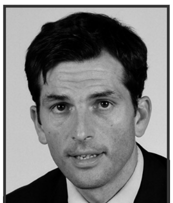
Assessing Volatility Indicators: The Benefit of Local Equity Volatility Indices

LIXIA LOH
Senior Researcher
EDHEC Risk Institute–Asia



LIONEL MARTELLINI
Professor of Finance
EDHEC Business School
Scientific Director
EDHEC-Risk Institute

STOYAN STOYANOV
Professor of Finance
EDHEC Business School
Head of Research
EDHEC Risk Institute–Asia

Introduction

Stock market volatility is an important input to asset allocation and risk management. With the increase in stock market uncertainty and the recent financial crises, there has been a growing interest in volatility as a *sentiment indicator* but also in volatility as an *asset class*. Investors and asset managers increasingly use OTC or exchange-traded volatility derivatives using volatility indices as underlyings to alleviate losses during market downturns, based on the negative correlation between equity returns and volatility which has been well-documented in the academic literature. There are two theoretical explanations for it, the leverage effect (see Black (1976)) and volatility feedback effect (see Poterba and Summers (1986)). The leverage effect hypotheses that market downturn increases the leverage of the firm and thus the risk of the stock. While the volatility feedback effect assumes that the volatility is incorporated in the stock prices, a positive volatility shock would increase the future required return on stock and stock prices are expected to fall simultaneously.From an investor perspective, the negative correlation presents hedging and diversification opportunities in case trading in volatility is possible. In addition, negative correlation and high volatility are particularly pronounced in stock market downturns, offering protection against stock market losses when it is most needed and when other forms of diversification do not provide very effective exposure (see Hill and Rattray (2004) or Szado (2009) for recent references).

Broadly speaking, we distinguish between different kinds of volatility measures:

- **Historical versus implied volatility measures.** Historical volatility measures are obtained by estimating the standard deviation of returns or more complex GARCH-type models from a past sample of equity returns. One advantage of these measures is that they can be estimated directly from time-series of individual stock or stock index returns. One drawback is that they are not directly observable, and are dependent on a sample of past returns. Finally, a model-free historical volatility measure is the *realized volatility* introduced by Anderson and Bollerslev (1998) which is computed from high-frequency data.
  More recently, implicit volatility estimates have been obtained from option prices. One advantage about these measures is that they are more forward-looking compared to historical volatility measures since they reflect market's expectations about future volatility. Some of these measures are referred to as model-free option implied (MFOI) volatility measures to emphasize the fact that they do not depend on any modelling but are extracted directly from option prices. The most popular volatility index is the VIX, which is built from prices of equity index options on the S&P500. Until 2009, only VIX futures and options had been available to investors due to the lack of mature index option market in most countries. European market volatility products based on the volatility index of EURO STOXX 50 (VSTOXX) have been launched since 2009; VSTOXX options were launched in 2009 and VSTOXX futures were launched in 2010. Stock market in Hong Kong, Japan and Russia only launched their first implied volatility future contract in 2012.
- **Systematic versus specific volatility.** Regardless of the method used in estimating volatility, another key distinction exists between systematic and specific volatility. For any given stock, total volatility can be decomposed into systematic volatility, driven by the stock exposure with respect to systematic risk factors, and specific volatility, which is driven by the uncertainty impacting a particular company.
  The recent financial literature has paid considerable attention to idiosyncratic volatility. Campbell *et al* (2001) and Malkiel and Xu (2002) document that idiosyncratic volatility increased over time, while Brandt *et al* (2009) show that this trend completely reversed itself by 2007, falling below pre-1990s levels and suggest that the increase in idiosyncratic volatility through the 1990s was not a time trend but rather an "episodic phenomenon". Bekaert *et al* (2008) confirm that there is no trend both for the United States and other developed countries. A second fact about idiosyncratic volatility is also a source of contention. Goyal and Santa-Clara (2003) put forward that idiosyncratic volatility has fore-

casting power for future excess returns, while Bali *et al* (2005) and Wei and Zhang (2006) find that the positive relationship is not robust to the sample chosen.

While representing two different underlying risk measures, one expects systematic and average specific volatility risk indicators to be highly correlated, since they both reflect the aggregate uncertainty faced by investors at a given point in time regarding economic fundamentals. A recently introduced cross-sectional model-free volatility (CSV) measure based on the cross-sectional dispersion of stock returns can be interpreted as an aggregate specific volatility of a given stock universe, see Garcia, Mantilla-Garcia and Martellini (2012).

Given the need for investors in different regions to obtain downside protection, one question of theoretical and practical importance is whether there exists a single volatility factor that can explain a dominant fraction of changes in volatility levels across different regions and segments of the worldwide equity markets, or whether distinct regional volatility indices/products are needed for distinct regions in the world.

Two strands of research on stock market volatility offer insights into the existence of regional and country specific factors in stock market volatility. In volatility spillover literature, studies have found that stock market volatility can be decomposed into local, regional and global volatility. Beside spillovers from the US market, Ng (2000) and Miyakoshi (2003) find evidence for regional volatility spillovers from regional market, Japan, to other Asian market. Worthington and Higgs (2004) find volatility spillovers among the developed and emerging Asian stock markets.

On the European market, several studies have documented evidence of increased market integration within European markets after the introduction of the single currency.Morana and Beltratti(2002), Kim *et al*(2005), Bartram *et al*(2007) and Baele (2005) show that increased trade integration, equity market development, and low inflation increase the EU shock spillover intensity. In the emerging European stock market (Hungary, Poland and the Czech Republic), Scheicher (2001) finds regional influence dominates global influence[1]. Brooks and DelNegro (2005) go a step further by decomposing the country effects into region effects and within-region country effects.

Another strand of stock market volatility research which shows the presence of country specific effect on stock market volatility is the macroeconomic determinants of stock market volatility. One of the earliest studies in this area is Officer (1973) who relates the change in stock market volatility to changes in real economic variables. A more recent study by Paye (2012) finds that macroeconomic uncertainty has a causal effect[2] on US stock market volatility. Diebold and Yilmaz (2008) and Engle and Rangel (2008) cover a large number of countries and they find that volatility of macroeconomic fundamentals affect stock market volatility. Generally, most of the existing literature finds that local and regional effects form the largest component of the stock market volatility and that, mostly, the local events cause jumps in stock market volatility.

Most of the aforementioned studies in the academic literature have been performed using model-dependent GARCH-type volatility measures or econometric models based on vector auto-regressions applied directly on stock and equity index returns. In this paper, we approach the question of whether local volatility factors are present using model-free volatility indicators. We employ three different model-free methodologies – option implied volatility, realized volatility, and cross-sectional volatility. Although MFOI volatility relates to market expectations about future volatility levels, both MFOI and realized volatility represent total volatility measures. In contrast, CSV represents a measure of aggregate specific volatility which is, however, empirically not disconnected from the market index return.

Our analysis covers the 8 markets for which data for the three volatility measures is available over a period of about 10 years - France, Germany, Switzerland, the UK, Japan, Korea, Hong Kong, and the Netherlands. We find that local MFOI volatility indices are generally more effective at hedging a local market exposure over the entire period, during US recessions, and during the financial crisis of 2008. The same conclusion is confirmed by the corresponding realized and CSV measures.

Finally, we carry out a formal principal component analysis (PCA) of the three sets of volatility indicators. PCA rules out US volatility as a global volatility factor and suggests that the global factor is more significantly exposed to a non-Asian volatility factor. The factor of second-order importance is of Asian flavour. Both conclusions are robust with respect to volatility indicator type. US volatility appears dominant in the factor of third-order importance only in the case of MFOI volatility.

From a practical perspective, our analysis suggests that a US volatility indicator cannot be taken as a sufficient risk statistics for regional equity markets. As a consequence, it appears that the development of local volatility indices is needed to contribute to the ability for investors to measure and manage uncertainty about volatility across international equity markets. Possible applications include more relevant volatility regime identification useful, for example, in tactical asset allocation or design of target volatility strategies based on a given exposure to a local equity market. Beside, our results imply that investors seeking to invest directly in volatility for speculation or hedging purposes can benefit from the development of a local volatility derivative market.

The paper is organized in the following way. Section 1 presents the pros and cons of model-free volatility measures. Section 2 describes the data and provides a comparison of the leverage effect for the three types of model-free volatility measures across different countries. Section 3examinesthe local market volatility factor.

I. Presentation of model-free volatility indicators and their pros and cons

In this section we focus on the pros and cons of three model-free volatility indicators: MFOI, realized volatility, and CSV.

I.1. MODEL-FREE OPTION-IMPLIED VOLATILITY

The MFOI volatility has become widely accepted as a forward-looking estimate of volatility. CBOE pioneered the VIX index in 1993 as the model-dependent 30-day B-S option-implied volatility of the at-the-money option of the S&P100 index. In 2003, the calculation method was updated with the model-free estimation and the reference equity market index was changed to the S&P500 index. Other stock exchanges followed suit across the world. In Europe, MFOI volatility is available in Belgium, Germany, France, the Netherlands, Switzerland, the UK. In Asia, since 2008 MFOI volatilities of the corresponding main equity market indices have been introduced by the National Stock Exchange of India, Korea Exchange, Osaka Securities Exchange, Hong Kong Stock Exchange, and Australian Securities Exchange and data have been backfilled in some cases starting from the beginning of the 2000s .

The precision of the CBOE method has recently been a topic of research. Jiang and Tian (2007) discuss the CBOE implementation in detail and report several problems which can lead to economically significant errors. Although imperfections in the CBOE method may have an impact on the estimated level of volatility, they do not seem to exercise a substantially adverse effect on the empirical relationship between the market index returns and VIX. Andersen and Bondarenko (2007) report a significant predictive power of VIX, of improved versions of VIX, and also of the Black-Scholes implied volatility. Apart from this paper, there is a significant body of literature on the power of option-implied volatility measures to predict realized volatility implying rich information content useful for both practitioners and academics, see Poon and Granger (2003) for a detailed survey of the academic literature and Bhabra *et al* (2001) for the significance of the maturity of the options market exemplified by the KOSPI 200 index option market.

Apart from the flaws of the CBOE approach, we have to point out that the MFOI volatility is not the same quantity as the volatility of the return distribution of the underlying asset. In fact, the model-free implied variance is the variance of the risk-neutral distribution which is derived by adjusting the physical distribution for the risk premia demanded by investors. As a consequence, option-implied variance measures incorporate this adjustment and deviate from realized variance measures. In fact, empirical studies report a positive difference between the two, which is also known as variance premium (see Bollerslev *et al* (2009) and Bakshi and Madan (2006)).[3] As far as computability goes, MFOI volatility is computable only for assets underlying options traded on the market. As a consequence, these measures of volatility cannot be aggregated directly across sectors, styles, or geographical regions. An aggregated volatility index is available only if an aggregated equity index is available underlying option contracts. An example is the VSTOXX index which is the MFOI volatility of the EURO STOXX 50 index and could be viewed as a regional volatility indicator for the Euro zone.

I.2. REALIZED VOLATILITY

Realized volatility was introduced by Anderson and Bollerselv (1998) and represents, essentially, a sum of high-frequency intraday squared returns. Formally, the calculation involves a two-step process. Firstly, the one-day period is subdivided into smaller intervals, typically 5-minute ones, and then the logarithmic return of the index over the smaller intervals is computed. Secondly, the realized volatility is calculated as the sum of the squared returns computed in the first step.

The apparent advantage of realized volatility is that it is extracted from higher frequency data of the same market index and is thus very directly related to the index returns in contrast to MFOI volatility which relies on the existing and a properly function option market. Martens and Zein (2004) studied equity, foreign exchange and commodities markets and the result shows that volatility forecasts based on historical intraday returns provide effective volatility forecasts that can compete with implied volatility.

Although there is positive empirical evidence about the properties of realized volatility, the estimator can be impacted by the behaviour of high-frequency data. McAleer and Medeiros (2008) discuss the various issues relating to modelling and forecasting realized volatilities and showed how microstructure noise could cause severe problems in terms of consistent estimation of the daily realized volatility estimator. The microstructure noise problem is discussed also by Aït-Sahalia *et al* (2011) who show that the asymptotic distribution of the estimator changes drastically in the presence of microstructure noise. The authors suggest an improved estimator that uses two different frequencies and then integrated variance is estimated as a suitable linear combination. For the purposes of this paper, however, we adopt the classical method based on 5-minute subintervals.[4]

As far as computability goes, realized volatility can be calculated as long as high frequency data for the corresponding index are available. As a result, an aggregated realized volatility indicator can be produced from an aggregated equity index (e.g. sector or regional) from its high-frequency returns. It is, however, not possible to aggregate already computed realized volatility indicators in a regional or global realized volatility indicator without a reference to a regional or global equity index because of the missing information about the corresponding correlations.

I.3. CROSS-SECTIONAL VOLATILITY

CSV indices are based on the cross-sectional dispersion of observed stock returns on a given date which is a measurable quantity and relies on no modelling assumptions. To interpret the quantity, however, we introduce a simple model that can be significantly generalized with no major change in the resulting interpretation, see Garcia, Mantilla-Garcia and Martellini (2012).

We assume without any loss of generality the following single conditional factor model for (excess) stock returns:

$$r_{it} = \beta_{it} F_t + \varepsilon_{it}$$

where F_t is the factor excess return at time t, β_{it} is the beta of stock i at time t, and ε_{it} is the residual or specific return on stock i at date t, with $E\left(\varepsilon_{it}\right)=0$ and $\operatorname{cov}\left(F_t,\varepsilon_{it}\right)=0$. We assume that the factor model under consideration is a strict factor model, that is $\operatorname{cov}\left(\varepsilon_{jt},\varepsilon_{it}\right)=0$ for i≠j and also that the betas are homogeneous, $\beta_{it}=\beta_t$ for all i, and that the residual variance is also homogeneous, $E\left(\varepsilon_{it}^2\right)=\sigma_\varepsilon^2\left(t\right)$ for all i.

Under these assumptions, Garcia, Mantilla-Garcia and Martellini (2012) show that cross-sectional variance converges towards specific variance at the limit as the number of constituents increases indefinitely,

$$CSV_{t,w_t}^2=\sum_{i=1}^{N_t} w_{it}\left(r_{it}-\overline{r}_{t,w_t}\right)^2 \underset{N_t\to\infty}{\rightarrow} \sigma_\varepsilon^2\left(t\right) \qquad \text{Eq.1}$$

where $\overline{r}_{t,w_t}$ is the weighted-return on the portfolio with weights $w_{i,t}$ at date t, CSV_t is the cross-sectional volatility, and N_t is the number of constituents in the universe for a given date t. The proof of this result is based upon limit theory.[5] Garcia, Mantilla-Garcia and Martellini (2012) show also that relaxing the homogeneity assumptions leads to a similar interpretation.

This result is important because it draws a formal relationship between the dynamics of the cross-sectional dispersion of realized returns and the dynamics of idiosyncratic variance. Note that this asymptotic result holds for any (non-trivial) weighting scheme. Of course, for a finite number of constituents N_t, different weighting schemes will generate different proxies for idiosyncratic variance. In fact, it can be shown that the estimator with equal weights is the best estimator for idiosyncratic variance within the class of estimators obtained under a strictly positive weighting scheme.

The method of estimation is in principle quite simple and is not model dependent. A degree of sophistication is needed, however, to deal with three practical issues – illiquidity of some of the stocks in the universe, lack of robustness of the classical estimator of variance, and aggregation to regional volatility indices. As far as aggregation goes, in contrast to MFOI and realized volatility, CSV measures can be aggregated directly preserving the interpretation of an average idiosyncratic volatility for the corresponding sector or region. Further details can be found in Garcia, Mantilla-Garcia and Martellini (2012).

II. Data description

To carry out the empirical analysis, we choose all marketsfor whichthe three types of volatility indicators exist with daily data available at least for a period of about 10 years. Since availability of MFOI volatility proves most restrictive, the markets considered are those having a MFOI volatility index. These countries include France, Germany, Switzerland, the UK, Japan, Korea, Hong Kong, and the Netherlands and the corresponding MFOI indicators are VCAC, VDAX, VSMI, VFTSE, VNKY, VKOSPI, VHSI, and VAEX, respectively. The data period runs from January 2000 to June 2012 for the European countries and from January 2001 to June 2012 for Hong Kong and Japan.The only exception is Korea for which the MFOI volatility is available from January 2003 to July 2012 which we include in the analysis although spanning only 9 years because of the liquidity of the Korean index option market. The market indices used are: CAC40, DAX30, SMI, FTSE100, TOPIX, KOPSI, HSI and AEX.

We used Bloomberg to download data for MFOI volatility and a public database for realized volatility indices at Oxford-Man Institute of Quantitative Finance from which we extracted the series based on the standard 5-minute aggregation.

In the calculation of the CSV indices, we followed the approach outlined in Section 1.3 with the full equity universes for each market downloaded from DataStream. The stock universes for the CSV calculation were constructed by taking into account market capitalization and liquidity. Within each single-country universe and for each day, we rank the stocks by market cap and we select the large- and mid-cap stocks that constitute 85% of the cumulative market cap. As far as liquidity is concerned, we select stocks that have a median monthly turnover at least 1% of its shares. To calculate the median monthly turnover, we use the median daily turnover for the past month which is then scaled up to a monthly figure. As a by-product, stocks that are not traded in more than half of the days in a month are excluded from the universe at this stage. These stock selection rules are typical in the construction of a broad, large-scale equity universe. Finally, having selected the cross-section of stocks, we calculate the cross-sectional volatility from the daily returns which becomes the CSV value for the corresponding market observed on the corresponding day.

III. Local volatility factors

In this section, we analyse the MFOI volatility, realized volatility, and cross-sectional volatility indicators of the corresponding markets to check if we can identify a local volatility factor. We carry out a rigorous regression analysis of the relationship between the local market index returns and the changes of the corresponding volatility measures, again, compared to the same type of relationship with the changes of US volatility measures. We also carry out a principal component analysis (PCA) of the set of volatility indices without any reference to a market returns.

III.1. A REGRESSION ANALYSIS

We analyze the relationship between volatility and market return means of a regression model which would allow checking the explanatory power of the different volatility measures on a stand-alone basis and would also be able to indicate if there is any incremental value added of including a volatility measure to one that already has some explanatory power.

The regression model used for MFOI and realized volatility is as follows

$$r_t = \alpha + \beta_1 \Delta VI_{1t} + \beta_2 \Delta VI_{2t} + e_t \qquad \text{Eq. 2}$$

where r_t denotes the daily log-return of the market indices specified in Section 2, ΔVI_{jt} is the change of a volatility indicator observed at time t. The independent variables in the model are always computed according to one and the same method. For MFOI volatility, for example, we consider the following indicators: the local market MFOI volatilityand VIX. For realized volatility, we consider the local realized and the S&P500 realized volatility. The betas are expected to be negative to reflect the presence of the leverage effect.

Table 1

Fitted betas and adjusted R^2 statistics for the regression models in Eq. 2 and Eq. 3. The models are estimated using the full samples for the corresponding countries. The symbol * denotes betas statistically significant at the 5% level and RV denotes realized volatility. In the regressions for the countries in Asia, the change in US volatility is lagged to reflect the difference in trading hours.

	Change in Local volatility	Change in US Volatility	Adjusted R^2		Change in Local volatility	Change in US Volatility	Adjusted R^2	
France	−0.4985*	–	0.3571	MFOI	−0.8756*	–	0.6034	Germany
	−0.0710*	–	0.1040	RV	−0.0510*	–	0.0640	
	0.0485*	–	0.1075	CSV	0.0494*	–	0.1228	
	–	−0.4329*	0.2398	MFOI	–	−0.4624*	0.2542	
	–	−0.049*	0.0590	RV	–	−0.044*	0.0430	
	–	0.0307*	0.0337	CSV	–	0.0362*	0.0435	
	−0.3973*	−0.2597*	0.4290	MFOI	−0.8258*	−0.0732*	0.6078	
	−0.0590*	−0.0270*	0.1190	RV	−0.0400*	−0.0290*	0.0800	
	0.0447*	0.0201*	0.1209	CSV	0.0450*	0.0202*	0.1359	
The Netherlands	−0.6746*	–	0.5222	MFOI	−0.5289*	–	0.2680	Switzerland
	−0.0860*	–	0.1260	RV	−0.0667*	–	0.0752	
	0.0200*	–	0.0451	CSV	0.0282*	–	0.0746	
	–	−0.4259*	0.2310	MFOI	–	−0.2916*	0.1520	
	–	−0.0470*	0.0540	RV	–	−0.0349*	0.0413	
	–	0.0317*	0.0335	CSV	–	0.0159*	0.0129	
	−0.5989*	−0.1443*	0.5417	MFOI	−0.4342*	−0.1657*	0.310	
	−0.0750*	−0.0270*	0.1420	RV	−0.0548*	−0.0229*	0.0906	
	0.0183*	0.0172*	0.0586	CSV	0.0269*	0.0078*	0.0773	
Hong Kong	−0.5964*	–	0.3926	MFOI	−0.5842*	–	0.5654	The UK
	−0.0620*	–	0.0730	RV	−0.0500*	–	0.0640	
	0.0359*	–	0.0593	CSV	0.0356*	–	0.0741	
	–	−0.3218*	0.1260	MFOI	–	−0.3515*	0.2300	
	–	−0.0115*	0.0026	RV	–	−0.0440*	0.0690	
	–	0.0188*	0.0109	CSV	–	0.0226*	0.0259	
	−0.5478*	0.0989*	0.3896	MFOI	−0.5293*	−0.1070*	0.5815	
	−0.0614*	−0.0035	0.0727	RV	−0.0350*	−0.0360*	0.1050	
	0.0352*	0.0160*	0.0664	CSV	0.0322*	0.0137*	0.0827	
Korea	−0.5557*	–	0.4351	MFOI	−0.4604*	–	0.4074	Japan
	−0.0720*	–	0.0910	RV	−0.0660*	–	0.0840	
	0.0198*	–	0.0258	CSV	0.0438*	–	0.0567	
	–	−0.2885*	0.0891	MFOI	–	−0.3269*	0.1710	
	–	−0.0145*	0.0038	RV	–	−0.0214*	0.0124	
	–	0.0199*	0.0110	CSV	–	0.0131*	0.0075	
	−0.5542*	−0.0394*	0.4425	MFOI	−0.4123*	−0.1405*	0.4222	
	−0.0717*	−0.0091*	0.0928	RV	−0.0652*	−0.0090*	0.0857	
	0.0194*	0.0145*	0.0321	CSV	0.0422*	0.0092*	0.0603	

A preliminary conditional correlation analysis carried out for CSV indicates a symmetric relationship between the change in CSV and the magnitude of the market return. As a result, we use a different regression model for CSV,

$$|r_t| = \alpha + \beta_1 \Delta VI_{1t} + \beta_2 \Delta VI_{2t} + e_t \qquad \text{Eq. 3}$$

where the volatility indicators are the local market CSV and the US CSV. In this model, the betas are expected to be positive which is interpreted as a positive relationship between the magnitude of the market return and the change in cross-sectional dispersion; that is, both sharp increases and plunges of the market are contemporaneous with an increase in cross-sectional dispersion.

We estimate the models with the volatility indicators included as stand-alone variables but also together with the US volatility factor in order to see the incremental impact. The volatility indicators are differenced for

Table 2

Fitted betas and adjusted R^2 statistics for the regression models in Eq. 2 and Eq. 3. The models are estimated using daily data from 01-Sep-2008 to 02-Feb-2009. The symbol * denotes betas statistically significant at the 5% level and RV denotes realized volatility. In the regressions for the countries in Asia, the change in US volatility is lagged to reflect the difference in trading hours.

	Change in Local volatility	Change in US Volatility	Adjusted R^2		Change in Local volatility	Change in US Volatility	Adjusted R^2	
France	−0.3081*	–	0.2630	***MFOI***	−0.6090*	-	0.6041	**Germany**
	−0.0857*	–	0.2004	***RV***	−0.0689*	-	0.1338	
	0.0969*	–	0.2120	***CSV***	0.0591*	-	0.2350	
	–	−0.3720*	0.3104	***MFOI***	-	−0.4038*	0.4025	
	–	−0.0725*	0.1692	***RV***	-	−0.0696*	0.1697	
	–	0.0584*	0.0877	***CSV***	-	0.0556*	0.0866	
	−0.2084*	−0.2808*	0.4135	***MFOI***	-0.5224*	−0.1193*	0.6309	
	−0.0590*	−0.0375*	0.2218	***RV***	-0.0326	−0.0526*	0.1916	
	0.0817*	0.0334	0.2293	***CSV***	0.0518*	0.0202	0.2360	
The Netherlands	−0.6675*	–	0.5443	***MFOI***	−0.2180*	–	0.0702	**Switzerland**
	−0.1247*	–	0.2292	***RV***	−0.0984*	–	0.1697	
	0.0127	–	−0.0062	***CSV***	0.0497*	–	0.1707	
	–	−0.4330*	0.3679	***MFOI***	–	−0.2789*	0.2298	
	–	−0.0832*	0.1958	***RV***	–	−0.0668*	0.1903	
	–	0.0760*	0.1257	***CSV***	–	0.0422*	0.0534	
	−0.5223*	−0.1933*	0.5910	***MFOI***	−0.0911	−0.2556*	0.2408	
	−0.0863*	−0.0487*	0.2720	***RV***	−0.0508	−0.0467*	0.2187	
	−0.0062	0.0663*	0.0620	***CSV***	0.0443*	0.0155	0.1669	
Hong Kong	−0.6227*	–	0.4802	***MFOI***	−0.4484*	–	0.3999	**The UK**
	0.0195	–	−0.0262	***RV***	−0.1159*	–	0.2296	
	0.0867*	–	0.1756	***CSV***	0.0648*	–	0.1418	
	-	−0.2165*	0.0729	***MFOI***	–	−0.3553*	0.3344	
	-	−0.0011	0	***RV***	–	−0.0717*	0.1969	
	-	0.0208	0	***CSV***	–	0.0520*	0.0755	
	-0.6804*	−0.1008	0.5175	***MFOI***	−0.3243*	−0.2196*	0.4971	
	0.0019	0.0092	0	***RV***	−0.0788*	−0.0454*	0.2837	
	0.0877*	0.0190	0.1753	***CSV***	0.0538*	0.0242	0.1455	
Korea	−0.4504*	–	0.4822	***MFOI***	−0.5339*	–	0.5743	**Japan**
	−0.0997*	–	0.1523	***RV***	−0.1189*	–	0.2476	
	0.0425*	–	0.1812	***CSV***	0.0638*	–	0.0772	
	–	−0.2012*	0.0910	***MFOI***	–	−0.3899*	0.3511	
	–	−0.0208	0.0059	***RV***	–	−0.0434*	0.0443	
	–	0.0196	0.0025	***CSV***	–	0.0181	0	
	−0.4466*	−0.0182	0.5015	***MFOI***	−0.4521*	−0.1636*	0.6032	
	−0.0972*	−0.0084	0.1470	***RV***	−0.1262*	0.0023	0.2794	
	0.0431*	0.0081	0.1759	***CSV***	0.0618*	0.0058	0.0680	

two reasons. Firstly, the change in a volatility indicator represents a proxy for the P&L from a strategy invested in volatility futures over one day and we can assess the hedging potential of such a strategy for an equity portfolio. Secondly, using increments instead of values deals with the issue of persistence (strong autocorrelation) and is a common approach in time-series analysis, see for example Hamilton (1994).

We estimate the regression models unconditionally, using all available history for the corresponding countries, and also conditionally – on US recessions and the financial crisis of 2008 – to test if in times of severe market turbulence the relationship changes. To reflect the difference in trading hours, we lag the changes in US volatility in the regressions for the Asian markets.

The results for the three methodologies obtained using the full samples are provided in Table 1. If we compare the one-dimensional regression, we notice that, without exception, the local country volatility performs better than US volatility across the three methodologies. The explanatory power of MFOI volatility, however, is much higher than that of the other two methodologies. The difference in the adjusted R2 of the local and the US MFOI regressions varies from country to country but ranges from 0.12 to 0.5 with the values in the European markets being on the low side indicating that VIX has a more significant impact in Europe than in Asia.

As far as the fitted coefficients in the one-dimensional models are concerned, as expected they are negative for MFOI and realized volatility and are positive for CSV. The betas of the local volatility are higher in absolute value than those of US volatility indicating better hedging properties of exposures to the local volatility factor.

The results of the bi-variate regressions indicate that US volatility contains information that can explain the returns of the local market indices because the corresponding betas are statistically significant. Nevertheless, the incremental impact on the adjusted R^2 statistic is marginal, with the exception of France and Switzerland, indicating that most of the information content is already incorporated in the local volatility. The betas of the US volatility are generally lower than the betas of the local volatilities implying a smaller incremental hedging benefit of an exposure to US volatility added to an existing exposure to the corresponding local volatility.

The results in Table 1 provide overwhelming evidence supporting the existence of a local volatility factor. The very high adjusted R^2 statistics imply a quite significant contemporaneous relationship and good market risk hedging properties of an exposure to the local MFOI volatility.

In the remaining part of this section, we outline the conditional MFOI volatility regression results and the ones based on realized volatility and CSV.[6] The conditional regression results with MFOI volatility are based on the periods identified by NBER as US recessions and also on the very turbulent period from 01-Sep-2008 to 02-Feb- 2009. A general observation is that the significance of the US volatility increases in the US recession periods and grows further in the period of the financial crisis.

The results for the period Sep-2008 – Feb-2009 are reported in Table 2. On a methodology level, MFOI volatility exhibits a higher explanatory power with the only exception of Switzerland. Table 2 confirms the main conclusions drawn from the full sample period – the local volatility factor is more significant than the US volatility factor with the following exceptions. Regarding MFOI volatility, the exceptions are France and Switzerland and regarding realized volatility the exceptionsare Germany and Switzerland. Finally, regarding CSV the exception is only the Netherlands for which the regression for the local factor is insignificant.

Based on the extensive empirical analysis involving three different measures of volatility, we can conclude that there is overwhelming evidence for the existence of a local volatility factor although it is most pronounced in MFOI volatility. The results are quite robust with respect to volatility indicator type and sample period and are in line with the empirical literature which is mostly based on parametric volatility models.

III.2. COUNTRY-BASED PRINCIPAL COMPONENT ANALYSIS

To study the overall correlation among the country volatility indicators, we run a principal component analysis (PCA) on the full set of variables using the full sample. The principal components represent unobservable latent factors that best explain the variability of the data set. The factors are also ordered by importance. Thus, the first principal component is the most significant factor by design.

Any principal component can be viewed as a portfolio constructed from the data set. In our case, we choose to work with differences rather than levels because of the high persistence property of volatility. As a consequence, any principal component can be interpreted as an abstract index the level changes of which have a particular linear exposure to the changes of the corresponding volatility indicators with the size of the exposure determined by the principal component decomposition. If it turns out that the first PCA factor is heavily exposed to only one volatility index, then this volatility index is a candidate for a global volatility factor.

Since it would be methodologically incorrect to mix the three types of volatility indicators together, we run carry out the PCA for the MFOI, the realized, and the CSV indicators separately.

Instead of carrying out the analysis on the differenced series directly, we standardize the data; that is, we run the analysis on the correlation matrix rather than the covariance matrix. The reason for this transformation is simple – if there is a variable with a variance much higher than the variance of the other variables, the first PCA factor is naturally highly exposed to it which has nothing to do with the correlation structure.

Table 3 provides the exposures of the three PCA factors by country. The first PCA factor, which is by far the most significant one for the three types of volatility, has almost equal exposures to all countries except the Asian countries where the exposures are smaller. This implies that if there is anything like a global volatility factor explaining most of the variability of the country-specific volatilities, it is definitely not heavily skewed towards the US. It has, however, more pronounced exposures to the non-Asian countries which is more apparent in the cases of CSV and realized volatility. The structure of the second PCA factor is very similar across the three types of volatility measures. For both MFOI and realized volatilities, it has a significantly positive exposure to the Asian countries and smaller negative exposure to the other countries. As a consequence, this PCA factor can be loosely interpreted as an Asian factor because of the significant positive exposures to Asia.[7]

Finally, the third PCA factor for MFOI volatility is highly exposed to the US and we can loosely interpret it as a VIX factor. Thinking about it as a global volatility factor, however, would be an exaggeration because it explains only about 10% of the total variability compared to the 60% explained by the first PCA factor. The third PCA factors for CSV and realized volatility do not support any such interpretations regarding US volatility.

It is curious that although the three methodologies are quite different, the correlation structure of the changes of the corresponding volatility indicators indicates that the first principal component, or the global volatility factor, is not heavily concentrated in any of the country-specific volatilities. Further on, the second PCA factor has a significant Asian exposure. Finally, the fact that VIX appears prominently only in the third PCA factor for MFOI volatility is in line with the conclusion from the analysis in Section 3.1that VIX cannot be regarded as a global volatility indicator.

An alternative way to check the interpretation of the PCA factors is to calculate the correlations between the corresponding PCA factors and the changes in the corresponding volatility measures.Table 4 provides the corresponding correlations for the case of MFOI volatility. Clearly the third PCA factor has a maximal correlation in absolute value with the changes in VIX while the first PCA factor, although highly correlated with VIX, has higher correlations with the European MFOI volatilities implying it would be difficult to interpret it as a VIX factor.

Table 3

The first three principal components for the three types of volatility measures.Results are based on the correlation structure. To reflect differences in trading hours, the European and the US volatilities are lagged relative to the Asian volatilities.

	CSV			MFOI volatility			Realized volatility		
	PCA 1	PCA 2	PCA 3	PCA 1	PCA 2	PCA 3	PCA 1	PCA 2	PCA 3
France	0.441	−0.078	0.135	0.370	−0.167	−0.273	0.455	−0.054	0.092
Germany	0.443	−0.168	0.029	0.412	−0.150	−0.160	0.434	−0.016	−0.008
Hong Kong	0.077	0.671	0.593	0.213	0.625	0.152	0.029	0.668	0.730
Japan	0.164	0.668	−0.363	0.210	0.616	−0.570	0.034	0.700	−0.560
Netherlands	0.317	−0.053	0.346	0.416	−0.161	0.017	0.448	−0.083	0.072
Switzerland	0.386	−0.108	0.168	0.384	−0.228	0.077	0.420	−0.056	0.062
UK	0.466	−0.128	−0.086	0.418	−0.172	−0.060	0.406	−0.013	−0.023
US	0.330	0.197	−0.584	0.329	0.267	0.736	0.245	0.222	−0.368
Explained variance	31%	12%	10%	58%	14%	9%	50%	12%	10%

Table 4

The correlation matrix of the three PCA factors and the changes in the corresponding MFOI volatilities.

	PCA 1	PCA 2	PCA 3	VCAC	VDAX	VHSI	VNKY	VAEX	VSMI	VFTSE	VIX
PCA 1	1	0%	0%	79%	88%	45%	45%	89%	82%	89%	70%
PCA 2	0%	1	0%	−20%	−18%	73%	72%	−19%	−27%	−20%	31%
PCA 3	0%	0%	1	−20%	−12%	11%	−41%	1%	6%	−4%	53%
VCAC	79%	−20%	−20%	1	70%	23%	23%	66%	58%	67%	43%
VDAX	88%	−18%	−12%	70%	1	25%	30%	75%	70%	78%	51%
VHSI	45%	73%	11%	23%	25%	1	53%	26%	22%	27%	44%
VNKY	45%	72%	−41%	23%	30%	53%	1	27%	17%	26%	40%
VAEX	89%	−19%	1%	66%	75%	26%	27%	1	74%	81%	54%
VSMI	82%	−27%	6%	58%	70%	22%	17%	74%	1	74%	45%
VFTSE	89%	−20%	−4%	67%	78%	27%	26%	81%	74%	1	51%
VIX	70%	31%	53%	43%	51%	44%	40%	54%	45%	51%	1

Summary and conclusion

There is both empirical and theoretical support for investors' willingness to seek to diversify or hedge equity exposures through a long exposure to equity volatility. There is, however, no strong evidence in the academic literature that VIX should be the default volatility exposure irrespective of the type of equity exposure. The only exception is perhaps the empirical literature on volatility spillover which finds evidence for spillover effects from the developed to the emerging markets. Therefore, in times of severe market crashes an exposure to VIX could provide protection and hedge losses in markets that may not be well correlated with the US market in normal circumstances. There is, in fact, a significant body of literature concluding that local volatility factors could be more effective for an equity exposure to a given market than an exposure to US volatility.

In this paper, we approached the question of the relevance of local volatility factors using model-free volatility indicators. We employed three different model-free methodologies – option implied volatility, realized volatility, and cross-sectional volatility. Although MFOI volatility relates to market expectations about future volatility levels, both MFOI and realized volatility represent total volatility measures. In contrast, CSV represents a measure of aggregate specific volatility which is, however, empirically not disconnected from the market index return.

Across all countries for which the three types of volatility indicators are available with about 10 years of data ending in July 2012 we find that local MFOI volatility indices are more effective at hedging a local market exposure over the entire period, during US recessions, and during the financial crisis of 2008. The same conclusion is confirmed by the corresponding realized and CSV measures.

A principal component analysis rules out US volatility as a global volatility factor and suggests that the global factor is more significantly exposed to non-Asian volatility. The factor of second-order importance has an Asian flavour. Both conclusions are robust with respect to volatility indicator type. Finally, US volatility appears dominant in the factor of third-order importance only in the case of MFOI volatility and is not invariant of methodology choice. Overall our analysis suggests that the development of local volatility indices is needed to contribute to the ability for investors to measure and manage uncertainty about volatility across international equity markets.

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1 Global influence is proxy by Financial Times (FT)/ Standard & Poor's Actuaries World index.

2 The causal effects are in the sense of Granger causality.

3 The variance premium is formally defined as the difference between the variance of the risk-neutral distribution and the variance of the physical distribution. See Bollerslev *et al* (2009) for additional information.

4 In fact, we use the 5-minute series provided in a public database of realized volatility indices, see the Oxford-Man Institute of Quantitative Finance at http://realized.oxford-man.ox.ac.uk/

5 We refer the interested reader to Garcia, Mantilla-Garcia and Martellini (2012) for more details.

6 We do not report the table based on NBER recession periods in the paper because of space limitations but it is available upon request.

7 Korea is excluded from this analysis because the data available for its MFOI volatility starts in January 2003. Although not included in the paper, truncating the sample to 2003 and including Korea in the analysis only confirms this interpretation.

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