i \sigma_{t-i}\right) \qquad \textbf{(2.11)}$$

2.1.2.6 Fractionally Integrated GARCH (FIGARCH)

Baillie et al. (1996) proposes FIGARCH model in order to provide a more flexible class of processes for conditional variances that are more capable of explaining and representing the long-run dependencies since many of the empirical works have reported that the persistent parameter is very close to 1. The lagged squared innovations in the conditional variance show a slow hyperbolic rate of decay in FIGARCH model:

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t + \beta(L)\sigma_t^2 \qquad \textbf{(2.12)}$$

where L denotes the lag or backshift operator, and $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_p L^p$ and $\beta(L) = \beta_1 L + \beta_2 L^2 + \cdots + \beta_q L^q$. With the notion that equation 2.12 can be written as the infinite order ARCH process and that the fractional differencing operator, $(1-L)^d$, has a binomial expansion which is most conveniently expressed in terms of the hypergeometric function, an alternative representation for FIGARCH(p, d, q) model is stated as follows after a lot of mathematical reformulations.

$$\sigma_t^2 = \omega(1-\beta(1))^{-1} + (1 - \left(1-\beta(L)\right)^{-1} \emptyset(L) \quad (1-L)^d)\varepsilon_t^2 \qquad \textbf{(2.13)}$$

where $\emptyset(L) = [1-\alpha(L)-\beta(L)][1-L]^{-1}$ is of order $m-1$ where $m = \max(p,q)$. FIGARCH model admits greater flexibility in modeling the conditional variance as it nests covariance stationary GARCH model and IGARCH model as special cases. For $0 < d < 1$, the FIGARCH model holds that a volatility shock is persistent, but eventually the process is mean reverting as the effects of a shock die out at a slow hyperbolic rate. Estimates that ara significantly different from zero of long memory parameter d indicate that volatility exhibits a long memory process.

2.1.3 Stochastic Volatility model

2.1.3.1 Kalman filter and State Space form

State space form of a system provides a very convenient way to model systems with multiple inputs and outputs. State space representation of a system can be used for prediction, filtering and smoothing. Once a system is presented as a state space form, the way is opened for the application of numerous important algorithms, one of which is the Kalman filtering. A state space model consists of a measurement equation in which N dimensional y_t time series are related to M dimensional state vector α_t and a transition equation that describes the evolution of state variables in time. This section mostly depend on Harvey (1989), which is a very good source to see the applications of state space forms and Kalman filter in finance topics besides many other time series topics. Let define the measurement equation as the following form:

$$y_t = Z_t \alpha_t + d_t + \varepsilon_t \tag{2.14}$$

where Z_t is an NxM matrix, d_t is an Nx1 vector, and ε_t, which is called measurement noise such as instrumentation errors, is an Nx1 vector of serially uncorrelated disturbances with mean zero and covariance matrix H_t. α_t is the state of the system. The state variables are in general unobservable but they are known to be generated by a first-order Markov process:

$$\alpha_t = T_t \alpha_{t-1} + c_t + R_t \eta_t \tag{2.15}$$

where T_t is an MxM matrix, c_t is an $Mx1$ vector and R_t is an Mxg matrix and η_t, which can be called process noise, is a $gx1$ vector of serially uncorrelated disturbances with mean zero and covariance matrix Q_t. The state space representation is completed by assuming uncorrelated disturbances in time,

$E(\varepsilon_t \eta_s') = 0$ for all $s, t = 1, 2 \dots T$ and that they are uncorrelated with initial state vector α_0 with mean $E(\alpha_0) = a_0$ and covariance $Var(\alpha_0) = P_0$, that is, $E(\varepsilon_t \alpha_0') = 0$ and $E(\eta_t \alpha_0') = 0$. The matrices Z_t, d_t, H_t, T_t, c_t, R_t and Q_t are called system matrices. If it is not stated, the system matrices are non-stochastic, which means they may change in time in a way that they can be predetermined. If the system matrices do not change with time, the system is called time-invariant or time-homogenous.

This mathematical formulation can be explained verbally as follows: α contains all the information about the present state of the system, which cannot be measured or observed directly. In place of α, one can observe and measure y which is a function of α corrupted by the measurement noise ε. Hence, one can use observations of y, which captures the underlying dynamics of the unobservable variable α with some noise ε, to estimate the unobservable α. As an example, the state space representation of $AR(2)$ model, $y_t = \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \varepsilon_t$, can be chosen as one of the following state space forms:

$$y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \alpha_t \qquad \alpha_t = \begin{bmatrix} y_t \\ \emptyset_2 y_{t-1} \end{bmatrix} = \begin{bmatrix} \emptyset_1 & 1 \\ \emptyset_2 & 0 \end{bmatrix} \alpha_{t-1} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \varepsilon_t$$

$$y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \alpha_t^* \qquad \alpha_t^* = \begin{bmatrix} y_t \\ y_{t-1} \end{bmatrix} = \begin{bmatrix} \emptyset_1 & \emptyset_2 \\ 1 & 0 \end{bmatrix} \alpha_{t-1}^* + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \varepsilon_t \tag{2.16}$$

In general, different state space forms are possible for a system, however, each has its own advanatge and disadvantages such as reducing the dimension of the state vector but creating correlation between measurement and transition equatin disturbances.

Kalman filter is originally developed to provide a solution for a problem in the area of the spacecraft navigation, and it turns out to be useful in many applications where the system states can not be observed directly or measured accurately. Kalman Filter carries important implication for the cases where the state variables can not be observed directly. Volatility of a financial security is a very good example as an unobservable state variable. Basically, what Kalman Filter does is to remove noise from the observations in order to figure out the unobserved true path of the state in an optimal way. In short, Kalman Filter provides an optimal way to estimate the state of the system α in equation 2.15 by using available measurement y in equation 2.14.

Let call a_{t-1} the optimal estimator of α_{t-1} based on the observations up to and including y_{t-1}, then covariance matrix of the estimation error

$$P_{t-1} = E[(\alpha_{t-1} - a_{t-1})(\alpha_{t-1} - a_{t-1})'] \qquad \textbf{(2.17)}$$

Given a_{t-1} and P_{t-1}, the optimal estimator of $\alpha_t$is given by

$$\alpha_{t|t-1} = T_t a_{t-1} + c_t \qquad \textbf{(2.18)}$$

and covariance matrix of the estimation error is

$$P_{t|t-1} = T_t P_t T_t' + R_t Q_t R_t' \qquad t = 1 \ldots . T \qquad \textbf{(2.19)}$$

Once the new observation y_t, becomes available, the estimator of α_t, $\alpha_{t|t-1}$ can be updated in order to find a linear combination of noisy measurement and prior estimate in a way that the weights of the linear combination provides an updated estimate which is optimal in some sense. The optimal weights that determines the combination of prior estimate and the new noisy observation is known as Kalman gain denoted by K_t. The updating equations are

$$\begin{aligned} a_t &= a_{t|t-1} + P_{t|t-1} Z_t' F_t^{-1} (y_t - Z_t a_{t|t-1} - d_t) \\ P_t &= P_{t|t-1} - P_{t|t-1} Z_t' F_t^{-1} Z_t P_{t|t-1} \\ F_t &= Z_t P_{t|t-1} Z_t' + H_t \qquad t = 1 \ldots . T \end{aligned} \qquad \textbf{(2.20)}$$

The Kalman filter is usually written as a single set of recursions going directly from a_t to a_{t+1}, or, alternatively $a_{t+1|t}$

$$a_{t+1|t} = (T_{t+1} - K_t Z_t) a_{t|t-1} + K_t y_t + (c_{t+1} - K_t d_t) \qquad \textbf{(2.21)}$$

where K_t Kalman gain matrix is given by

$$K_t = T_{t+1} P_{t|t-1} Z_t' F_t^{-1} \qquad \textbf{(2.22)}$$

The recursion for the error covariance matrix is

$$P_{t+1|t} = T_{t+1}(P_{t|t-1} - P_{t|t-1} Z_t' F_t^{-1} Z_t P_{t|t-1}) T_{t+1}' R_{t+1} Q_{t+1} R_{t+1}' \qquad \textbf{(2.23)}$$

Given the initial conditions α_0 and P_0, Kalman Filter provides the optimal estimator of the state vector as each new observation becomes available. The conditional mean of y_t in equation 2.14 at time $t-1$:

$$\tilde{y}_{t|t-1} = Z_t a_{t|t-1} + d_t \tag{2.24}$$

can be interpreted as the minimum mean square estimator (MMSE) of y_t in a Gaussian model, and as minimum mean square linear estimator (MMSLE) otherwise. The innovations which present the new information in the latest observation are

$$v_t = y_t - \tilde{y}_{t|t-1} = Z_t\left(\alpha_t - \alpha_{t|t-1}\right) + \varepsilon_t \tag{2.25}$$

As it can be seen from Kalman filter equations 2.21, 2.22 and 2.23, the innovation term play a key role in updating the estimator of the state vector. The larger the innovation terms, the greater the correction in the estimator of α_t. There are two common sources of uncertainty coming from both measurement noise, i.e H_t, and inherent in the system itself, Q_t. Since the aim is to quantify correctness of our model of the real world, the uncertainty must be a part of its behavior, which is characterized by the system noise Q_t. This means that it is wanted that the system noise directly influences the estimates. The measurement noise, on the other hand, is a hindrance to estimate the states of the real world and it is expected that its influence is smaller as much as possible for estimations. In Kalman Filter, the filter gain matrix K_t operates on the difference between a measurement and prior estimate of what the measurement should be. Therefore, a larger Q_t increases P_t, which results in a large K_t; whereas a larger H_t tends to decrease K_t. A decreased K_t does not weight the measurement as much since it is noisy, whereas a larger K_t causes more of the measurement to be incorporated in the estimate Zarchan and Musoff (2001).

2.1.3.2 Inference methods

The time variation property of volatility of the financial securities are most popularly modeled by GARCH family models in literature and practice. Another approach involving time variation is stochastic volatility model in which the variance is modeled as an unobserved component. The lack of estimation procedures for SV models made them an unattractive class of models for a long time in comparison to GARCH family models. Among the first studies in stochastic volatility are Clark

(1973), Tauchen and Pitts (1983) and Taylor (1986). A practical drawback of the inference for the stochastic volatility models is the intractability of the likelihood function since variance is unobservable and the model is non-Gaussian, which result in a likelihood function in the form of a multiple integral.

Consider the univariate stochastic model:

$$\begin{aligned} r_t &= e^{0.5\sigma_t}\varepsilon_t \\ \sigma_t &= \gamma + \varphi\sigma_{t-1} + \eta_t \end{aligned} \qquad \begin{aligned} &\eta_t \sim NID(0, \sigma_\eta^2) \\ &\varepsilon_t \sim NID(0,1) \\ &E(\varepsilon_t, \eta_t) = 0 \end{aligned} \tag{2.26}$$

where $r_t = R_t - \mu$ is the mean adjusted return. Since working in logarithms ensures that σ_t^2 is always positive and provides linearity, by taking logarithms of the squared mean adjusted returns, the following more convenient form is obtained:

$$\begin{aligned} ln(r_t^2) &= \sigma_t + \zeta_t \\ \sigma_t &= \gamma + \varphi\sigma_{t-1} + \eta_t \end{aligned} \qquad \begin{aligned} &\zeta_t = \ln(\eta_t^2),\ E(\zeta_t, \eta_t) = 0 \\ &\eta_t \sim NID\left(0, \sigma_\eta^2\right) \end{aligned} \tag{2.27}$$

In recent years, many estimation techniques for SV models have been developed. The early attempts to estimate SV models used a generalized method of moments (GMM) procedure as in Hansen and Scheinkman (1995), Melino and Turnbull (1990). Increased computer power has made simulation-based estimation techniques increasingly popular. The most widely used approach in the literature involves the Markov Chain Monte Carlo (MCMC) methods, especially Metropolis-Hastings and Gibbs sampling algorithms in the context of SV models (Jacquier et al., 1994, Kim et. al 1998). Another way for the inference is the Quasi Maximum Likelihood Approach (QML) approach whose details are introduced in this section after briefly introducing GMM and MCMC methods. The QML approach relies on the fact that the nonlinear SV model can be transformed into a linear non-Gaussian state space model and from this linear form, quasi maximum likelihood estimates of the parameters can be computed.

In GMM approach, the fundamental point is to exploit the stationary and ergodic properties of the SV model which yield the convergence of sample moments to their unconditional expectations.

Let consider a sample of size T and $g_T(\beta)$ denotes the $mx1$ vector of differences between each sample moment and its theoretical expression in terms of the model parameters β. The GMM estimator is constructed by minimizing the criterion function:

$$\hat{\beta} = \arg \min_{\beta} g_T\,(\beta) W_T g_T(\beta) \quad \textbf{(2.28)}$$

in which W_T is the weighting matrix determining the importance of each moments in the estimation. Unfortunately, the subjectiveness in the choice and number of the moments used in the estimation and the different available approaches for the computation of the weighting matrix makes GMM estimator not be a efficient one.

The QML approach relies on the fact that the nonlinear SV model can be transformed into a linear non-Gaussian state space model and from this linear form quasi maximum likelihood estimates of the parameters can be computed. The exact likelihood function can also be constructed as a mixture of distributions for the observations conditional on the volatilities. The problem with the likelihood function is that it has no explicit form and makes the estimation procedure intractable. This is where MCMC methods comes into play. The main idea behind MCMC is that it creates a Markov process whose stationary transition distribution is close enough to stationary distribution of sample, $P(\omega|r)$, with the data r and parameter vector $\omega = (\gamma, \varphi, \sigma_\eta)$ in equation 2.27. However, there are many different ways to obtain Markov chains for a given $P(\omega|r)$. Gibbs sampling is the most popular way to do that. Suppose that the likelihood function of the model, but the three conditional distributions of single parameter given the others are available. Hence, the following three conditional distributions are available:

$$f_1(\gamma|\varphi, \sigma_\eta, r) \quad f_2(\varphi|\gamma, \sigma_\eta, r) \quad f_3(\sigma_\eta|\varphi, \gamma, r) \quad \textbf{(2.30)}$$

where f_i denotes the conditional distribution of the corresponding parameter given the data and the model and the other parameters. In application, the exact forms of the conditional distributions are not known. What is required is the ability to draw a random number from each of the three conditional distribution. Let say that $\varphi_0$and $\sigma_{\eta,0}$ be two arbitrary starting values of φ and σ_η. What Gibbs sampler does in one iteration is first to draw a random sample from $f_1(\gamma|\varphi_0, \sigma_{\eta,0}, r)$ and call it γ_1, then to draw a random sample from $f_2(\varphi|\gamma_1, \sigma_{\eta,0}, r)$ and call it φ_1 and then to draw a random sample from $f_3\left(\sigma_\eta|\varphi_1, \gamma, r\right)$ and call it $\sigma_{\eta,1}$. This procedure continues until a sufficiently large sample size m by using the new parameters as starting values, which provides a random draw from the joint distribution of the three parameters, under some regularity condition.

Another inference method for SV model is the QML method as it is mentioned before. The QML approach relies on the fact that the nonlinear SV model can be transformed into a linear non-Gaussian state space model and from this linear form, quasi maximum likelihood estimates of the parameters can be computed. The state space equation 2.26 is the form used in the QML. If the ε_t in equation 2.26 is standard normal, then in the QML approach, ζ_t in equation 2.27 follows the $\ln(X^2)$ distribution whose mean and variance are known to be $-1{,}27$ and $\pi^2/2$, respectively. Then the state space model of the system can be rewritten as follows (Harvey et al., 1994):

$$\begin{aligned} &ln(r_t^2) = -1.27 + \sigma_t + \xi_t && \xi_t \sim NID\left(0, \tfrac{\pi^2}{2}\right) \\ &\sigma_t = \gamma + \varphi\sigma_{t-1} + \eta_t && \eta_t \sim NID\left(0, \sigma_\eta^2\right) \end{aligned} \tag{2.31}$$

where $\xi \quad = \zeta \quad + 1.27$ and $E(\xi_t, \zeta_t) = 0$. According to QML method, estimates can be obtained by treating ξ_t as if it were normally distributed with mean 0 and variance $\frac{\pi^2}{2}$ and maximizing the resulting likelihood function for parameter vector $\omega = (\gamma, \varphi, \sigma_\eta)$. Then measurement and transition equations are, respectively, as follows:

$$\begin{aligned} y_t &= A_t\alpha_t + \xi_t \\ \alpha_t &= c_t + B_t\alpha_{t-1} + \eta_t \end{aligned} \tag{2.32}$$

where $y_t = \ln(r_t^2) + 1.27$. The matrix representation of the state space from of the system which helps to the formation of the Kalman Filter:

$$\begin{aligned} &A_t = [1 \quad 0] && B_t = \begin{bmatrix} \varphi & 0 \\ 0 & 0 \end{bmatrix} && H_t = \frac{\pi^2}{2} \\ &c_t = \begin{bmatrix} \gamma \\ 0 \end{bmatrix} && \theta_t = \begin{bmatrix} \sigma_\eta^2 & 0 \\ 0 & 0 \end{bmatrix} && \end{aligned} \tag{2.33}$$

The Kalman filter for the state space form in equation 2.31:

$$v_t = y_t - A_t \qquad F_t = A_t P_t A_t' + H_t$$
$$K_t = (B_t P_t A_t') F_t^{-1} \qquad L_t = B_{t+1} - K_t A_t \tag{2.34}$$
$$\alpha_{t+1} = B_{t+1}\alpha_t + K_t v_t \qquad P_{t+1} = B_{t+1} P_t L_t' + \theta_t$$

The parameters in $\omega = (\gamma, \varphi, \sigma_\eta)$ are obtained by optimizing the Gaussian loglikelihood:

$$\ln(f(\omega)) = -0.5 \sum_{t=1}^{T} ln2\pi + ln|F_t| + v_t' F_t^{-1} v_t \tag{2.35}$$

The prediction equations for the Kalman filter and h-day forecasts of the volatility:

$$\hat{\alpha}_{t|t-1} = c_t + B_t \hat{\alpha}_{t-1|t-2} \qquad \hat{r}_{t|t-1}^2 = e^{\hat{y}_{t|t-1} - 1.27}$$
$$\hat{y}_{t|t-1} = A_t \hat{\alpha}_{t|t-1} \qquad \hat{\sigma}_{t+h}^2 = \sum_{i=t}^{t+h-1} \hat{r}_{i|i-1}^2 \tag{2.36}$$

2.2 Comparison Of Forecasts

2.2.1 Error statistics

A sound comparison of model performances is as important as performing the forecasts. The choices of error statistics and the way that conclusions drawn from them are the crucial decisions in comparison procedure. Both symmetric and asymmetric error statistics are relevant for the evaluation of volatility forecasts since asymmetry in the error statistic can be especially important for participants of derivative market. For example, the major parameter determining the value of an option contract is the volatility of the underlying, and the investors who take long/short position may prefer to penalize over/under-predictions more heavily to reduce to exposure to volatility modelling risk. However, it should be noted that the symmetric error statistics are more suitable to evaluate a model over all success in terms of fitting to observed data. Hence, performance results of the models are primarily deduced based on the symmetric error statistics, while asymmetric error statistics are used to determine which models have tendency in making over(under) prediction in general with the purpose of addressing the different needs of the investors.

The following symmetric and asymmetric error statistics are chosen in the scopeof the dissertation. Symmetric error statistics:

$$\text{Mean Square Error (MSE)} = \frac{1}{n}\sum_{i=1}^{n}(\sigma_i - \hat{\sigma}_i)^2$$

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\sigma_i - \hat{\sigma}_i)^2} \qquad \textbf{(2.37)}$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n}\sum_{i=1}^{n}|\sigma_i - \hat{\sigma}_i|$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\sigma_i - \hat{\sigma}_i|}{\sigma_i}$$

where n is the number of out-of-sample forecasts.

Asymmetric error statistics[1]:

$$\text{MME-U} = \frac{1}{n}\left[\sum_{i=1}^{k}|\sigma_i - \hat{\sigma}_i| + \sum_{i=1}^{l}|\sigma_i - \hat{\sigma}_i|^{0.5}\right]$$

$$\text{MME-O} = \frac{1}{n}\left[\sum_{i=1}^{k}|\sigma_i - \hat{\sigma}_i|^{0.5} + \sum_{i=1}^{l}|\sigma_i - \hat{\sigma}_i|\right] \qquad \textbf{(2.38)}$$

where k denotes the number of over predictions and l the number of underpredictions, which is $k + l = n$.

$$\text{MLAE} = \frac{1}{n}\sum_{i=1}^{n} ln|\sigma_i - \hat{\sigma}_i|$$

$$\text{LINEX} = \frac{1}{n}\sum_{i=1}^{n}\left[e^{-a(\sigma_i - \hat{\sigma}_i)} + a(\sigma_i - \hat{\sigma}_i) - 1\right] \qquad \textbf{(2.39)}$$

where the choice of the value of the parameter a is subjective, which allows different weights to over and under predictions. When $a > 0$, it punishes heavily under predictions. In the study, it is taken as 5.

2.2.2 Reality Check, Superior Predictive Ability and Model Confidence Set

To evaluate by just looking at the rank implied by the error statistics does not provide a sound comparison. Fortunately, in the last decade, some important statistical techniques have been proposed to check whether the rank of the model performances deduced from a certain error statistic is statistically significant or not. Reality Check (RC) of White (2000) and Superior Predictive Ability (SPA) of Hansen (2001) tests allow one to determine whether the differences obtained from the error statistics are significant or not. The null hypotheses of both RC and SPA are that the models included in the analysis do not have superior performance relative to the benchmark, while the alternative hypothesis is that at least one of the models has superior

[1] Mean Mixed Error-Under(MME-U), Mean Mixed Error-Over (MME-O), Mean Logarithm of Absolute Error (MLAE)

forecasting performance relative to the benchmark. This implies that the performance of the model that has the best error statistic is superior than the benchmark eventhough one would not tell anything about the comparison between the best model and models other than the benchmark. During the empirical analysis, it has seen that the best model does not always show significantly superior performance than the benchmark according to some error statistics, while it does according to some other error statistics. Therefore, these tests can also be used to determine which error statistics can really distinguish the superior performances of models. The difference between these two tests is that RC is quite sensitive to the set of the models included in the analysis. That is, if the comparison involves irrelevant or poor alternatives, then RC is not able to reject the null hypothesis even though it is the case. When the model set comprises reasonable alternative both RC and SPA produce quite similar results. In this study, when RC and SPA test are performed, the simplest model RW is chosen as the benchmark model.

Another technique used to distinguish model performances is the Model Confidence Set (MCS) procedure of Hansen et al. (2003). The MCS method characterizes the entire set of models as those that are/are not significantly outperformed by other models, on the other hand, RC/SPA tests only provide evidence about the relative performance according to the benchmark model. Hansen et al. (2003) illustrate the difference between RC/SPA and MCS with analogy of the difference between confidence interval of a parameter and point estimate of a parameter. The significance of the performance of the best model relative to the benchmark can be determined with RC/SPA tests, however, RC/SPA tell nothing about the case in which other models performances are very close to the model that shows the best performance. At that point, The MCS helps one determine whether other models performances are close to the best model or not by grouping the models into two categories (sets), namely inferior and superiors models sets, why assigning probability values to each model. If p-value of a model is greater than a subjectively determined p-value, then it is accepted as in the superior set. The critical p-value for the study is chosen as 0.9. All of the three techniques are used for the evaluation of the forecasting performances. First step is to determine which error statistics give significant results by applying SPA and RC tests. At this step, the best performing model can be confidently stated as a best performing model according to corresponding error statistic, however, to what extent that the best performing model is significantly superior than the other models can only be determined by the MCS procedure, which is the second step of the evaluation process[2].

2.3 Data And Methodology

This section briefly introduces the data and methodology used for forecasting. 19 emerging stock market indices chosen based on SP/IFC classification are obtained from Bloomberg Databases in daily frequency, which are Argentina (MERVAL), Brazil (IBOV), Chile (IPSA), Mexico (MEXBOL), Peru (IGBVL), Venezuela (IBVC), Czech Republic (PX), Hungary (BUX), Poland (WIG20), Russia (RTSI), Turkey (XU100), China (SHCOMP), India (SENSEX), Korea (KOSPI), Malaysia (FBMKLCI), Philippines (PCOMP), Srilanka (CSEALL), Taiwan (TWSE), Thailand (SET)[3]. The data period for each index is the same between 2nd January 1995 and 23th April 2010 except Russia for which it starts on 2nd April 1995. Figure 2.1, Figure 2.2, Figure 2.3 present the logarithmic return series of the markets and Table 2.1 presents their basic descripitive statistics in order to give a glance to general view of the data.

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[2] the p-values of the tests can be found in the appendix
[3] The Bloomberg tickers for corresponding stock exchange index is given in the parenthesis.

Table 2.1: Sample statistics on daily return series.

	Mean	Max	Min	Standard Deviaton	Median	Skewness	Kurtosis
Argentina	0,0004	0,1612	-0,1476	0,0228	0,0011	-0,2075	7,9971
Brazil	0,0007	0,2882	-0,1723	0,0239	0,0014	0,4661	15,1874
Chile	0,0004	0,1180	-0,0767	0,0117	0,0004	0,2964	10,7749
Mexico	0,0007	0,1215	-0,1431	0,0166	0,0009	0,0674	8,8769
Peru	0,0006	0,1282	-0,1144	0,0147	0,0004	-0,2707	12,2692
Venezuella	0,0010	0,2006	-0,2066	0,0175	0,0003	0,3454	21,8652
Czech	0,0004	0,1180	-0,0767	0,0117	0,0004	0,2964	10,7749
hungary	0,0007	0,1362	-0,1790	0,0184	0,0010	-0,6579	13,4164
Poland	0,0003	0,0815	-0,1032	0,0184	0,0002	-0,1275	5,1116
Russia	0,0008	0,2020	-0,2120	0,0285	0,0019	-0,3707	9,7184
Turkey	0,0014	0,1777	-0,1998	0,0276	0,0013	0,0513	7,6781
China	0,0004	0,2699	-0,1791	0,0193	0,0007	0,4177	18,7103
India	0,0004	0,1599	-0,1181	0,0173	0,0010	-0,1125	7,9224
Korea	0,0001	0,1128	-0,1280	0,0193	0,0007	-0,2541	6,5993
Malaysia	0,0001	0,2082	-0,2415	0,0151	0,0002	0,4649	49,2119
Philippness	0,0000	0,1618	-0,1309	0,0154	-0,0001	0,2979	13,6170
Srilanka	0,0004	0,1829	-0,1390	0,0122	0,0001	0,3360	31,4476
Taiwan	0,0000	0,0652	-0,0698	0,0155	0,0002	-0,1538	4,9160
Thailand	-0,0002	0,1135	-0,1606	0,0175	-0,0004	0,1079	9,3720

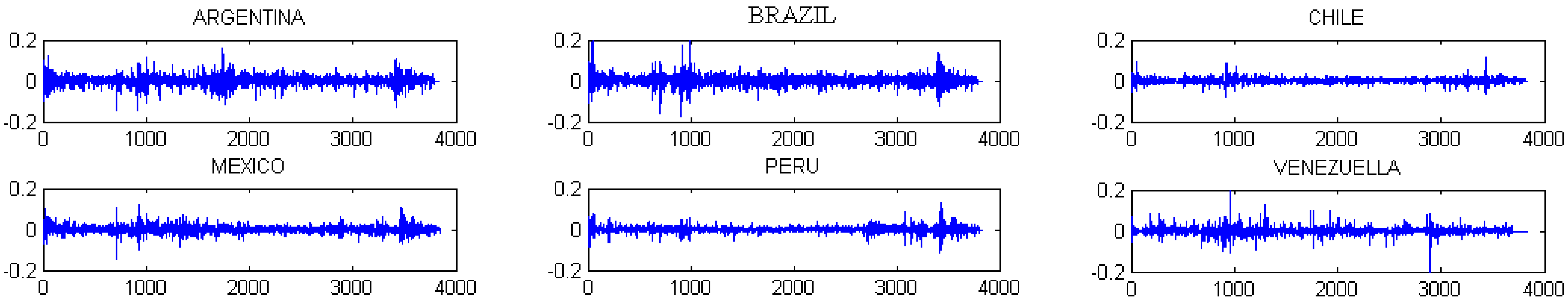

Figure 2.1 : Daily return series for Latin America.

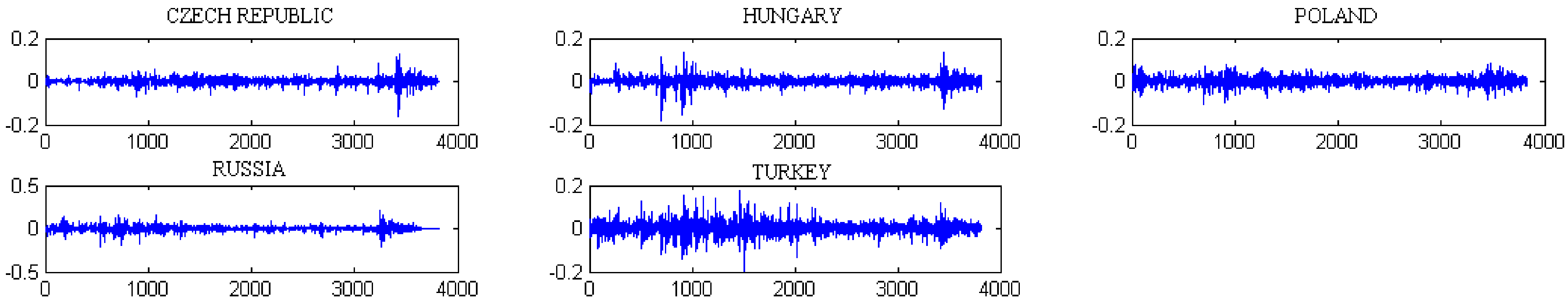

Figure 2.2 : Daily return series for Europe.

At the first step, the decision how to measure volatility, i.e. standard devaition or variance needs to be made. Here, standard deviation form is chosen, however, all the equations are writen in the variance form through out the dissertation in order to eliminate visual crowd that the square root creates. In short, estimations are evaluated by taking the squared root. More importantly, due to the fact that volatility is a latent variable, there are different estimations for obsvered volatility which mainly based on removing mean and serial dependencies in returns, which metioned more detailed in the introduction of Section 2. To measure observed volatility, mean adjusted daily squared return approach is chosen:

$$\sigma_t^2 = (R_t - \mu)^2 \tag{2.40}$$

where R_t is the logarithmic return and μ is the sample mean. As for the forecast horizon, model performances are analyzed in eight different forecast horizons, i. e. h = 1, 5, 10, 20, 60, 120, 240 days in order to see whether the model performance are changing according to horizons and, if positive, how. Since the data is in daily frequency, observed volatility in equation (2.40) is valid only for 1-day forecast horizon. h-day obsreved volatilitiy is are estimated as the sum of the daily volatilities for the relevant horizon h = 5, 10, 20, 60, 120, 240, which is

$$\sigma_t^2 = \sum_{t=i}^{t=i+h-1} (R_t - \mu)^2 \tag{2.41}$$

where i = 1, 1+h, 1+2h, 1+3h, ... and $t = w, w + s, w + 2s, ...$

The data is divided into two parts since the focus is to compare the out-of-sample forecasts. The rolling scheme in which the sample size and forward shifting step was fixed at $w = 2000$ and $s = 20$, respectively, is applied for both simple models introduced in Section 2.1.1 and parametric models introduced in Section 2.1.2 and 2.1.3. The equations 2.1, 2.2, 2.3 and 2.4, which produce forecasts for RW, HM, MA and EWMA, respectively, provide the forecasts for corresponding model for 1-day forecast horizon. h-day volatility forecasts for the simple models are estimated by simple scaling rule ,which is $\widehat{\sigma}_t\sqrt{h}$.

The process for h-day volatility forecasts for the parametric models, i.e GARCH family models and Stochastic Volatility, are more complicated and require more detailed verbal explanation since the parameters of the models need to be updated for

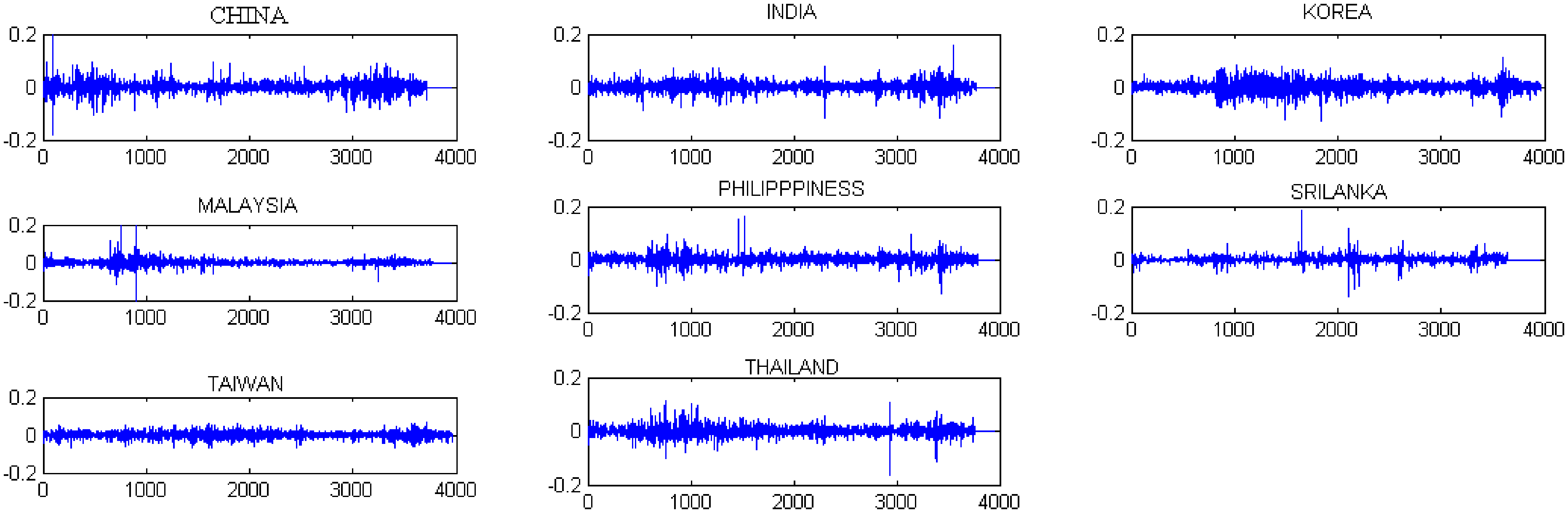

Figure 2.3 : Daily return series for Asia.

every forecast. The rolling scheme in which the sample size was fixed at 2000 observations is applied for the parameter estimations. For the first forecast of the 1-day forecast horizon, $\hat{\sigma}^2_{2001}$, the parameters in equations 2.6, 2.8, 2.9,2.10, 2.11, 2.13 and 2.27 are estimated by using the sample between the 1st observation and 2000th observation. For the first forecast of 5-day forecast horizon, the same parameters are used to forecast volatility for consecutive five days, which are $\hat{\sigma}^2_{2001}$, $\hat{\sigma}^2_{2002}$, $\hat{\sigma}^2_{2003}$, $\hat{\sigma}^2_{2004}$, $\hat{\sigma}^2_{2005}$. Then, they are summed to estimated the first 5-day forecast as mathematically formulated in equation 2.41. And for the first forecast of 10-day forecast horizon, $\hat{\sigma}^2_{2001}$, $\hat{\sigma}^2_{2002}$, $\hat{\sigma}^2_{2003}$, $\hat{\sigma}^2_{2004}$, $\hat{\sigma}^2_{2005}$, $\hat{\sigma}^2_{2006}$, $\hat{\sigma}^2_{2007}$, $\hat{\sigma}^2_{2008}$, $\hat{\sigma}^2_{2009}$, $\hat{\sigma}^2_{2010}$ are obtained and summed by using the same parameter estimates. And this process is followed in the same way for the first forecast of 20-day, 60-day, 120-day and 240-day forecast horizons.

For the second forecast of 1-day forecast horizon, $\hat{\sigma}^2_{2021}$, the parameters in equations 2.6, 2.8, 2.9,2.10, 2.11, 2.13 and 2.27 are estimated by using new sample which is obtained by shifting the sample forward by 20 observations, which involves the sample between the 21st observation and 2020th observation. For the second forecast of 5-day forecast horizon, the same parameters are used to forecast volatility for consecutive five days, which are $\hat{\sigma}^2_{2021}$, $\hat{\sigma}^2_{2022}$, $\hat{\sigma}^2_{2023}$, $\hat{\sigma}^2_{2024}$, $\hat{\sigma}^2_{2025}$. Then, they are summed to estimated the second 5-day forecast as mathematically formulated in equation 2.41. And for the second forecast of 10-day forecast horizon, $\hat{\sigma}^2_{2021}$, $\hat{\sigma}^2_{2022}$, $\hat{\sigma}^2_{2023}$, $\hat{\sigma}^2_{2024}$, $\hat{\sigma}^2_{2025}$, $\hat{\sigma}^2_{2026}$, $\hat{\sigma}^2_{2027}$, $\hat{\sigma}^2_{2028}$, $\hat{\sigma}^2_{2029}$, $\hat{\sigma}^2_{2030}$. are obtained and summed by using the same parameter estimates. And this process is followed in the same way for the second forecast of 20-day, 60-day, 120-day and 240-day forecast horizons. This process is recursively performed until the end of the sample.

There are also a few decisions needed to be taken during the empirical anlaysis. First of all, (1,1) lag structure is chosen beforehand for GARCH family models. One lag delay in both past innovations and past conditional volatilities is presumably enough for the elimination of the heteroscedasticity in the return series because of the following reasons: There is a general notion of that (1,1) lag structure is the most parsimonious lag structure for GARCH family models in the literature (Andersen et al., 1999, West and Cho, 1995, Ederington and Guan, 2005). This is especially supported by the extensive study of Hansen and Lunde (2005) in which they evaluated 330 different GARCH family models. They reported that (2,2) lag structure rarely performs better than the same model with fewer lags. Secondly, the trade off between the number of parameters estimated by the use of in-sample data and out-of-sample performances of the models makes (1,1) lag structure very reasonable to use in forecasting. Despite of these favorable supports, Lagrange Multiplier test is performed after every model estimation to check the validity of this assumption. The test results show that (1,1) lag structure is enough to eliminate the heteroscedasticity in the time series with very few exceptions[4]. The test results are reported in the appendix.

After the forecasts are obtained for each stock market at 8 different horizons with 11 volatility models, the process of the comparison of the model performances is built in a way that it allows to evaluate the results in a broad perspective. First of all, both symmetric and asymmetric error statistics, which are introduced in section 2.2.1, are used. While the symmmetric error statistics, i.e MSE, RMSE, MAE, MAPE, are the main statistics by which the successes of the models are determined, the asymmetric error statistics, i.e MME-U, MME-O, LINEX, MLAE, are served the purpose of the detection of the tendecy of models in making over(under) prediction[5]. The final stage of the evaluation process is to be able to differentiate the values of error statistics in a sound and statistical way. To accomplish this, the recently developed econometrical methods, i.e RC, SPA AND MCS, are used. Section 2.2.2 gives the details of this methods and how they are used in the study. The comparison process constructed in the study is a completely new way of evaluation of error statistics in the volatility forecasting literature, therefore, it is crucial to understand this step in order to be able to see how the results are generalized in such an extensive context.

All the estimations and calculations are performed in Matlab. For the parameter estimation of FIGARCH, NAGARCH, APARCH models and MCS, SPA and RC

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[4] Only 104 out of 9618 estimated models can not eliminate the heteroscedasticity in the time series.In detail, Only 88 out of 1603 estimated APARCH(1,1) model can not eliminate heteroscedasticity according to Engle's LM test with 0.05 significant level, which implies that APARCH(1,1) is not enough for Poland, India and Thailand for some periods. The test results are reported in the appendix.

[5] The detailed explanation about the choice of error statistics and the reasons in the context of the role of volatility in finance are provided in section 2.2.1.

estimations Prof. Kevin Sheppard's matlab codes, which are provided in his website[6], are used by modifying the codes to the context of the analysis in the study.

2.4 Results

In this section, the out-of-sample forecasts of 11 models for short-term (1-day, 5-day, 10-day), medium-term (20-day, 60-day and 120-day) and long-term (180-day and 240-day) forecast horizons are performed and compared. Tables 2.2 to Table 2.9 present the results. Since the results in the tables are based on the error statistics and test results, which can be found in the appendix, the following points should be taken into account in order to be able understand how conclusions are drawn from the tables. First of all, the best performing model of each error statistic is reported in the tables, as the first input of the cells of the corresponding table. When RC/SPA tests determine best performing model significantly different from the benchmark, the model is superscripted by "*" and is called "the significant best model". Hence, if there is not any model superscripted by "*" in a cell than the performances of models are not significantly different from each other for the correponding error statistic. This is the first step of the evaluation of the results of the error statistic, which infact provide one to determine which error statistic results should be taken into account for the rest of the comparison process.

Let consider 1-day volatility forecast results for PERU in Table 2.2. According to MSE, NAGARCH is the best model while EWMA is the best model according to RMSE. However, RC/SPA test results show that MSE can not distinguish the model performances as statistically significant while RMSE does. Therefore, the best model according to MSE is not taken into account for the rest of the analysis, and the result of RMSE, i.e EWMA, is superscripted to show that it will be taken into account for the rest of the comparison process. That is, only superscripted models and corresponding error statistics are evaluated after that point. As explained in section 2.2.2, even though a model is determined as the significant best model with the help of RC/SPA tests, this doesn't tell anything about the difference between the best model and the second best model, third best model and so on. The second step of the evaluation process addresses to this issue by determining of the MCS of the

[6] http://www.kevinsheppard.com/wiki/Category:MFE.

significant best model if there is one. If there exists a MCS for a significant best model, then the models in the MCS are added to place where the significant best model is in the table. Therefore where the intersection of a column and a row includes more than one model, this represents the set of models performances of which are almost the same as that of the significant best model.

After this point, this set of models will be called ”MCS set of superiors” of the corresponding significant best model. If we back to the example of PERU, MCS set of superiors of EWMA is NAGARCH and GRJ-GARCH in Table 2.2. Lastly, the success of the models are evaluated based on the symmetric error statistic, and the asymmetric error statistic are used to determine the tendency of the models in making under/over prediction, which is considered as beneficial for those who put much more weight to under/over prediction in their decision processes.

Short-Term Forecast Horizons: First thing that should be noticed in Table 2.2 is the outperformance of SV model for 1-day forecast horizon . For 14 out of 19 stock markets, SV is the significant best model according to more than one error statistics for most of the markets. For a few of these markets, namely Argentina, Czech and China, the MCS set of superiors of SV comprises GARCH family models, which means that SV is sharing the same performance level as GARCH family models for 3 out of 14 markets. Even though the performance of GARCH family models is close to that of SV for these three market SV is successful in 14 markets. Therefore, it is not wrong to make the that for 1-day forecast horizons SV model is the best model to forecast stock market volatility in emerging markets.

On the other hand, as soon as the forecast horizon is increased to 5-day, this outstanding success of SV is completely vanished since it does not show the best performance even for one market as it can be seen from Table 2.3. This is a quite strong indication of that the smaller the forecast horizon, the better the performance of SV gets. So it is a very high possibility that SV outperforms in intraday frequencies eventhough intraday frequency in volatility forecasting is out of the scope of the study. For 5-day forecast horizon, GARCH family models have dominance over the others by outperforming in 11 out of 19 emerging markets.

EWMA is the second model by outperforming in 7 out of 19 markets. When the MCS set of superiors of the models are examined, the MCS set of superiors of

GARCH family models includes EWMA only in 2 out of 11 markets, and the MCS set of superiors of EWMA includes GARCH family models in 3 out of 7 markets. This implies that there is not an important intersection in which these two models shows the same out-performance in the same markets. Over all, when MCS results are taken into account, GARCH family models outperform in **15** markets (**11** as the best model + **4** as the MCS set of superiors of other models), while EWMA outperforms in **9** markets (**7** as the best model + **2** as the MCS set of superiors of other models). Table 2.10 provides quick overlook this whole **11+4** and **7+2** summation and generalization process by reporting the number of cases (markets) in which a certain model is the best model and the number of cases (markets) in which the model is the MCS set of superiors. So GARCH family model are considerably successful for 5-day forecast horizon. Therefore, it would be more reasonable to choose GARCH family models to forecast volatility for 5-day horizon in the case that one choose a volatility model without performing any forecasting analysis. As for the results of 10-day forecasts in Table 2.4, GARCH family models and EWMA show out-performance in almost equal number of markets, and again the MCS set of superiors of either one include each other in the same number of markets. Another model, namely RW is found as the significant best model for 5 out of 19 markets for 10-day forecast horizon. However, the MCS set of superiors of RW involves GARCH family models and EWMA for 4 out of these 5 markets. This implies RW does not show an outstanding performance in these 4 markets, it just shares the same performance level as those of EWMA and GARCH family models for 4 markets, which eventually strengthens the generalization of out-performance of GARCH family models and EWMA for 10-day forecasts. Furthermore, if it is remembered that EWMA is a different presentation of Integrated GARCH model , this is a very strong support for the choice GARCH family models at 10-day forecast horizon. It is also noteworthy to state that although 1-day, 5-day and 10-day horizons are defined as a short-term forecast horizon, the results differentiate from one another significantly. This indicates how quickly models performance are changing according to horizons.

Medium-Term Forecast Horizons: For 20-day forecast horizon, the out-performance of GARCH family models is noteworthy in Table 2.5. GARCH family models are the significant best model for 9 out of 19 markets. Also, they are MCS set of superiors of both EWMA , 4 out of 8 markets, and RW, 2 out of 2 markets. This implies that GARCH family models are the significant best model for 9 markets and they show almost the same performance level as EWMA and RW for additional 6 markets, that is, in total, for 15 out of 19 markets, GARCH family models have superior performance. For both 60-day and 120-day forecast horizon in Table 2.6 and Table 2.7, respectively, EWMA and GARCH family models outperform in almost equal number of markets. However, it should be noted that, as the forecast horizon increases, the success of EWMA is getting closer and closer to GARCH family models in terms of the number of countries in which it shows superior performances, and more importantly MA start to outperform in some markets. For 60-day forecast horizon, MA is the significant best model in 3 markets, but in these markets, it shares the same performance level as those of GARCH family models and EWMA. On the other hand, for 120-day forecast horizon MA is the significant best model in 5 markets, and it shares the same performance as those of GARCH family models and EWMA only in 1 out of these 5 markets, which is the first sign of that how MA gets stronger as the forecast horizon increases.

Long-Term Forecast Horizons: For 180-day forecast horizon, MA is the significant best model for almost half of the markets in Table 2.8, while the rest of the markets are shared by GARCH family models and EWMA. As for 240-day forecast horizon in Table 2.9, MA has dominance over the other models by outperforming 12 out of 19 markets.

When the results of asymmetric error statistics are evaluated, the first striking result is that SV model consistently underpredicts, and GARCH family models overpredict for almost all forecast horizons. Table 2.11 provides the generalization of the overprediction and underprediction patterns of the models for different forecast horizon. The preference of overprediction or underprediction is specific to investors' positions. Generally, investors in financial markets finds beneficial to choose models that overpredict for the sake of being in the safe side. However, it should be noted that GARCH family models overpredict at the ordinary times not at the stressed time high volatilite periods, which implies that investors, who use GARCH family models for prediction, are being too cautious in ordinary times, and not ready enough for the high risk periods. Therefore it is recommended that the investors should ask themselves the question of how this overprediction (or underprediction) pattern in

Table 2.2 : The best performing models for 1-day forecasts.

	Symmetric Error Statistics				Asymmetric Error Statistics			
	MSE	**RMSE**	**MAE**	**MAPE**	**MME-U**	**MME-O**	**MLAE**	**LINEX**
ARGENTINA	NAGARCH*	SV*, GARCH, GRJ-GARCH EGARCH, NAGARCH FIGARCH, APARCH	SV*, GARCH, GRJ-GARCH EGARCH, NAGARCH, FIGARCH, APARCH	SV	SV*	HM*	SV*	NAGARCH*
BRAZIL	EWMA*	SV*	SV*	SV	SV*	HM*	SV*, FIGARCH NAGARCH, APARCH	EWMA*
CHILE	NAGARCH*	SV*	SV*	RW	SV*	HM*	SV	NAGARCH*
MEXICO	EWMA*, NAGARCH, GJR-GARCH, EGARCH APARCH, FIGARCH, GARCH,	EWMA*	EWMA*	RW	SV*	HM*	SV	EWMA*, NAGARCH, GARCH GRJ-GARCH, EGARCH APARCH, FIGARCH
PERU	NAGARCH	EWMA*, NAGARCH GRJ-GARCH	EWMA	SV	SV*	FIGARCH*	GRJ-GARCH	NAGARCH
VENEZUELLA	APARCH	SV*	SV	SV	SV*	GARCH *, HM, EGARCH GRJ-GARCH, NAGARCH	SV	APARCH
CZECH	GRJ-GARCH*	SV*, GRJ-GARCH, EWMA EGARCH, NAGARCH	SV	SV*	SV*	FIGARCH*	SV	GRJ-GARCH*
HUNGARY	EGARCH	SV*	SV*	SV*	SV*	EGARCH*, NAGARCH GJR-GARCH	SV*	GRJ-GARCH
POLAND	FIGARCH	EWMA*	EWMA*	SV*	SV*	HM*	SV*	FIGARCH*
RUSSIA	EWMA	SV*	SV	RW	SV*	HM*	SV	RW
TURKEY	SV*	SV*	SV*	SV*	SV*	HM*	SV*	SV*, MA, EWMA , GARCH GRJ-GARCH, EGARCH, NAGARCHAPARCH, FIGARCH
CHINA	APARCH*	SV*, EWMA, NAGARCH EGARCH, APARCH	SV*, EWMA, NAGARCH EGARCH, APARCH	SV	SV*	HM*, EWMA, GRJ-GARCH,EGARCH, FIGARCH, GARCH	SV	APARCH*
INDIA	GRJ-GARCH*, EWMA APARCH, EGARCH	EWMA*, GRJ-GARCH, NAGARCH APARCH, EGARCH	EWMA*, GRJ-GARCH, NAGARCH APARCH, EGARCH	SV	SV*	HM*	EGARCH	GRJ-GARCH*, EWMA EGARCH, APARCH
KOREA	NAGARCH*, SV, EGARCH	SV*	SV*	SV*	SV*	HM*	SV	NAGARCH*
MALAYSIA	SV*	SV*	SV*	SV	SV*	HM*	SV	SV*
PHILIPPINES	GRJ-GARCH*	GRJ-GARCH*, EWMA GARCH, NAGARCH, FIGARCH APARCH, EGARCH, SV	GRJ-GARCH*, SV EGARCH, NAGARCH APARCH, FIGARCH	SV*	SV*	HM*, EWMA GARCH	APARCH	GRJ-GARCH*
SRILANKA	EWMA	SV*	SV	SV	SV *	EWMA*, HM FIGARCH	SV	EWMA

Table 2.2 (continued) : The best performing models for 1-day forecasts.

	Symmetric Error Statistics				Asymmetric Error Statistics			
TAIWAN	APARCH*, EGARCH, NAGARCH, FIGARCH GRJ-GARCH, SV	SV*	SV*	SV*	SV*	HM*	SV*	APARCH*, EGARCH NAGARCH, FIGARCH
THAILAND	FIGARCH*, SV, EGARCH NAGARCH, APARCH, EWMA	SV*	SV*	SV	SV*	NAGARCH*, HM, GRJ-GARCH, GARCH, EWMA	SV	NAGARCH*, SV, EGARCH FIGARCH, APARCH, EWMA

Note: First model in a cell of the table is the best model according to relevant error statistic. When it is superscripted with *, this implies that it is the significant best model due to RC/SPA resuts. The cells including more than one model confidence set of the correponding significant best model ,plese read section IV for more detailed expalanations about regarding of the tables

Table 2.3 : The best performing models for 5-day forecasts.

	Symmetric Error Statistic				Asymmetric Error Statistic			
	MSE	**RMSE**	**MAE**	**MAPE**	**MME-U**	**MME-O**	**MLAE**	**LINEX**
ARGENTINA	GRJ-GARCH*	EGARCH*	EGARCH*	EGARCH	SV*	HM	EGARCH*	GRJ-GARCH*
BRAZIL	EWMA	EWMA*	EWMA	SV	SV*	GRJ-GARCH*	APARCH	EWMA
CHILE	APARCH*, GRJ-GARCH EWMA, NAGARCH GARCH, EGARCH	APARCH* EWMA	APARCH* EWMA	EWMA	SV*	GARCH*	APARCH	APARCH*, GRJ-GARCH EWMA, NAGARCH GARCH, EGARCH
MEXICO	NAGARCH	EWMA*, EGARCH, APARCH, RW NAGARCH, GRJ-GARCH,	EWMA	RW	SV*	GARCH*	EWMA	NAGARCH
PERU	RW	RW*, GRJ-GARCH, NAGARCH, EWMA, EGARCH, APARCH FIGARCH	RW	APARCH	SV*	FIGARCH*	APARCH	RW
VENEZUELLA	APARCH	APARCH*	APARCH*	SV*	SV*	FIGARCH*, EGARCH GRJ-GARCH, HM	APARCH*	APARCH
CZECH	GRJ-GARCH	GRJ-GARCH*, EWMA NAGARCH, GARCH FIGARCH, APARCH EGARCH, RW	GRJ-GARCH	APARCH	SV*	FIGARCH*, GARCH	APARCH	FIGARCH
HUNGARY	FIGARCH	FIGARCH*	FIGARCH	APARCH	SV*	FIGARCH*, HM	EWMA	FIGARCH
POLAND	EWMA	EWMA*, APARCH	EWMA	EWMA	SV*	HM*, GARCH EGARCH	APARCH	GARCH
RUSSIA	EWMA	EWMA*	EWMA	SV	SV*	GARCH*	APARCH	EWMA
TURKEY	APARCH*	EWMA*	EWMA*	SV*	SV*	GARCH*	EWMA	APARCH
CHINA	EGARCH	APARCH*	APARCH	APARCH	SV*	GRJ-GARCH*	APARCH*	EGARCH
INDIA	GRJ-GARCH	EGARCH*	EGARCH*	APARCH	SV*	GARCH*	APARCH*, RW,EGARCH	GRJ-GARCH
KOREA	EGARCH	NAGARCH*	NAGARCH	SV	SV*	HM*	RW	EGARCH
MALAYSIA	EGARCH	EGARCH*	EGARCH*	SV	SV*	GRJ-GARCH	EWMA	EGARCH*
PHILIPPINES	EGARCH	APARCH*, EGARCH, RW NAGARCH, GRJ-GARCH	APARCH	RW	SV*	HM*	APARCH	EGARCH
SRILANKA	EWMA	EGARCH*, APARCH FIGARCH, RW	EGARCH	SV	SV*	GARCH*	RW	EWMA

Table 2.3 (continued) : The best performing models for 5-day forecasts.

	Symmetric Error Statistics				Asymmetric Error Statistics			
TAIWAN	EWMA*	EWMA*	EWMA*	RW	RW	FIGARCH*, APARCH EGARCH, HM, NAGARCH	EWMA*	EWMA*
THAILAND	EWMA	EWMA*	EWMA	EWMA	RW	APARCH*, HM, SV FIGARCH	EWMA	EWMA

Note: As in Table 2.2

Table 2.4 : The best performing models for 10-day forecasts.

	Symmetric Error Statistic				Asymmetric Error Statistic			
	MSE	**RMSE**	**MAE**	**MAPE**	**MME-U**	**MME-O**	**MLAE**	**LINEX**
ARGENTINA	GRJ-GARCH*	EGARCH*	EGARCH*	EGARCH*	SV*	HM*, GRJ-GARCH, MA GARCH, EGARCH	EGARCH*	GRJ-GARCH
BRAZIL	EWMA	EWMA*	EWMA	EWMA	SV*	GARCH*	EWMA	EWMA
CHILE	GRJ-GARCH	APARCH*, EWMA, EGARCH NAGARCH, GRJ-GARCH RW, FIGARCH, GARCH	APARCH	RW	SV*	GARCH*, HM FIGARCH	RW	GRJ-GARCH
MEXICO	EWMA	RW*, EWMA	RW	RW	SV*	GARCH*	RW	EWMA
PERU	RW	RW*, GRJ-GARCH, GARCH EGARCH, EWMA	RW	RW	SV*	MA*	RW	RW
VENEZUELLA	APARCH	APARCH*	APARCH	SV	SV*	EGARCH*	APARCH	APARCH
CZECH	GRJ-GARCH	FIGARCH*, APARCH, GARCH EGARCH, EWMA, GRJ-GARCH	FIGARCH	APARCH	SV*	FIGARCH*	APARCH	GRJ-GARCH
HUNGARY	FIGARCH	FIGARCH,*	FIGARCH	EWMA	SV*	FIGARCH*	EWMA	FIGARCH
POLAND	EWMA	EWMA*	EWMA	EWMA	SV*	GARCH*	APARCH	EWMA
RUSSIA	EWMA	EWMA*	EWMA	APARCH	SV*	GARCH*	APARCH	EWMA
TURKEY	EWMA	RW*	RW	RW	SV*	GRJ-GARCH*	RW	EWMA
CHINA	EGARCH	APARCH*	APARCH	APARCH	SV*	GRJ-GARCH*, GARCH	APARCH	EGARCH
INDIA	GARCH	EWMA*, GARCH	EWMA	EWMA	SV*	GARCH*	RW	GARCH
KOREA	APARCH	RW*, NAGARCH, FIGARCH EGARCH, APARCH, EWMA	RW	RW	SV*	HM*	RW	GRJ-GARCH
MALAYSIA	MA	RW*	RW	RW	SV*	GARCH*, MA	RW	EGARCH
PHILIPPINES	EGARCH	EGARCH*	EGARCH	APARCH	SV*	HM*	EGARCH	EGARCH
SRILANKA	EWMA	EWMA*, EGARCH, RW APARCH, FIGARCH	EWMA	SV	SV*	GRJ-GARCH*	EGARCH	EWMA
TAIWAN	EWMA*	EWMA*	EWMA	RW	RW	SV*	EWMA*	EWMA*
THAILAND	GRJ-GARCH	FIGARCH*, RW, GARCH GJR-GARCH, EGARCH, NAGARCH	FIGARCH	RW	SV*	HM*	EWMA	GRJ-GARCH

Note: As in Table 2.2.

Table 2.5 : The best performing models for 20-day forecasts.

	Symmetric Error Statistic				Asymmetric Error Statistic			
	MSE	**RMSE**	**MAE**	**MAPE**	**MME-U**	**MME-O**	**MLAE**	**LINEX**
ARGENTINA	NAGARCH*	NAGARCH*	NAGARCH*	NAGARCH*	SV*	GARCH*	NAGARCH*	NAGARCH*
BRAZIL	GRJ-GARCH	EWMA*, RW, EGARCH	EWMA	EWMA	SV*	GRJ-GARCH*, GARCH NAGARCH, EGARCH	RW	GRJ-GARCH
CHILE	GRJ-GARCH	EGARCH*	EGARCH	EGARCH	SV*	GARCH*, HM	FIGARCH	GRJ-GARCH
MEXICO	GRJ-GARCH	RW*, EGARCH, FIGARCH	RW	RW	SV*	GARCH*	RW	GRJ-GARCH
PERU	GRJ-GARCH	EGARCH*	EGARCH	EGARCH	APARCH*	EWMA*	EGARCH	RW
VENEZUELLA	EWMA	EWMA*	EWMA	APARCH	SV*	EGARCH*	EWMA	RW
CZECH	GRJ-GARCH	GRJ-GARCH*, GARCH, APARCH EGARCH, FIGARCH	GRJ-GARCH	APARCH	SV*	FIGARCH*	FIGARCH	GARCH
HUNGARY	FIGARCH	FIGARCH*, EWMA RW, APARCH	FIGARCH	APARCH	SV*	FIGARCH*	RW	FIGARCH
POLAND	FIGARCH	EWMA*, APARCH, RW NAGARCH, FIGARCH	EWMA	EWMA	SV*	GARCH*	APARCH	FIGARCH
RUSSIA	RW	EWMA*	EWMA	EWMA	SV*	GARCH*	APARCH	RW
TURKEY	EWMA	EWMA*	EWMA	EWMA	SV*	GARCH*, GRJ-GARCH	EWMA	EWMA
CHINA	EWMA	EWMA*, APARCH, EGARCH	EWMA	APARCH	SV*	GARCH*, GRJ-GARCH	EWMA	EWMA
INDIA	GARCH	GARCH*	GARCH	FIGARCH	SV*	GARCH*	FIGARCH	GARCH
KOREA	GRJ-GARCH	APARCH*, GRJ-GARCH, RW NAGARCH, EGARCH, FIGARCH	APARCH	RW	SV*	EGARCH*	NAGARCH	GRJ-GARCH
MALAYSIA	EWMA	EWMA*	EWMA	EWMA	SV*	GRJ-GARCH*, GARCH	EWMA	EWMA
PHILIPPINES	FIGARCH	APARCH*, GJR-GARCH FIGARCH, EGARCH	APARCH	APARCH	SV*	HM*, FIGARCH EGARCH, GARCH	APARCH	FIGARCH
SRILANKA	EGARCH	EWMA*, EGARCH, RW	EWMA	SV	SV*	GARCH*, GRJ-GARCH	RW	EGARCH
TAIWAN	EGARCH	RW*, FIGARCH, EGARCH EWMA, APARCH	RW	RW	SV*	GRJ-GARCH*, GARCH FIGARCH	APARCH	EGARCH
THAILAND	FIGARCH	FIGARCH*	FIGARCH	RW	SV*	GARCH*	FIGARCH	GRJ-GARCH

Note: As in Table 2.2.

ordinary times affects their positions and pricing decisions. Especially in option markets, investors can take positions on the volatility of the underlying. For instance, investors who use straddle/strangle are exposed to different risks inherent in forecasting of volatility of the underlying. Let think about an investor who applies straddle strategy on an underlying places his bids based on the volatility forecast of the underlying for the relevant horizon. There is a possibility that he prices the options contracts higher than they should be in case that he uses GARCH family models. Or let think that he writes straddles on a certain underlying. In this case if he forms his volatility expectation of the underlying by the forecast of SV model, he is exposed to risk of predicting the volatility lower than it should be. Therefore he increases the possibility of loss in his position without having been sufficiently compensated for the risk that he carries due to lower ask price that he places for the option contracts. At that point, there are a few things to be mentioned about the use of symmetric and asymmetric error statistics. If a model is best model according to both type of error statistics, this model is what investors look for if they have preferences over underprediction or overprediction. If a GARCH family model is the significant best model according to both symmetric and asymmetric error statistics, it should be interpreted as the model produces the closest prediction to the observed volatility but usually the predictions are higher than the observed one, which is very suitable for those who apply straddle if we back to the example above. Or another suitable approach can be taking the linear combination of the models that make over predictions or under predictions.

Beside the performance of the models, there are a few points needed to be mentioned. First of all, as the forecast horizon increases, the significant best models uniquely outperform in the relevant markets. That is, while more than one models share the same performance levels for the most of the markets for 1-day forecast horizon, as the horizon increases difference in the model performances gets bigger, and eventually for 240-day forecast horizon, the MCS set of superiors of the significant best models are empty sets for the all markets. Secondly, as a side result of this study, it is found that RMSE is the only symmetric error statistic that can always distinguish the model performances no matter what the forecast horizon is. If the scope of this study is taking into account, the success of RMSE is so consistent that it is not wrong to say that RMSE is the most strongest symmetric error statistic

Table 2.6 : The best performing models for 60-day forecasts.

	Symmetric Error Statistic				Asymmetric Error Statistic			
	MSE	**RMSE**	**MAE**	**MAPE**	**MME-U**	**MME-O**	**MLAE**	**LINEX**
ARGENTINA	NAGARCH	EWMA*, GRJ-GARCH NAGARCH, FIGARCH EGARCH, GARCH, MA	EWMA	EWMA	SV*	GARCH*	FIGARCH	NAGARCH
BRAZIL	GRJ-GARCH	EGARCH*	EGARCH	EWMA	SV*	GARCH*	EWMA	GRJ-GARCH
CHILE	GRJ-GARCH	EGARCH*	EGARCH	EGARCH	SV*	HM*	EWMA	MA
MEXICO	FIGARCH	FIGARCH*, RW APARCH, EWMA	FIGARCH	RW	SV*	GARCH*, FIGARCH GRJ-GARCH	NAGARCH	FIGARCH
PERU	GRJ-GARCH	GRJ-GARCH*	GRJ-GARCH	EGARCH	APARCH*	EWMA*	EGARCH	MA
VENEZUELLA	EWMA	EWMA*	EWMA	EWMA	SV*	EGARCH*	MA	EGARCH
CZECH	GARCH	GRJ-GARCH*	GRJ-GARCH*	EGARCH*	SV*, APARCH	GARCH*	EGARCH	GARCH
HUNGARY	MA	MA*, EWMA FIGARCH, RW	MA	EWMA	SV*	FIGARCH*	MA	FIGARCH
POLAND	EWMA	EWMA*	EWMA	EWMA	SV*	NAGARCH*	NAGARCH	GARCH
RUSSIA	RW	EWMA*	EWMA	EWMA	SV*	EGARCH*	EWMA	RW
TURKEY	EWMA	EWMA*	EWMA	EWMA	SV*	EGARCH*	EWMA	EWMA
CHINA	EWMA	MA*	MA	MA	APARCH*	FIGARCH*	MA	EWMA
INDIA	GARCH	GARCH *	GARCH	RW	SV*	GARCH*	RW	GARCH
KOREA	GRJ-GARCH	APARCH*, EWMA GRJ-GARCH, RW	APARCH	RW	SV*	GRJ-GARCH*, EGARCH	RW	GRJ-GARCH
MALAYSIA	EWMA	EWMA*	EWMA	EWMA	SV*	GRJ-GARCH	EWMA	EWMA
PHILIPPINES	FIGARCH	MA*, EWMA FIGARCH	MA	EWMA	SV*	HM*	EWMA	FIGARCH
SRILANKA	HM	EWMA*	EWMA	RW	SV*	EGARCH*	EWMA	HM
TAIWAN	EGARCH	RW*	RW	RW	SV*	FIGARCH*, GARCH GRJ-GARCH	RW	EGARCH
THAILAND	FIGARCH	FIGARCH*	FIGARCH	FIGARCH	SV*	HM*	FIGARCH	FIGARCH

Note: As in Table 2.2.

Table 2.7 : The best performing models for 120-day forecasts.

	Symmetric Error Statistic				Asymmetric Error Statistic			
	MSE	**RMSE**	**MAE**	**MAPE**	**MME-U**	**MME-O**	**MLAE**	**LINEX**
ARGENTINA	EGARCH*	EGARCH*	EGARCH*	GARCH*,EWMA EGARCH, MA	APARCH*	EGARCH*,GARCH	MA*, GARCH GRJ-GARCH	EGARCH*
BRAZIL	EGARCH	EGARCH*, EWMA	EGARCH	EWMA	SV	GARCH*, EGARCH GRJ-GARCH	MA	GRJ-GARCH
CHILE	MA	MA*, EGARCH, FIGARCH NAGARCH, EWMA	MA	EWMA	SV*	HM*	RW	MA
MEXICO	FIGARCH	FIGARCH*	FIGARCH	FIGARCH	SV	HM*	RW	FIGARCH
PERU	MA	HM*,MA, GRJ-GARCH	HM	EGARCH	EGARCH	MA*	MA	MA
VENEZUELLA	EGARCH	EWMA*	EWMA	EWMA	SV*	EGARCH*	EWMA*	EGARCH
CZECH	GARCH	GARCH*	GARCH*	MA*	APARCH*	GARCH*	HM*, EWMA FIGARCH, MA	FIGARCH
HUNGARY	MA	MA*	MA	MA	APARCH	FIGARCH*	MA	HM
POLAND	MA	MA*	MA	EWMA	SV	GARCH*	MA	MA
RUSSIA	EGARCH	EWMA*	EWMA	EWMA	SV*	FIGARCH*	EWMA	HM
TURKEY	MA*	EWMA*	EWMA*	EWMA*	SV*	FIGARCH*, MA, GARCH	EWMA	MA
CHINA	EWMA*	EWMA*	EWMA*	MA*, EWMA FIGARCH	EWMA	FIGARCH*	FIGARCH*	EWMA*
INDIA	FIGARCH	FIGARCH*	FIGARCH	EGARCH	SV	FIGARCH*	FIGARCH	FIGARCH
KOREA	GRJ-GARCH	RW*, GRJ-GARCH, MA EWMA, APARCH, FIGARCH	RW	RW	SV	GRJ-GARCH*,HM EGARCH	RW*, FIGARCH, MA APARCH, EWMA	GRJ-GARCH
MALAYSIA	EWMA	EWMA*	EWMA	EWMA	SV	MA*	EWMA*	EWMA
PHILIPPINES	MA	MA*	MA	MA	APARCH	HM*	MA	MA
SRILANKA	HM	HM*	HM	HM	SV*	EGARCH*	EWMA	HM
TAIWAN	EWMA	EWMA*, EGARCH, RW FIGARCH, APARCH	EWMA	EWMA	SV*	GARCH*	RW, APARCH MA, EWMA	EGARCH
THAILAND	FIGARCH	FIGARCH*	FIGARCH	FIGARCH	SV*	HM*	FIGARCH	FIGARCH

Note: As in Table 2.2.

Table 2.8 : The best performing models for 180-day forecasts.

	Symmetric Error Statistic				Asymmetric Error Statistic			
	MSE	**RMSE**	**MAE**	**MAPE**	**MME-U**	**MME-O**	**MLAE**	**LINEX**
ARGENTINA	EGARCH*	MA*	MA*	MA*	APARCH	EGARCH*	MA*	EGARCH*
BRAZIL	EGARCH	MA*, EWMA EGARCH	MA	EWMA	SV	EGARCH*	MA	MA
CHILE	MA	MA*	MA	MA	APARCH	HM*	FIGARCH	MA
MEXICO	MA	MA*	MA	MA	APARCH	HM*	MA	MA
PERU	MA	MA*	MA	MA	EGARCH	MA*	MA	MA
VENEZUELLA	EGARCH	EWMA*	EWMA	EWMA	SV *	EGARCH*	EWMA	EGARCH
CZECH	GARCH	GARCH*	GARCH*	HM*	APARCH*	GARCH*	EWMA*	FIGARCH
HUNGARY	MA	MA*	MA	MA	APARCH	HM*	FIGARCH	HM
POLAND	MA	MA*	MA	MA	APARCH	GARCH*, HM	EWMA	MA
RUSSIA	HM	EWMA*, MA	EWMA	EWMA	SV	EGARCH*, HM, MA EWMA, FIGARCH	MA	HM
TURKEY	MA*	EWMA*	EWMA*	EWMA*	SV *	FIGARCH*	EWMA	MA
CHINA	EWMA	EWMA*, FIGARCH	EWMA*,FIGARCH	FIGARCH*, EWMA	EWMA	FIGARCH*	FIGARCH	EWMA*
INDIA	FIGARCH	FIGARCH*	FIGARCH	FIGARCH	RW	FIGARCH*	FIGARCH	FIGARCH
KOREA	MA	MA*	MA	MA	SV	GRJ-GARCH*	MA	MA
MALAYSIA	EWMA	EWMA*	EWMA*	EWMA*	SV*	HM*, MA, EGARCH	EWMA	EWMA
PHILIPPINES	MA	MA*	MA*	MA*	MA*	HM*	MA	MA*
SRILANKA	HM*	HM*	HM*	HM	SV	HM*	HM	HM*
TAIWAN	EGARCH	APARCH*, EWMA EGARCH	APARCH	APARCH	SV	GARCH*	FIGARCH	EGARCH
THAILAND	FIGARCH	FIGARCH*	FIGARCH	FIGARCH	SV	HM*	FIGARCH	HM*

Note: As in Table 2.2.

Table 2.9 : The best performing models for 240-day forecasts.

	Symmetric Error Statistic				Asymmetric Error Statistic			
	MSE	**RMSE**	**MAE**	**MAPE**	**MME-U**	**MME-O**	**MLAE**	**LINEX**
ARGENTINA	EGARCH*	MA*	MA*	MA*	APARCH	EGARCH*	MA	EGARCH*
BRAZIL	MA	MA*	MA	MA	EWMA	GRJ-GARCH*, EGARCH	MA	MA
CHILE	MA	MA*	MA*	MA*	APARCH	HM*	FIGARCH	MA
MEXICO	MA	MA	MA	MA*	APARCH	HM*	EWMA	MA
PERU	MA	MA*	MA*	MA*	MA	MA*	MA*	MA*
VENEZUELLA	EGARCH	EWMA*	EWMA	EWMA	SV*	EGARCH*	EWMA	EGARCH
CZECH	GARCH	GARCH*	GARCH*	HM*	APARCH*	GARCH*	MA*	FIGARCH*
HUNGARY	MA	MA*	MA	MA*	MA	HM*	MA*	HM
POLAND	MA	MA*	MA	MA	MA	GARCH*	MA	MA
RUSSIA	HM	MA*	MA	MA	SV	MA*, HM	APARCH	HM
TURKEY	MA*	MA*	MA*	MA*	SV*	MA*	EWMA	MA*
CHINA	MA*	MA*	MA*	MA*	MA*	FIGARCH*	FIGARCH*	MA*
INDIA	MA	HM*	HM	HM	SV	GARCH*	HM*	MA
KOREA	MA	MA*	MA	MA	SV*	HM*	MA	MA
MALAYSIA	EWMA	EWMA*	EWMA*	EWMA*	SV*	MA*	EWMA*	MA
PHILIPPINES	MA*	MA*	MA*	MA*	SV*	HM*	MA*	MA*
SRILANKA	HM*	HM*	HM*	HM*	SV*	EGARCH*	HM	HM*
TAIWAN	APARCH	APARCH*	APARCH	APARCH	APARCH*	GARCH *	APARCH	EGARCH
THAILAND	FIGARCH	FIGARCH*	FIGARCH*	FIGARCH	SV	HM*	FIGARCH	HM

Note: As in Table 2.2.

in terms of the power of distinguishing, which implies that researchers who are working in volatility forecasting topic can use RMSE without testing the significance of best model.

Even though it is not the main motivation of this study, the results provides a very good reference for the choice of volatility model for different forecast horizon. Table 2.12 presents the best volatility model for each emerging market at different forecast horizon. Especially for those who consistently invest in international stock markets, Table 2.12 provides the best model for the volatility of the relevant market. General tendecy both in academia and in practice is to use GARCH family models for forecasting volatility. This tendecy is so strong that choosing GARCH family models is almost default. However, Table 2.12 tells us that this wide spread use of GARCH family models is not that appropriate in any case. From the table, one can find that the simple models like EWMA and MA are the best model for many forecast horizons. The results are not commented here country to country, the reader can make inferences easily. However, there are a few pattern that needs to be mentioned specifically. For three emerging markets in Europe, namely Turkey, Poland and Russia, EWMA is the best model for a wide range of forecast horizon. Hence, for the actors in these markets, the best choices for volatility model is EWMA not GARCH family models. Many institution use GARCH family models to calculate their market risk as a part of their capital adequacy ratio. However, the Table 2.11 in which overprediction and underprediction tendecies of the models in general are reported implies that GARCH family models usually overpredicts, which means that these institutions may have unneccessarily low capital adequacy ratios. On the other hand, the stock market in Czech Rebuclic has a pattern in terms of the best volatility model where GARCH family models are the best volatility models for the all forecast horizon. Another emerging market that shows pattern worth mentinoning is Thailand. For Thailand, FIGARH model is quite successfull at almost all forecast horizon.

Table 2.10: Generalization of results based on symmetric error statistic.

	The Significant Best Model	MCS set
1-Day	14 markets: SV	3 markets: GARCH family
	4 markets: EWMA	2 markets: GARCH family
	1 market: GARCH family	empty set
5-Day	11 markets : GARCH family	2 markets: EWMA
	7 markets: EWMA	3 markets: GARCH family
	1 counrty: RW	1 market: GARCH family
10-Day	8 markets : GARCH family	2 markets: EWMA, 2 markets: RW
	6 markets: EWMA	2 markets: GARCH family, 1 market: RW
	5 markets: RW	2 marktes: GARCH family, 2 markets: EWMA
20-Day	9 markets : GARCH family	1 market: EWMA, 1 market: RW
	8 markets: EWMA	4 market: GARCH family, 3 markets: RW
	2 markets: RW	2 markets: GARCH family, 1 market: EWMA
60-Day	8 markets : GARCH family	2 markets: EWMA, 2 markets: RW
	7 markets: EWMA	1 market: GARCH family
	3 markets: MA, 1 market: RW	2 market: EWMA, 2 market: GARCH, 1 market: RW
120-Day	6 markets : GARCH family	1 market: EWMA
	6 markets: EWMA	1 market: GARCH family
	5 markets: MA, 2 market: HM, 1 market: RW	3 market: GARCH family, 2 markets: EWMA, 1 market: MA
180-Day	9 markets : MA	1 market: GARCH family, 1 market: EWMA
	5 markets : EWMA, 1 market: HM	1 market: GARCH family
	4 markets : GARCH family	1 market: EWMA
240-Day	12 markets : MA	empty set
	3 markets : GARCH family	empty set
	2 markets : EWMA, 1 market: HM	empty set

Table 2.11 : Generalization of results based on asymmetric error statistic.

	UNDER PREDICTIONS	OVER PREDICTIONS
1-Day	19 markets : SV	12 markets: HM 6 markets: GARCH family 1 market : EWMA
5-Day	17 markets : SV 2 countrıes : RW	16 markets: GARCH family 2 markets: HM 1 market : MA
10-Day	18 markets : SV	14 markets: GARCH family 3 markets: HM 1 market: EWMA, 1 market: RW
20-Day	18 markets : SV 1 market : APARCH	17 markets: GARCH family 1 market: HM 1 market: EWMA
60-Day	17 markets : SV 2 markets : APARCH	15 markets: GARCH family 2 markets : HM 1 market: EWMA, 1 market: MA
120-Day	7 markets : SV 2 markets : APARCH	13 markets: GARCH family 4 markets : HM 2 markets : MA
180-Day	6 markets : SV 1 market: APARCH 1 market: MA	11 markets: GARCH family 7 markets : HM 1 market: MA
240-Day	6 markets : SV 2 markets: APARCH 1 market: MA	9 markets: GARCH family 5 markets : HM 5 markets : MA

Table 2.12: The best models at different forecast horizons.

	Forecast Horizon							
	1-Day	5-Day	10-Day	20-Day	60-Day	120-Day	180-Day	240-Day
ARGENTINA	SV	EGARCH	EGARCH	NAGARCH	EWMA	EGARCH	MA	MA
BRAZIL	SV	EWMA	EWMA	EWMA	EGARCH	EGARCH	MA	MA
CHILE	SV	APARCH	APARCH	EGARCH	EGARCH	MA	MA	MA
MEXICO	EWMA	EWMA	RW	RW	FIGARCH	FIGARCH	MA	MA
PERU	EWMA	RW	RW	EGARCH	GRJ-GARCH	HM	MA	MA
VENEZUELLA	SV	APARCH	APARCH	EWMA	EWMA	EWMA	EWMA	EWMA
CHECZH	GRJ-GARCH	GRJ-GARCH	FIGARCH	GRJ-GARCH	GRJ-GARCH	GARCH	GARCH	GARCH
HUNGARY	SV	FIGARCH	FIGARCH	FIGARCH	MA	MA	MA	MA
POLAND	EWMA	EWMA	EWMA	EWMA	EWMA	MA	MA	MA
RUSSIA	SV	EWMA	EWMA	EWMA	EWMA	EWMA	EWMA	MA
TURKEY	SV	EWMA	RW	EWMA	EWMA	EWMA	EWMA	MA
CHINA	SV	APARCH	APARCH	EWMA	MA	EWMA	EWMA	MA
INDIA	EWMA	EGARCH	EWMA	GARCH	GARCH	FIGARCH	FIGARCH	HM
KORE	SV	NAGARCH	RW	APARCH	APARCH	RW	MA	MA
MALAYSIA	SV	EGARCH	RW	EWMA	EWMA	EWMA	EWMA	EWMA
PHILIPPNESS	GRJ-GARCH	APARCH	EGARCH	APARCH	MA	MA	MA	MA
SRILANKA	SV	EGARCH	EWMA	EWMA	EWMA	HM	HM	HM
TAIWAN	SV	EWMA	EWMA	RW	RW	EWMA	APARCH	APARCH
THAILAND	SV	EWMA	FIGARCH	FIGARCH	FIGARCH	FIGARCH	FIGARCH	FIGARCH

3. CAUSALITY BETWEEN STOCK MARKET AND MACRO ECONOMIC VOLATILITY

There is a vast amount of literature on volatility transmission between different types of markets such as stock and bond markets, developed and emerging markets. (Karolyi, 1995; Caporale et al., 2006; Goeij and Marquering, 2004; Baele et al., 2010). The common purpose of these studies is to figure out the underlying dynamics of the volatility of stock markets. From this perspective, very little attention has been paid to the interaction between macro economic volatility and stock market volatility, especially in emerging markets. Schwert (1989) is one of the very first studies in which it is attempted to figure out the relation between stock market volatility and macroeconomic volatility for the case of USA. The findings of the study imply that there does not exist a significant relation between macroeconomic volatility and stock market volatility. On the other hand, Binder and Mergers (2001) and Beltratti and Morana (2006) provide some evidence on the existence of a significant relation between macroeconomic volatility and stock market volatility in contrast to Schwert (1989). The Binder and Mergers (2001) report a quite strong relation in which they take interest rate, inflation, the equity risk premium and the ratio of expected profits to expected revenues for the economy as explanatory variables. Beltratti and Morana (2006) report that there is a bidirectional casual relation between stock market volatility and interest rates, money supply growth volatilities. There are also studies for other developed countries in which the results support the significant relations between macroeconomic volatility and stock market volatility. Kearney and Daly (1998) report a very strong relation between Australian stock market volatility and money supply, industrial production and current account volatility while there is no significant relation with the foreign exchange rate volatility. Another research reporting favourable results in the existence of a significant relation between macroeconomic volatility and stock market volatility is Errunza and Hogan (1998) in which they performed the analysis for 7 European countries, and they found that money supply is important for Germany, France, Italy, and the Netherlands, and industrial production is important for UK, Switzerland and Belgium. However, Morelli (2002) in which the relation is examined for the case of UK does not support any significant relation. Overall, the results indicate that the relation between macroeconomic volatility and stock market volatility does exist to some extent even though significant macroeconomic variables are not the same for each country and methodologies show variability in the studies.

To the best of our knowledge, there is a gap for emerging markets in the literature on analyzing the relation between macroeconomic volatility and stock market volatility. The researches for emerging markets especially focus on the relation in the mean level in terms of the relation between macroeconomic variables and stock markets. On the other hand, the focuses of researches dealing with finding out the underlying dynamics of the volatility of stock markets are the volatility spillover and contagion between stock markets in different countries. Therefore, the relation between macroeconomic volatility and stock market volatility for emerging countries is waiting to be found out when it is taken into acoount that the results for the developed countries are contrary and specific to the stock market in question.

From theoretical point of view, the fundamental pricing formula in finance is the expectation of the present value of the future cash flows, which implies the strong relation between fundamentals and equities. At the aggregate level, it tells us that uncertainty in macroeconomic conditions of a country affects the riskiness of the stock index in that country by changing the cash flows and discount rates in the economy (Schwert, 1989). According to this, it is plausible to expect that the change in macroeconomic volatility would cause a change in volatility of stock indices. On the other hand, some researchers advocate that stock markets are the indicators of the macroeconomic conditions of the countries by assuming that new information in the markets is almost simultaneously priced in the stock market. Therefore, the empirical analysis is needed to determine the direction of the relation if there is one.

In the most general terms, the relation between two variables can be described in two different ways: They may move together due to the same variables that they are affected, which shows itself in form the of correlation. Or a change in one variable can cause a change in the other one, i.e. causality in one direction, or while the change in one variable affect the other, the change in the second variable can also affect the first one , i.e. bidirectional causality. In this section, the aim is to figure out the bidirectional causal relations in Granger-sense between macro economic volatility and stock market volatility.

There are two common methodologies to examine the relation between macroeconomic volatility and stock market volatility in the literature. The first one, which can be called two-step procedure, involves estimating the volatility series separately and then applying the regression independently to these volatility series. This procedure may introduce bias into a number of diagnostics and causes invalid inferences (Kearney and Daly, 1998). The other approach involves the use of Multivariate GARCH models. They, especiall BEKK representation, provides a suitable way to examine the causal relations between variables simultaneously. As a result, in this section, it is attempted to find out if there exists a casual relation between macro economic volatility and stock market volatility for four emerging countries, namely Turkey, Czech Republic, Brazil and India by using BEKK-MGARCH(1,1) model. Macroeconomic variables included in the study are inflation and industrial production as the indicators of the real economic activity in the country, and money supply and interest rate as the indicators of the monetary dynamics of the economy.

3.1 Multivariate GARCH Models

The Capital Asset Pricing Model (CAPM), the fundamental pricing model developed by Sharpe (1964) and Lintner (1965) basically provides a mathematical formulation for the risk premium of an asset where its risk is measured by the covariation of the asset with the market portfolio. However, the empirical test results can not provide an evidence that risk premiums of assets comply with the CAPM results. This unfavorable results are based on the assumptions on the model accoridng to researchers, and the most important one of these assumptiom is considered to be the constant covariation between the asset and market. First multivariate version of the GARCH type model is developed to relax this assumption by time-varying covariance matrices by Bollerslev et al. (1988), namely Vector GARCH model (VEC). Before introducing the multivariate GARCH models, let first explain the common basics of the models

$$\varepsilon_t = r_t - \mu_t \ ,$$
$$\varepsilon_t = H_t^{1/2}\epsilon_t \qquad \epsilon_t \sim IID(0,1) \tag{3.1}$$

where r_t is the $nx1$ vector of return, which is demeaned by a certain conditional mean model μ_t. ε_t is the $nx1$ vector of innovations, H_t is the nxn matrix of conditional covariance and 0 is $nx1$ vector of zeros and 1 is the nxn identity matrix. The conditional covariance of the innovations is in fact $H_t = E_{t-1}(\varepsilon_t \varepsilon_t')$. All of the MGARCH models aims to model this conditional covariance matrix in different parametrization structure with different considerations, which will be explained in the next subsections.

3.1.1 Vector GARCH

Vector GARCH (VEC) is the analogy of standart univariate GARCH model in multivariate setting which is described by Bollersev et. Al. (1988). A very general presentation of VEC-MGARCH(p,q) is as follows:

$$\mathrm{vech}(H_t) = C + \sum_{i=1}^{q} A_i^* \mathrm{vech}\left(\varepsilon_{t-i}\varepsilon_{t-i}'\right) + \sum_{j=1}^{p} B_j^* \mathrm{vech}\left(H_{t-j}\right) \tag{3.2}$$

In the first-order case VEC-MGARCH(1,1):

$$vech(H_t) = C + A^*\ vech\left(\varepsilon_{t-1}\varepsilon_{t-1}'\right) + B^*\ vech(H_{t-1}) \tag{3.3}$$

where $vech()$ denotes the column stacking operator lower portion of a symmetric matrix. $vech()$ provides a convinient way to stack a nxn matrix into a $n^* = n(n+1)/2$ dimensional vector.

$$Z = \begin{bmatrix} a & b & c \\ b & d & e \\ c & e & f \end{bmatrix} \qquad vech(Z) = [a\ b\ c\ d\ e\ f]' \tag{3.4}$$

So, in equation 3.2, C is a n^*x1 vector; A_i^* and B_j^* are the n^*xn^*matrices for an n variable system. In order to visualize the model in the matrix from let consider the bivariate case $n = 2$ and $p = q = 1$.

$$\begin{bmatrix} H_{11,t} \\ H_{12,t} \\ H_{21,t} \\ H_{22,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} H_{11,t-1} \\ H_{12,t-1} \\ H_{21,t-1} \\ H_{22,t-1} \end{bmatrix} \tag{3.5}$$

where $c_2 = c_3$, $a_{12} = a_{13}$, $a_{22} = a_{23}$, $a_{32} = a_{33}$, $a_{42} = a_{43}$, $b_{12} = b_{13}$, $b_{22} = b_{23}$, $b_{32} = b_{33}$, $b_{42} = b_{43}$, due to the equality of $H_{12,t-1}$ and $H_{21,t-1}$, $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$ and $\varepsilon_{2,t-1}\varepsilon_{1,t-1}$.

The most important issue in multivariate GARCH models is to be able to satisfy the positive definiteness of the conditional covariance matrix of H_t. Especially for the VEC model, in practice it is very difficult to use the model since it is impossible to derive general conditions on A^* and B^* which will ensure that H_t is positive definite. Different version of VEC model, the diagonal VEC model developed by , in which the parameter matrices A^* and B^* are diagonal matrices, is more practical since it is relatively straight forward to find conditions which ensure that conditional covariance are positive semi-definite. However, the diagonal VEC does not allow to study interractions between variables, hence relations between variables, since the crossproducts are assumed to equal zero beforehand in the model.

3.1.2 BEKK

The positive definiteness issue of conditional covariance matrix has led Baba, Engle, Kraft and Kroner (BEKK) to develop a differently parameterized version of VEC model, which is introduced Engle and Kroner (1995). They propose the new parametrization in a way that model can omit the redundant parameters in VEC model since all the covariance equations appear twice, which leads to different parameters that have to have the same value. Therefore, the biggest advantage of BEKK parameterization is that it requires fewer parameters to estimate and ensures the positive definiteness of the conditional covariance matrices, which is the most important issue for the estimation of the MGARCH models. For an N variable system, the number of parameters to be estimated is $N(5N+1)/2$ in BEKK representation while it is $N(N+1)[N(N+1)+2]/2$ in VEC representation. Also for VEC representation, $[N^2(p+q)+0.5(N+l)]$ number of restrictions in which p and q are the lags of GARCH specification have to be satisfied in order to guarantee the positive definiteness, which eventually increase the computational burden even more (Kearney and Patton, 2000).

The basic steps to obtain BEKK representation from VEC representation are as follows:

$$\begin{gathered}\varepsilon_t|\Psi_t \sim N(0,H_t), \qquad h_t = vech(H_t), \qquad \eta_t = vech(\varepsilon_t\varepsilon_t') \\ h_t = C^* + A_1^*\eta_{t-1} + \cdots + A_p^*\eta_{t-p} + B_1^*h_{t-1} + \cdots + B_q^*h_{t-q}\end{gathered} \tag{3.6}$$

Where Ψ_t is the information set, C^* is the constant term vector, A_i^* and B_i^* are n^*xn^*matrices for an n variable system where $n^* = n(n+1)/2$. In the matrix form, as an example, let consider the bivariate case of $p = q = 1$ for this presentation:

$$\begin{aligned}\begin{bmatrix}H_{11,t}\\H_{12,t}\\H_{22,t}\end{bmatrix} = \begin{bmatrix}c_1^*\\c_2^*\\c_3^*\end{bmatrix} + \begin{bmatrix}a_{11}^* & a_{12}^* & a_{13}^*\\a_{21}^* & a_{22}^* & a_{23}^*\\a_{31}^* & a_{32}^* & a_{33}^*\end{bmatrix}\begin{bmatrix}\varepsilon_{1,t-1}^2\\\varepsilon_{1,t-1}\varepsilon_{2,t-1}\\\varepsilon_{2,t-1}^2\end{bmatrix} \\ + \begin{bmatrix}b_{11}^* & b_{12}^* & b_{13}^*\\b_{21}^* & b_{22}^* & b_{23}^*\\b_{31}^* & b_{32}^* & b_{33}^*\end{bmatrix}\begin{bmatrix}H_{11,t-1}\\H_{12,t-1}\\H_{22,t-1}\end{bmatrix}\end{aligned} \tag{3.7}$$

In BEKK represantation, these parameter matrices are rearranged in a way that they can be written in quadratic terms which ensures the positivity of the conditional variance and covariances. For the above case in equation 3.7:

$$\begin{aligned}\begin{bmatrix}H_{11,t} & H_{12,t}\\H_{21,t} & H_{22,t}\end{bmatrix} = {} & \begin{bmatrix}c_{11} & 0\\c_{21} & c_{22}\end{bmatrix}\begin{bmatrix}c_{11} & 0\\c_{21} & c_{22}\end{bmatrix}' \\ & + \begin{bmatrix}a_{11} & a_{12}\\a_{21} & a_{22}\end{bmatrix}\begin{bmatrix}\epsilon_{1,t-1} & \epsilon_{1,t-1}\epsilon_{2,t-1}'\\\epsilon_{1,t-1}\epsilon_{2,t-1}' & \epsilon_{2,t-1}\end{bmatrix}\begin{bmatrix}a_{11} & a_{12}\\a_{21} & a_{22}\end{bmatrix} \\ & + \begin{bmatrix}b_{11} & b_{12}\\b_{21} & b_{22}\end{bmatrix}\begin{bmatrix}H_{11,t-1} & H_{12,t-1}\\H_{21,t-1} & H_{22,t-1}\end{bmatrix}\begin{bmatrix}b_{11} & b_{12}\\b_{21} & b_{22}\end{bmatrix}'\end{aligned} \tag{3.8}$$

Then for the most general BEKK(p,q) is in closed-form :

$$H_t = CC' + \sum_{k=1}^{K}\sum_{i=1}^{P} A_{ik}\,\epsilon_{1,t-i}\;\epsilon'_{1,t-i}A'_{ik} + \sum_{k=1}^{K}\sum_{j=1}^{q} B_{jk}H_{t-j}\,B'_{ik} \qquad \textbf{(3.9)}$$

where C, A_{ik} and B_{jk} are the nxn parameter matrices, n is the number of variables and the summation limit K determines the generality of the process.

3.2 Testing Causality With MGARCH And Bootstrapped Testing

The idea behind Granger causality is that cause must precede the effect. That is, if variable x causes variable y, then lagged variable x has a potential to explain variable y. In the literature, two common approaches are followed to test the causality in volatility of financial time series. The first approach is based on the cross correlation function (CCF) of univariate time series in which the interaction between variables is ignored (Cheung and Ng, 1996, Kanas and Kouretas, 2002). The second approach involves the use of multivariate GARCH models. Cheung and Ng (1996), in which they propose CCF, states that non-simultaneous modeling provides an easy way to implement for cases involving large number of variables and a robust way of examining causality to violations of the distributional assumptions. However, this non-synchronous estimation strategy introduces bias in a number of diagnostic test statistics and generates potentially invalid inferences. On the other hand, multivariate GARCH models, namely VEC and BEKK, provide very good set up for testing the lagged relations between variables by taking into account the interrelations between variables and time-varying dynamics. As in other studies in the literature such as Caporale et al. (2006), Caporale et al. (2002), Karolyi (1995), Goeij and Marquering (2004) and since emerging economies are more prone to changes in risk sensitivities due to shifting in industrial structure as stated in Campbell (1996), the BEKK-MGARCH modeling is very important tool for the analysis of the bidirectional causal relations.

According to bivariate BEKK model, the closed form representation of the conditional variance covariance equations in equation 3.8 is as follows:

$$H_{11,t} = c_{11}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{12}\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{12}^2\epsilon_{2,t-1}^2 + b_{11}^2 H_{11,t-1} + 2b_{11}b_{12}H_{12,t-1} + b_{12}^2 H_{22,t-1} \quad \textbf{(3.10)}$$

$$H_{22,t} = c_{21}^2 + c_{21}^2 + a_{22}^2 \varepsilon_{1,t-1}^2 + 2a_{22}a_{21}\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{21}^2\epsilon_{2,t-1}^2 + b_{22}^2 H_{22,t-1} + 2b_{22}b_{21}H_{21,t-1} + b_{21}^2 H_{21,t-1} \quad \textbf{(3.11)}$$

$$H_{21,t} = c_{11}c_{21} + (a_{22}a_{11} + a_{12}a_{21})\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{11}a_{21}\epsilon_{1,t-1}^2 + a_{12}\, a_{22}\epsilon_{2,t-1}^2 + b_{11}b_{21}H_{11,t-1} + b_{22}b_{12}H_{22,t-1} + (b_{22}b_{11} + b_{12}b_{21})H_{21,t-1} \quad \textbf{(3.12)}$$

As it can be seen from the different forms of bivariate BEKK GARCH(1,1) model, off diagonal elements of A and B matrices, in fact, models the volatility transmission between variables. To apply zero restrictions on these coefficients allows one to test the causality between variables. If A and B are restricted as an(a) upper(lower) triangular form, it provides us to test the causality from second (first) variable to first(second) variable by means of likelihood ratio (LR) tests. However, the existence of the significant causal relations between variables is directly related to the critical values of LR test, therefore distributional assumptions are of paramount importance for statistical inference. This is where the importance of bootstrapped testing comes into play. The bootstrapped testing procedure has the following advantages over the standard testing procedure : (1) It does not use an asymptotic result and will work well even when the sample size is not very large. (2) It does not make specific distributional assumptions, whereas the standard test procedure assumes a multinominal distribution of the variables with unknown parameters. (3) Bootstrap results are almost always more accurate compared to asymptotic results (Efron and Tibshirani, 1993). Especially the distributional assumptions becomes much more critical for the emerging markets since macro economic data is not long enough to satisfy asymptotic result. Therefore a bootstrap procedure analogous to that described in Davison and Hinkley (1997) is used in the study. Let define likelihood ratio as

$$LR = 2(\ell_{UNRES} - \ell_{RES}) \quad \textbf{(3.13)}$$

where ℓ_{UNRES} and ℓ_{RES} are the likelihood value of unrestricted and restricted model, respectively. Zero hypothesis of LR test is that there is no significant difference between restricted and unrestricted model. Large positive values of LR give favorable evidence to unrestricted model according to equation 3.13. Bootstrapping the likelihood ratio consists of generating R (in this study $R = 999$) data sets from the model under the null hypothesis, i.e. restricted model, with the parameters substituted by their Quasi Maximum Likelihood estimates and then ordering likelihood ratios as $LR_1^* < LR_2^* < \cdots < LR_R^*$. If α is chosen as the significance level of the test then the bootstrapped critical value of the likelihood ratio is calculated as $LR^*_{(R+1)(1-\alpha)}$.

As for the weaknesses of the methodology, the first issue is the estimations of the conditional mean and conditional covariance parameters separately. However, the fact that the macroeconomic history of the data is not very long for the emerging economies leads us to the choose to estimate the least number of parameters as much as possible, which is a common approach in the literature as in Engle and Sheppard (2001) and Bauwens et al. (2006). Also, Carnero and Eratalay (2009) performs Monte Carlo experiments to compare the finite sample of multi-step estimators of various MGARCH models[7] and they reported that the small sample behaviors of the multi-step estimators are very similar. Secondly, the bivariate analysis may lead to exclusion of other important variables, but again, the issue of data availability for macroeconomic variables makes multivariate analysis more than two not so appropriate due to increasing number of parameters.

3.3 Analysis Of Bidirectional Causality

3.3.1 Data and preliminary analysis

In this part, the causality between stock market return volatility and macroeconomic volatility in either direction for four emerging economies, namely Turkey, Czech Republic, Brazil and India, are examined in bivariate setting. In parallel with the literature, industrial production and inflation for real activity; money supply and interest rate for the monetary dynamics of the country are chosen as the indicators of macroeconomic conditions of the counties. A detailed description of data, i.e

[7] Unfortunately BEKK is out of the scope their studies.

sources, tickers, frequencies and time periods and abbreviations for the variables can be found in the Table 3.1. The fact that macroeconomic data for emerging markets does not have a long history requires us that time periods and frequencies are arranged specifically to each bivariate analysis in order to use the whole data in hand for each variable. Inflation, industrial production and money supply is in monthly frequency; as for interest rates, the frequency is either monthly or weekly where the decision is based on the availability of data in higher frequency and variation in the data. If the daily data exists, weekly data is obtained from the daily data by using the end-of-week date values since the daily variation is not enough to use it in daily frequency. Otherwise, monthly data is used when the daily data is not available.

Macroeconomic variables are expressed in terms of growth rates estimated analogous to logarithmic return series of ctosk markets, $R_t = \ln(\frac{X_t}{X_{t-1}})$ where X_t is the variable value at date t in order to be parallel with the stock market return. In order to be able to continue to analysis further and to evaluate the stationarity of time series, the unit root test of the return series are performed. Test results are presented in the Table 3.2, which allows further modelling. Variables, R_t, are filtered by AR(1) process with the inclusion of monthly dummy variables due to the seasonal tendencies in macro economic variables as it is represented in equation 3.14

$$R_t = \mu + \emptyset R_{t-1} + \sum_{i=1}^{12} \delta_i D_i + \varepsilon_t \qquad \textbf{(3.14)}$$

where D_i are i^{th} month of the year and δ_i corresponding regression coefficient.

Table 3.1: Details of Data.

Variable	Source	Ticker	Period	Obs	Frequency
Turkey					
CPI	Bloomberg	TUCPI	31.01.1992-30.05.2010	221	monthly
IP	Bloomberg	TUIOI	31.01.1997-30.05.2010	161	monthly
M1	Datastream	-	31.01.1992-30.05.2010	221	monthly
INT	Bloomberg	TRLIB3M	02.08.2002-23.07.2010	417	weekly
Stock Exchange	Bloomberg	XU100	31.01.1992- 23.07.2010	*	*
Czech Republic					
Variable	Source	Ticker	Period	Obs	Frequency
CPI	Bloomberg	9356639	31.01.1994-30.06.2010	198	monthly
IP	Bloomberg	9356629	31.01.1998 - 30.06.2010	150	monthly
M1	Bloomberg	CZMSM1	31.01.1994 - 30.06.2010	198	monthly
INT	Bloomberg	PRIB01M	09.01.1998 - 29.01.2010	630	weekly
Stock Exchange	Bloomberg	PX	31.01.1994- 01.09.2010	*	*
Brazil					
Variable	Source	Ticker	Period	Obs	Frequency
CPI	Bloomberg	2236639	31.01.1991 - 30.06.2010	234	monthly
IP	Bloomberg	2236629	31.01.1991 - 30.06.2010	234	monthly
M1	Bloomberg	BZMS1	31.01.1995 - 30.06.2010	186	monthly
INT	Bloomberg	BZDIOVRA	29.07.1994-30.06.2010	195	monthly
Stock Exchange	Bloomberg	IBOV	31.01.1991- 02.09.2010	*	*
India					
Variable	Source	Ticker	Period	Obs	Frequency
CPI	Bloomberg	5346639	31.01.1980 - 31.05.2010	365	monthly
IP	Bloomberg	5346657	31.01.1980 - 31.05.2010	365	monthly
M1	Bloomberg	5341137	31.01.1980 - 31.05.2010	365	monthly
INT	Bloomberg	GINAY91	05.09.1997 - 29.09.2010	669	weekly
Stock Exchange	Bloomberg	SENSEX	31.01.1980 - 29.09.2010	*	*

Note: CPI, IP, M1, INT stand for consumer price index, industrial production, money supply M1 and short term interest rate, respectively. Stock exchanges used in the study are Istanbul Stock Exchange 100 index, ISE, for Turkey; Praue Stock Exchange, PX, for Czech Republic; Brazil Bovespa Index, IBOV, for Brazil and Bombay Stock Exchange Sensitive Index, SENSEX, for India. A * indicates that the number of observation and frequency of the stock exchange is set according to macro variable with which it is analyzed

Table 3.2: ADF test results.

Turkey		Czech		Brazil		India	
CPI	45.1	CPI	75.5	CPI	81.5	CPI	78.8
IP	173.1	IP	104.9	IP	92.0	IP	465.1
M1	159.9	M1	124.8	M1	130.2	M1	106.9
INT	163.9	INT	220.2	INT	131.8	INT	260.5
Monthly	114.1	*Monthly(CPI,M1)*	70.5	*Monthly(M1)*	93.8	*Monthly*	1719.1
Weekly	193.8	*Monthly(IP)*	59.0	*Monthly(CPI, IP)*	72.1	*Weekly*	2163.5
		Weekly	258.5	*Monthly(INT)*	1301.4		

Note: CPI, IP, M1 and INT are respectively stand for the inflation, industrial production, money supply and short term interest rate. As for the stock exchange, since the analysis is performed in the bivariate setting, stock exchange data are rearranged according to corresponding macroeconomic variable and therefore the frequency and the period for the stock exchanges varies. The words in italic is for the stock exchange and presents the frequency of the series, the words in the paranthesis is used to show the corresponding macro variable used in the corresponding bivariate analysis. Different monthly series for different macro variables are due to the different time intervals of the data.

3.3.2 Results

The BEKK-GARCH(1,1) parameter estimates with robust standard errors are reported in Tables 3.3 to Table 3.6 for Turkey, Czech Republic, Brazil and India. Tables also include the loglikelihood ratio test statistics, their corresponding chi-square p values and Ljung-Box (LB) diagnostics. According to LB test statistics, overall results provide the evidence that lag (1,1) structure is sufficiently capture the autocorrelation in both residuals and squared residuals except for a few cases. Before examining the causality between macroeconomic volatility and corresponding stock market volatility, there are some common points that deserve attention from the parameter estimations of the bivariate BEKK-MGARCH(1,1) model. First of all, cross section volatility dependence shows itself in the conditional covariance coefficients for both stock market volatilities and corresponding macro variable volatility. This is not a surprise but it is a sign of that the models are capable of catching the dynamics of the bivariate analysis. That is, if there exits cross sectional relation between variables it shows itself in the parameters of the conditional covariances, H_{21} or equivalently H_{12}, not in the parameter estimates of conditional variances of the other variable H_{22} when H_{11} is the primary variable that we examine the volatility dynamics[8]. Secondly, the persistence in the conditional covariances are

[8] Check the equations (6), (7) and (8) to see the whole parameterization structure for conditional variances

varied. Some, e.g. those of ISE-INT, SENSEX-M1 show high persistence, while some shows almost none, e.g ISE-M1 and PX-IP[9]. This implies that, for instance, when the covariation of ISE and short term interest rates volatility increases, this high covariation continues for a certain period of time. Lastly, for some bivariate models, e.g ISE-IP, ISE-INT, PX-INT and IBOV-M1, the sign of the coefficient of conditional covariance in the stock market volatility is negative. At first look, this seems paradoxical in the sense that how the volatility of stock markets could decrease when the covariation between variables increase, however, this might be a sign of lead-lag relation between variables, hence indirectly the sign of existence of the causality between corresponding variables since if the volatility of one of the variables is leading to another then it may show itself in the negative correlation.

When the causality between bivariates are examined, the standard log likelihoods ratios of restricted and unrestricted models and their p-values according to chi-square distribution can be found in Tables 3.3 to Table 3.6. According to these results, most of the bivariates show causality in either one direction or bidirection. However, when bootstrapped test results, whose details are introduced in the previous sections, are examined in Table 3.7, only a few of them indicate the significant causal relations.

For the case of Turkey, there exists a casual relation between stock market and industrial production, i.e. stock market is Granger-cause of industrial production, which may imply that expectations about the production level of the country show itself in the stock market and investors take into account the industrial production level when they are making decisions while inflation level is not[10]. This is the case where the stock market is the indicator of the macro economic conditions of the country. The other important result is that the money supply M1 is Granger-cause of ISE. Hence, the variation in the growth rate of money supply of the Turkish economy affects the volatility of stock markets. This indicates that investors in Turkey give considerable importance to monetary policies of Central Bank of Turkey, which is

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[9] Please check the table in the appendix for abbreviations.

[10] The variable name is used directly to say the volatility of the corresponding variable. For instance, instead of saying that the volatility of the stock market is Granger-cause of volatility of the industrial production, a shorter version is preferred for the convenience, which is the stock market is the Granger-cause of the industrial production since the focus of the study is only on causal relations in the second moments of the variables

Table 3.3: BEKK-MGARCH(1.1) estimates for Turkey.

	Upper Restricted		Lower Restricted		Unrestricted	
Parameters	Coeff	S.E	Coeff	S.E.	Coeff	S.E.
ISE and Inflation						
c11	0.1374	0.0001	0.1373	0.0001	0.1374	0.0001
c21	-0.0006	0.0000	-0.0007	0.0000	-0.0006	0.0000
c22	0.0176	0.0000	0.0175	0.0000	0.0175	0.0000
a11	-0.0863	0.0188	-0.1027	0.0243	-0.0877	0.0212
a21	-0.2069*	0.1281	0.0000	0.0000	-0.0014	0.0000
a12	0.0000	0.0000	-0.0022	0.0000	-0.2011	0.0928
a22	0.2458	0.0040	0.2451	0.0039	0.2458	0.0038
b11	0.0000*	0.0001	0.0000*	0.0019	0.0000*	0.0001
b21	0.0000*	0.0005	0.0000	0.0000	0.0000*	0.0005
b12	0.0000*	0.0000	0.0000*	0.0000	0.0000*	0.0047
b22	0.0000*	0.0001	0.0000*	0.0075	0.0000*	0.0001
LogL	695.6851		695.6089		695.6893	
LR Test	0.0084	(0.9958)	0.1609	(0.9227)		
LB(5)-CPI	3.4118	(0.6367)	3.3821	(0.6413)	3.4106	(0.6369)
LB2(5)-CPI	2.819	(0.7278)	2.7897	(0.7323)	2.8199	(0.7277)
LB(5)-ISE	9.7592	(0.0824)	9.7594	(0.0823)	9.7751	(0.08186)
LB2(5)-ISE	1.94E-01	(0.9991)	0.22677	(0.9988)	0.1942	(0.99917)
ISE and Industrial Production						
c11	0.0883	0.0203	0.1032	0.0012	0.0011	0.0002
c21	0.0071	0.0005	0.0197	0.0002	-0.0319	0.0000
c22	-0.0470	0.0000	0.0000*	0.0000	0.0000*	0.0037
a11	0.4523	0.0501	-0.0970	0.0151	0.1230	0.0100
a21	0.9959	0.1334	0.0000	0.0000	-0.1617	0.0026
a12	0.0000	0.0000	-0.1586	0.0019	0.1782	0.0372
a22	-0.0695*	0.0422	0.5419	0.0177	0.5308	0.0159
b11	0.0408*	0.0282	-0.6149	0.1410	0.9794	0.0001
b21	-1.3292	13.6116	0.0000	0.0000	0.0250	0.0010
b12	0.0000	0.0000	0.1975	0.0098	-0.3104	0.0498
b22	0.1901	0.0799	0.3578	0.0184	0.3993	0.0112
LogL	358.9427		361.6509		365.7137	
LR Test	13.5421	(0.0011)	8.1256	(0.0172)		
LB(5)-IP	1.8662	(0.8673)	4.0801	(0.5379)	3.2592	(0.6600)
LB2(5)-IP	0.33381	(0.9969)	2.6182	(0.7586)	1.4961	(0.9135)
LB(5)-ISE	14.326	(0.0136)	14.332	(0.0136)	13.707	(0.0175)
LB2(5)-ISE	8.4584	(0.1327)	4.497	(0.4802)	4.7651	(0.4452)

Table 3.3 (continued): BEKK-MGARCH(1.1) estimates for Turkey.

	Upper Restricted		Lower Restricted		Unrestricted	
Parameters	Coeff	S.E	Coeff	S.E.	Coeff	S.E.
ISE and Money Supply						
c11	0.1211	0.0001	0.1380	0.0001	0.1230	0.0001
c21	0.0067	0.0000	0.0025	0.0000	0.0063	0.0000
c22	0.0433	0.0000	0.0414	0.0000	0.0418	0.0000
a11	0.1072	0.0144	0.0126	0.0035	0.1324	0.0114
a21	-1.5230	0.2719	0.0000	0.0000	0.0672	0.0009
a12	0.0000	0.0000	0.0976	0.0039	-1.4276	0.2822
a22	0.1711	0.0230	0.1551*	0.1680	0.2199	0.0132
b11	0.0000*	0.0004	0.0000*	0.0184	0.0000*	0.0000
b21	0.0000*	0.0002	0.0000	0.0000	0.0000*	0.0000
b12	0.0000	0.0000	0.0000*	0.0242	0.0000*	0.0002
b22	0.0000*	0.0000	0.0000*	0.0221	0.0000*	0.0001
LogL	501.3319		499.3072		502.7745	
LR Test	2.8851	(0.2363)	11.9919	(0.0174)		
LB(5)-CPI	3.4616	(0.6292)	3.3256	(0.6499)	3.6199	(0.6053)
LB2(5)-CPI	1.2852	(0.9365)	2.7534	(0.7379)	1.4501	(0.9188)
LB(5)-ISE	21.4600	(0.0007)	20.6990	(0.0009)	21.3980	(0.0007)
LB2(5)-ISE	8.8940	(0.1134)	6.1872	(0.2884)	7.2155	(0.2051)
ISE and Interest Rate						
c11	0.0144	0.0000	0.0357	0.0002	0.0169	0.0001
c21	-0.0007	0.0000	-0.0077	0.0000	-0.0040	0.0000
c22	0.0058	0.0000	0.0000	0.0000	0.0000	0.0000
a11	-0.2315	0.0038	-0.2140	0.0837	-0.1945	0.0600
a21	-0.0233	0.0150	0.0000	0.0000	-0.0804	0.0201
a12	0.0000	0.0000	-0.0658	0.0166	0.0919	0.0331
a22	0.4071	0.0075	0.3594	0.0145	0.3020	0.0200
b11	0.9092	0.0030	0.5555	0.1739	0.8686	0.0219
b21	-0.0640	0.0082	0.0000	0.0000	0.0628	0.0014
b12	0.0000	0.0000	0.1447	0.0120	-0.2284	0.0098
b22	0.8965	0.0012	0.8663	0.0058	0.9396	0.0028
LogL	1643.1544		1645.6457		1651.2243	
LR Test	16.1396	(0.0003)	11.1572	(0.0038)		
LB(5)-IP	2.0807	(0.8379)	1.7429	(0.8835)	2.0101	(0.8477)
LB2(5)-IP	1.4198	(0.9221)	3.8907	(0.5653)	1.9912	(0.8504)
LB(5)-ISE	14.6330	(0.0121)	13.1700	(0.0218)	12.7430	(0.0259)
LB2(5)-ISE	8.8006	(0.1173)	6.5519	(0.2562)	9.2886	(0.0981)

Note: Details of the data and variables can be found in the appendix. Parameters are from the equation (5) or (6), (7), (8). The number in the parenthesis are the probability values of the corresponding tests. LB(5) and LB2(5) are respectively the Ljung-Box test of significance of autocorrelations of five lags in the standardized and standardized squared residuals. A * indicates the rejection at the 5 percent level

Table 3.4: BEKK-MGARCH(1.1) estimates for Czech.

	Upper Restricted		Lower Restricted		Unrestricted	
Parameters	Coeff	S.E	Coeff	S.E.	Coeff	S.E.
PX and Inflation						
c11	0.0575	0.0001	0.0536	0.0002	0.0588	0.0001
c21	-0.0006	0.0000	-0.0007	0.0000	-0.0009	0.0000
c22	0.0014	0.0000	0.0013	0.0000	0.0002	0.0001
a11	0.4866	0.0161	0.4187	0.0097	0.4632	0.0164
a21	5.0789*	24.4846	0.0000	0.0000	0.0068	0.0000
a12	0.0000	0.0000	0.0022	0.0000	5.0588*	15.0188
a22	0.3900	0.0824	0.4378	0.0271	0.4260	0.0652
b11	-0.3061*	0.2418	0.5487	0.0497	-0.2662	0.1600
b21	-2.9805*	24.0106	0.0000	0.0000	-0.0128	0.0007
b12	0.0000	0.0000	0.0055	0.0001	-3.1342*	14.2786
b22	0.8641	0.0051	0.8581	0.0028	0.8426	0.0191
LogL	1044.4380		1041.7250		1045.4914	
LR Test	2.1067	(0.3488)	7.5328	(0.0231)		
LB(5)-CPI	2.608	(0.7601)	2.0722	(0.8390)	2.5978	(0.7617)
LB2(5)-CPI	2.5381	(0.7707)	0.91593	(0.9690)	2.6596	(0.7522)
LB(5)-PX	6.619	(0.2505)	7.7986	(0.1676)	7.966	(0.1581)
LB2(5)-PX	3.5225	(0.6199)	3.7372	(0.5878)	3.1196	(0.6820)
PX and Industrial Production						
c11	-0.0044	0.0001	0.0315	0.0059	-0.0003	0.0000
c21	0.0138	0.0000	0.0094	0.0006	-0.0176	0.0000
c22	0.0000	0.0000	-0.0131*	0.0119	0.0000*	0.0006
a11	0.4147*	0.0125	0.3084*	0.5227	0.3281	0.0141
a21	-0.7890	0.0401	0.0000	0.0000	0.1763	0.0028
a12	0.0000	0.0000	0.1728*	0.1422	-0.8323	0.0260
a22	0.2451	0.0125	0.2206*	0.6207	0.1399	0.0084
b11	0.8260	0.0031	0.8573*	0.4750	0.8207	0.0021
b21	0.2266	0.0114	0.0000	0.0000	-0.0953	0.0008
b12	0.0000	0.0000	-0.1028	0.0087	0.3289	0.0079
b22	0.9093	0.0007	0.8296*	1.6702	0.8211	0.0097
LogL	450.3855		444.4832		455.7636	
LR Test	10.7564	(0.0046)	22.5608	(0.0000)		
LB(5)-IP	3.3851	(0.6408)	3.4577	(0.6298)	3.4780	(0.6267)
LB2(5)-IP	2.7993	(0.7309)	0.8932	(0.9707)	2.5104	(0.7749)
LB(5)-PX	28.5710	(0.0000)	32.9000	(0.0000)	30.3130	(0.0000)
LB2(5)-PX	9.2177	(0.1007)	9.3515	(0.0958)	6.6663	(0.2467)

Table 3.4 (continued): BEKK-MGARCH(1.1) estimates for Czech.

	Upper Restricted		Lower Restricted		Unrestricted	
Parameters	Coeff	S.E	Coeff	S.E.	Coeff	S.E.
PX and Money Suppy						
c11	0.0253	0.0002	0.0161	0.0000	0.0214	0.0001
c21	-0.0090	0.0000	-0.0034	0.0000	-0.0084	0.0000
c22	0.0000	0.0000	0.0000	0.0000	0.0000*	0.0000
a11	0.3135	0.0138	0.2732	0.0053	0.2929	0.0203
a21	-0.2959	0.1209	0.0000	0.0000	-0.0026	0.0005
a12	0.0000	0.0000	-0.0338	0.0001	-0.2879	0.1051
a22	0.1955	0.0104	-0.0751	0.0118	0.1981	0.0100
b11	0.8650	0.0114	0.9366	0.0004	0.8973	0.0077
b21	0.6165	0.0815	0.0000	0.0000	-0.0054	0.0002
b12	0.0000	0.0000	0.0206	0.0000	0.5519	0.0593
b22	0.8833	0.0024	0.9751	0.0003	0.8949	0.0031
LogL	723.7554		726.1669		724.0383	
LR Test	0.5659	(0.7536)	4.2571	(0.1190)		
LB(5)-M1	1.7250	(0.8857)	1.7094	(0.8877)	1.7269	(0.8855)
LB2(5)-M1	1.8512	(0.8693)	0.6263	(0.9868)	2.0720	(0.8391)
LB(5)-PX	5.0222	(0.4132)	6.3954	(0.2696)	5.0665	(0.4078)
LB2(5)-PX	0.7481	(0.9802)	1.1884	(0.9460)	0.7585	(0.9796)
PX and Interest Rate						
c11	0.0053	0.0000	0.0096	0.0000	0.0019	0.0000
c21	-0.0208	0.0000	-0.0097	0.0000	-0.0139	0.0000
c22	0.0000*	0.0006	0.0107	0.0001	0.0000	0.0002
a11	0.3615	0.0152	0.3581	0.0204	0.1600	0.0148
a21	-0.2233	0.0070	0.0000	0.0000	-0.3874	0.0084
a12	0.0000	0.0000	-0.3532	0.0130	0.0747	0.0182
a22	-0.6433	0.2075	0.2408	0.1019	0.2714	0.0547
b11	0.8999	0.0022	0.8962	0.0036	0.9341	0.0006
b21	-0.1484	0.0173	0.0000	0.0000	0.1414	0.0057
b12	0.0000	0.0000	0.1829	0.0101	-0.3654	0.0256
b22	0.0218	0.0052	0.5101	0.0472	0.5088	0.0242
LogL	2771.8162		2792.7041		2801.6426	
LR Test	59.6527	(0.0000)	17.8770	(0.0001)		
LB(5)-INT	7.4383	(0.1900)	6.0323	(0.3031)	7.2362	(0.2037)
LB2(5)-INT	6.0557	(0.3008)	4.7142	(0.4518)	3.7327	(0.5885)
LB(5)-PX	11.6640	(0.0397)	8.3152	(0.1397)	8.7609	(0.1190)
LB2(5)-PX	1.5847	(0.9031)	1.3739	(0.9272)	1.5109	(0.9118)

Note: As in Table 3.3

Table 3.5: BEKK-MGARCH(1.1) estimates for Brazil.

	Upper Restricted		Lower Restricted		Unrestricted	
Parameters	Coeff	S.E	Coeff	S.E.	Coeff	S.E.
IBOV and Inflation						
c11	0.0235	0.0001	0.0238	0.0000	0.0249	0.0000
c21	0.0001	0.0000	0.0014	0.0000	-0.0008	0.0000
c22	0.0046	0.0000	0.0048	0.0000	0.0049	0.0000
a11	0.3935	0.0064	0.3554	0.0076	0.3998	0.0072
a21	-1.2095	0.2941	0.0000	0.0000	0.0246	0.0002
a12	0.0000	0.0000	0.0264	0.0004	-1.1849	0.2110
a22	0.6074	0.0463	0.6365	0.0673	0.5541	0.0427
b11	0.9003	0.0007	0.9179	0.0006	0.8970	0.0007
b21	0.5961	0.2381	0.0000	0.0000	-0.0009	0.0003
b12	0.0000	0.0000	-0.0064	0.0004	0.2768*	0.3559
b22	0.7161	0.0350	0.6265	0.0467	0.6678	0.0274
LogL	870.2703		870.3009		873.7644	
LR Test	6.9881	(0.0304)	6.9270	(0.0313)		
LB(5)-CPI	18.3010	(0.0026)	19.0420	(0.0019)	18.1300	(0.0028)
LB2(5)-CPI	0.5795	(0.9889)	0.8152	(0.9761)	0.6291	(0.9866)
LB(5)-IBOV	10.1090	(0.0722)	7.7031	(0.1734)	8.3623	(0.1374)
LB2(5)-IBOV	1.5554	(0.9066)	1.8705	(0.8668)	1.7588	(0.8814)
IBOVand Industrial Production						
c11	0.0217	0.0000	0.0242	0.0000	0.0218	0.0001
c21	0.0010	0.0000	0.0017	0.0000	-0.0033	0.0001
c22	0.0045	0.0000	-0.0061	0.0000	-0.0059	0.0000
a11	0.3547	0.0110	0.4025	0.0081	0.3968	0.0297
a21	-1.0626*	0.9866	0.0000	0.0000	0.0790	0.0002
a12	0.0000	0.0000	0.0771	0.0003	-1.1284	0.5116
a22	0.7011	0.0295	0.6654	0.0100	0.6177	0.0102
b11	0.9160	0.0008	0.9058	0.0008	0.9047	0.0010
b21	0.4635*	0.4401	0.0000	0.0000	-0.0035	0.0004
b12	0.0000	0.0000	-0.0164	0.0002	0.1066*	0.6488
b22	0.7140	0.0092	0.3796	0.0204	0.3629	0.0059
LogL	822.5474		823.0684		826.0505	
LR Test	7.0061	(0.0301)	5.9641	(0.0507)		
LB(5)-IP	19.5780	(0.0015)	18.4930	(0.0024)	18.5780	(0.0023)
LB2(5)-IP	0.7701	(0.9789)	0.7117	(0.9823)	1.2721	(0.9378)
LB(5)-IBOV	7.9854	(0.1570)	11.3820	(0.0443)	9.4371	(0.0928)
LB2(5)-IBOV	7.4280	(0.1907)	13.5700	(0.0186)	21.3940	(0.0007)

Table 3.5 (continued) : BEKK-MGARCH(1.1) estimates for Brazil.

	Upper Restricted		Lower Restricted		Unrestricted	
Parameters	Coeff	S.E	Coeff	S.E.	Coeff	S.E.
IBOV and Money Suppy						
c11	0.0119	0.0000	0.0173	0.0001	0.0139	0.0000
c21	0.0085	0.0000	0.0094	0.0000	0.0087	0.0000
c22	-0.0069	0.0000	0.0000*	0.0000	-0.0037	0.0001
a11	-0.0715	0.0034	0.1770	0.0122	0.0024*	0.0028
a21	0.2470	0.0493	0.0000	0.0000	0.0497	0.0003
a12	0.0000	0.0000	0.0638	0.0005	0.2031	0.0492
a22	0.7293	0.0209	0.7478	0.0208	0.7595	0.0219
b11	0.9821	0.0001	0.9657	0.0013	0.9825	0.0001
b21	-0.2803	0.0112	0.0000	0.0000	-0.0023	0.0001
b12	0.0000	0.0000	-0.0225	0.0002	-0.2524	0.0100
b22	0.6900	0.0035	0.6879	0.0042	0.6848	0.0043
LogL	579.5591		574.8205		581.6586	
LR Test	4.1989	(0.1225)	13.6761	(0.0011)		
LB(5)-M1	5.6155	(0.3454)	6.3219	(0.2762)	5.8851	(0.3176)
LB2(5)-M1	2.8466	(0.7236)	2.9457	(0.7084)	3.1645	(0.6746)
LB(5)-IBOV	3.9611	(0.5550)	5.2268	(0.3888)	4.6805	(0.4561)
LB2(5)-IBOV	5.4341	(0.3652)	3.6995	(0.5934)	3.9822	(0.5520)
IBOV and Interest Rate						
c11	0.0119	0.0001	0.0767	0.0013	0.0163	0.0000
c21	-0.0055	0.0000	-0.0005	0.0001	-0.0147	0.0001
c22	0.0000	0.0000	0.0000*	0.0004	0.0000*	0.0000
a11	-0.2765	0.0082	-0.0346	0.0086	-0.1060	0.0090
a21	0.1133	0.0138	0.0000	0.0000	0.7317	0.0358
a12	0.0000	0.0000	0.7131	0.0367	0.1051	0.0022
a22	0.2463	0.0231	0.0935	0.0090	0.0649	0.0269
b11	0.9393	0.0004	0.6204	0.1538	0.9698	0.0004
b21	-0.0309	0.0006	0.0000	0.0000	0.0495	0.0017
b12	0.0000	0.0000	-0.0754	0.0093	0.0086	0.0011
b22	0.9693	0.0003	0.7605	0.0032	0.7544	0.0030
LogL	355.5677		370.7388		379.0605	
LR Test	46.9856	(0.0000)	16.6434	(0.0002)		
LB(5)-INT	4.6585	(0.4590)	6.8504	(0.2320)	3.8892	(0.5655)
LB2(5)-INT	1.0537	(0.9581)	10.3920	(0.0649)	2.5738	(0.7654)
LB(5)-IBOV	5.6308	(0.3438)	6.6862	(0.2450)	6.6107	(0.2512)
LB2(5)-IBOV	0.5696	(0.9894)	1.0114	(0.9617)	2.3166	(0.8038)

Note: As in Table 3.3

Table 3.6 : BEKK-MGARCH(1.1) estimates for India.

	Upper Restricted		Lower Restricted		Unrestricted	
Parameters	Coeff	S.E	Coeff	S.E.	Coeff	S.E.
SENSEX and Inflation						
c11	0.0150	0.0000	0.0176	0.0001	0.0159	0.0007
c21	0.0001	0.0000	-0.0008	0.0000	-0.0004	0.0000
c22	0.0025	0.0000	0.0023	0.0000	0.0028	0.0002
a11	0.2811	0.0029	0.3060	0.0051	0.2924	0.0223
a21	-0.1877*	3.2312	0.0000	0.0000	-0.0146	0.0016
a12	0.0000	0.0000	-0.0134	0.0001	-0.2257*	1.6204
a22	0.2664	0.0448	0.2676	0.0094	0.2808	0.1283
b11	0.9424	0.0005	0.9298	0.0013	0.9354	0.0057
b21	-0.1285*	3.1448	0.0000	0.0000	0.0057	0.0002
b12	0.0000	0.0000	0.0054	0.0000	-0.2925*	12.8869
b22	0.8673	0.1072	0.8563	0.0274	0.8139*	2.0448
LogL	1758.7683		1760.6897		1760.9533	
LR Test	4.3700	(0.1125)	0.5271	(0.7683)		
LB(5)-CPI	0.72349	(0.9816)	0.9202	(0.9687)	0.7614	(0.9794)
LB2(5)-CPI	4.849	(0.4345)	5.2361	(0.3877)	5.0674	(0.4077)
LB(5)-SENSEX	1.791	(0.8772)	1.3566	(0.9290)	1.2838	(0.9365)
LB2(5)-SENSEX	3.2421	(0.6627)	6.6977	(0.2441)	5.5535	(0.3520)
SENSEX and Industrial Production						
c11	0.0139	0.0000	0.0146	0.0000	0.0119	0.0024
c21	0.0207	0.0002	-0.0153	0.0014	0.0089	0.0175
c22	-0.0068	0.0016	-0.0138	0.0020	0.0194	0.0035
a11	0.2631	0.0067	0.2837	0.0033	0.2329	0.0810
a21	0.0985	0.0256	0.0000	0.0000	0.0742	0.0023
a12	0.0000	0.0000	0.0724	0.0020	0.0581	0.0187
a22	0.5873	0.0074	0.5468	0.0070	0.5511	0.0085
b11	0.9440	0.0002	0.9439	0.0002	0.9294	0.0024
b21	0.0863*	0.1159	0.0000	0.0000	0.0316*	0.0375
b12	0.0000	0.0000	0.0796	0.0106	0.3915*	1.7574
b22	-0.2169	0.0270	-0.1896	0.0186	-0.1515*	0.1131
LogL	1225.4369		1229.3138		1229.4013	
LR Test	7.9288	(0.0190)	0.1749	(0.9163)		
LB(5)-IP	0.7004	(0.9830)	0.6520	(0.9855)	0.7692	(0.9790)
LB2(5)-IP	4.3092	(0.5058)	3.9799	(0.5523)	3.6457	(0.6015)
LB(5)-SENSEX	18.2470	(0.0027)	19.1050	(0.0018)	18.9570	(0.0020)
LB2(5)-SENSEX	2.0298	(0.8450)	3.5979	(0.6086)	3.6457	(0.6015)

Table 3.6 (continued) : BEKK-MGARCH(1.1) estimates for India.

	Upper Restricted		Lower Restricted		Unrestricted	
Parameters	Coeff	S.E	Coeff	S.E.	Coeff	S.E.
SENSEX and Money Suppy						
c11	0.0122	0.0140	0.0132	0.0000	0.0144	0.0000
c21	0.0015	0.0067	-0.0010	0.0000	-0.0020	0.0000
c22	0.0077	0.0007	0.0009	0.0000	0.0004	0.0000
a11	0.2849	0.0028	0.2943	0.0051	0.3080	0.0053
a21	-0.7665*	62.6993	0.0000	0.0000	-0.0176	0.0003
a12	0.0000	0.0000	-0.0179	0.0002	-0.1712*	0.3054
a22	-0.2375*	0.2840	-0.0754	0.0033	-0.0758	0.0112
b11	0.9409	0.0005	0.9431	0.0005	0.9357	0.0006
b21	-0.4327*	217.1592	0.0000	0.0000	0.0077	0.0000
b12	0.0000	0.0000	0.0074	0.0000	0.1111	0.0256
b22	0.6925*	14.2005	0.9812	0.0002	0.9715	0.0005
LogL	1526.6755		1524.6543		1527.3413	
LR Test	5.3741	(0.0681)	1.3317	(0.5138)		
LB(5)-M1	0.8832	(0.9714)	0.7670	(0.9791)	0.7963	(0.9773)
LB2(5)-M1	4.3856	(0.4953)	4.6239	(0.4635)	4.7487	(0.4473)
LB(5)-SENSEX	9.4559	(0.0922)	10.6260	(0.0593)	10.5430	(0.0612)
LB2(5)-SENSEX	2.5049	(0.7758)	1.9896	(0.8506)	2.3808	(0.7943)
SENSEXand Interest Rate						
c11	0.0054	0.0000	0.0050	0.0000	0.0054	0.0000
c21	-0.0116	0.0000	-0.0031	0.0000	-0.0092	0.0000
c22	0.0097	0.0000	0.0140	0.0000	-0.0093	0.0000
a11	0.2293	0.0018	0.2478	0.0017	0.1662	0.0046
a21	-0.0822	0.0019	0.0000	0.0000	0.1419	0.0050
a12	0.0000	0.0000	0.1354	0.0057	-0.0759	0.0015
a22	0.4400	0.0083	0.4349	0.0059	0.4218	0.0063
b11	0.9647	0.0001	0.9608	0.0001	0.9754	0.0002
b21	0.0832	0.0011	0.0000	0.0000	-0.0259	0.0006
b12	0.0000	0.0000	-0.0270	0.0011	0.0769	0.0007
b22	0.7946	0.0043	0.7963	0.0041	0.8186	0.0039
LogL	2603.6710		2606.0433		2609.0698	
LR Test	10.7976	(0.0045)	6.0531	(0.0485)		
LB(5)-INT	3.8230	(0.5752)	3.1931	(0.6702)	3.7642	(0.5838)
LB2(5)-INT	5.9009	(0.3160)	7.2519	(0.2026)	12.1530	(0.0328)
LB(5)-SENSEX	3.6638	(0.5988)	3.6649	(0.5986)	3.5310	(0.6187)
LB2(5)-SENSEX	3.0084	(0.6987)	3.7524	(0.5856)	3.6580	(0.5996)

Note: As in Table 3.3.

the primary authority controlling the money supply in the economy. The interest rate is not a statistically significant Granger-cause of stock market according to the bootstrapped test result, however, the LR test statistic and bootstrapped critical value are very close to each other.

For Czech Republic, according to the bootstrapped test results, industrial production and interest rate are the Granger causes of the Prag stock exchange. This indicates that the variation in production growth gives early warning signals about the risk level of the country for the investors in Prag Stock Exchange. When it comes to the casuality from short-term interest rate, determination of which is the one of main responsibilities of Czech National Bank (CNB), to stock market, this may imply that the variation in the repo rates that CNB determines gives signals about the increase risk in the Czech economy to investors.

For Brazil, there is a bidirectional causality between the short term interest rate and Bovespa stock exchange, i.e the short term interest rate is the Granger-cause of stock market and stock market is the Granger-cause of the short term interest rate at the same time. However, when the parameter estimates are examined, the effect of conditional covariances are very small. The fact that they are mostly driven by their own conditional variances and that the conditional covariance is very persistence may indicate Central Bank SELIC rates and stock market in Brazil are driven by the same dynamics but not by a casual relation between them.

Lastly, for the case of India, none of the bivariate analysis provides evidence to casual relation in between. In India, the main role of The Reserve Bank of India is to maintain credible financial system via regulations, which makes it different from the other cases in which central banks have critical role in monetary policies. This distinction between the role of central banks in the countries shows itself in the causal relation between corresponding macro variable and stock market. This distinction is another supportive result for that the empirical analysis has capable of catching the volatility dynamics between variables. Overall, the casual analysis between stock market volatility and macro economic volatility provide some evidence that investors closely follow some macroeconomic variables as indicators of the riskiness of the country.

Table 3.7: Critical values of bootstrapped likelihood ratio tests.

	Turkey				Czech			
	ISE--->MV		**MV---->ISE**		**PX--->MV**		**MV---->PX**	
	LR	Bootstrapped LR	LR	Bootstrapped LR	LR	Bootstrapped LR	LR	Bootstrapped LR
CPI	0,0084	NP	0,1609	NP	2,1067	NP	7,5328	13,1668
IP	13,5421	12,4384	8,1256	11,3527	10,7564	13,2516	22,5608	12,9781
M1	2,8851	NP	11,9919	9,9093	0,5659	NP	-4,2571	NP
INT	16,1396	24,4976	11,1572	11,8445	59,6527	15,5309	17,8770	15,2415
	Brazil				**India**			
	IBOV--->MV		**MV---->IBOV**		**SENSEX--->MV**		**MV---->SENSEX**	
	LR	Bootstrapped LR	LR	Bootstrapped LR	LR	Bootstrapped LR	LR	Bootstrapped LR
CPI	6,9881	57,0310	6,9270	35,7855	4,3700	NP	0,5271	NP
IP	7,0061	41,3430	5,9641	NP	7,9288	15,0174	0,1749	NP
M1	4,1989	NP	13,6761	14,9187	5,3741	NP	1,3317	NP
INT	46,9856	15,7014	16,6434	13,0476	10,7976	18,8287	6,0531	13,8153

Note: For those bivariate analysis in which the LR statistics is already insigni_cant according to asymptotic critical values of X2 distribution, the bootstrapped testing has not been performed in order to reduce the computational burden. The abbreviation NP, which stands for "Not Performed" is used to show these cases. Arrows in the columns show the direction of the causal relation between bivariates. In this representation, MV stands for the macro economic variable in the corresponding row of the test statistic. Please check the table in the Appendix for the abbreviation of the stock market exchanges.

4. CONCLUSION AND RECOMMENDATIONS

Volatility of financial assets is a topic that intensely researched for a long time but still has not evolved the state where parties involved with the markets somehow are not content with the results. Research areas in this topic can be grouped into three main categories: First group involves the studies that proposes new models and inference method for the proposed models, which are based on the time series properties of financial asset returns. Second group studies deal with the implementation and forecast evaluation of these proposed models. And the studies in the last group aim at figuring out the underlying dynamics of volatility of the markets, which are mostly analysis the relation between volatilities of different variables such as transmission, correlation and causality etc. This study aims to fill two gaps in the literature about emerging equity markets volatilities. Firstly, the forecast evaluations of the existing volatility models for 19 emerging stock market indices for forecast horizons from 1 days to 240 days are performed with the purpose of examining whether there really is a certain model which is superior than the alternatives for the majority of the emerging markets. The coverage of the study in terms of models, forecast horizon and countries included besides applied methodology provides to reach more general conclusions relative to the other studies in the literature. The most general results can be listed as follows:

Firstly, SV is the best performing model for 1-day forecast horizon for the majority of the emerging market. For forecast horizon between 10 and 120 days, GARCH family models and EWMA show superior performance in almost equal number of countries, and, EWMA outnumbers GARCH family models as the forecast horizon increases. For long-term forecast horizon, MA outperforms for most of the countries. That is, as the forecast horizon increases, there is a movement from the sophisticated models to more naive models. When asymmetric error statistics are taken into account, SV consistently underpredicts, while GARCH-family models overpredict.

All the existing models follow a mechanical approach and are based on the time series properties of the return series. However, the underlying dynamics of volatility of financial securities have been researched in order to obtain a deeper understanding in volatility processes, and hence have better control over financial and investment decisions. In this perspective, the volatility transmissions between financial markets and stock exchanges of countries have been the subject of considerable number of studies for both developed and emerging markets. As for the relation between macro economic volatility and stock market volatility, some of the researches provide evidence to significant relation for developed markets while some do not. On the other hand, this relation has been barely examined for emerging markets. The second part of the study aims to provide some insight in this relation from causality perspective with the help of one of the MGARCH models, namely BEKK. The results provide some evidence to causal relation between macro economic volatility, i.e. inflation, industrial production, money supply and short term interest rate, and stock market volatility for countries comprising Turkey, Czech Republic, Brazil and India. The results can be summarized as follows: The industrial production is an important macro economic indicators for the cases of Turkey and Czech Republic. Also, for these countries, the policies of central banks give signals about the riskiness of the country for the investors in stock markets. For the case of Turkey, money supply which is controlled by central bank of Turkey, is found as Granger-cause of stock market, while short-term interest rate is Granger-cause of stock market for the case Czech Republic in which repo rates are determined by Czech National Bank. For the case of Brazil, the test results indicates the bidirectional causality between short term interest rate and stock market, however, this bidirectional casuality seems to be due to the fact that they are driven by the same underlying dynamics, not because of causality. For India, none of the chosen macro variables shows causal relation with the stock market, which may indicate that the other macro economic variables not included in the study are followed by the investor as indicators. As a result, it is not wrong to say that there exits causal relations between macro economic indicators of the countries and their stock markets volatilities to some extent, but they are specific to countries dynamics.

As a future work, the set of the countries can be expand so that it includes developed markets as well. With the addition of developed markets in the coverage help to see if there are differences in model performances in developed and emerging markets. If there is significant one, then it precludes that volatility modeling should depend on some structural underlying dynamics not only time series properties, which eventually direct the researches to the state where the relation between certain macro economic, regional and structural variables and stock markets is analyzed. However, to be able to perform such an analysis requires a great deal of time and effort is a most important drawback. In terms of causal analysis, the number of variables can be increased in order to find out the other causal relations that the stock market volatility might have, and also the simultaneous analysis of more then two variable provide better understanding in the underlying dynamics of volatility. However, the data issues such as availability and history of the data make it very difficult to perform an extensive relational analysis.

APPENDICES

APPENDIX A: Arch Test Results (in CD-Rom).

APPENDIX B: Error Statistics (in CD-Rom).

APPENDIX C: RC/SPA Test Statistics (in CD-Rom).

APPENDIX D: MCS Results (in CD-Rom).

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