

**Market Risk and the Concept of
Fundamental Volatility: Measuring
Volatility Across Asset and Derivative
Markets and Testing for the Impact of
Derivatives Markets on Financial Markets**

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Measuring Volatility across Asset and Derivative Markets and Testing for the
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Abstract

This paper proposes an unobserved fundamental component of volatility as a measure of risk. This concept of fundamental volatility may be more meaningful than the usual measures of volatility for market regulators. Fundamental volatility can be obtained using a stochastic volatility model, which allows us to ‘filter’ out the signal in the volatility information. We decompose four FTSE100 stock index related volatilities into transitory noise and unobserved fundamental volatility. Our analysis is applied to the question as to whether derivative markets destabilise asset markets. We find that introducing European options reduces fundamental volatility, while transitory noise in the underlying and futures markets does not show significant changes. We conclude that, for the FTSE100 index, introducing a new options market has stabilised both the underlying market and existing derivative markets.

Keywords: Fundamental Volatility, Kalman Filter, Stochastic Volatility Model, Implied Volatility

JEL Classification: C32, G18

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1. Introduction

Traditionally, the efficient market hypothesis views price volatility as a result of the random arrival of new information which changes returns. However, empirical studies such as Shiller (1981), Schwert (1989), and French and Roll (1986) suggest that volatility cannot be explained only by changes in fundamentals. Significant amounts of volatility in asset prices come from ‘noise trading’ of irrational traders. From this point of view, volatility may be defined as the sum of transitory volatility caused by noise trading and unobserved fundamental volatility caused by stochastic information arrival. Our modelling of fundamental volatility in this paper assumes that the fundamental volatility is an unobserved random variable; it changes through time.

There are many volatilities related to only one underlying asset which are measurable at a given time point: the return volatility of the underlying asset, futures return volatility on the asset, and call and put option implied volatilities over various maturities and exercise prices, etc. However, it is natural to assume that there is only one fundamental volatility defined over the underlying asset and all its derivatives. This is because information which affects the fundamentals of the underlying asset is the same across all derivatives of the asset and, thus, results in the same fundamental volatility. Other factors will also influence this single fundamental volatility as well as information arrival: the structure of related markets, the distribution of assets held by investors, transaction costs and numerous other factors in the global economy, including all the macroeconomic information available at the time. This study does not address these other factors which may be important. Our decision to not include them was driven by unavailability of data and the difficulties of specifying a plausible model that covers all these points.

Our study proceeds by decomposing the FTSE100 stock index related volatilities into transitory noise and fundamental volatility and utilises the decomposition to investigate the effect of the introduction of derivatives on the volatility. Using the stochastic volatility model (SVM) developed by Harvey and Shephard (1993, 1996) and Harvey, Ruiz, and Shephard (1994), we calculate the portion of transitory noise in the observed volatility (i.e., signal-to-noise ratio), and are able to infer the fundamental volatility process and also the relationship between transitory noises of different volatilities. Our analysis reveals the following results. Noise in the options market is not correlated with noise in the underlying and/or futures markets. However, the different noises associated with different options contracts are correlated with each other, and noise in the underlying market is correlated with that of the futures market. In addition, fundamental volatility has a high degree of persistence, a feature often observed in high frequency financial data; see Engle and Bollerslev (1986).

An interesting area of study for volatility is to investigate the effect of the introduction of derivatives on the underlying asset volatility. In a frictionless no-arbitrage world, derivatives are redundant assets and will not effect the underlying market. However, in the real world where markets are incomplete, effects of the introduction of derivatives markets on the underlying market exist. Derivative markets may stabilise underlying markets by more efficient risk allocation or destabilise underlying markets by increasing speculation.

Our study investigates the effects of the introduction of derivatives on the unobserved fundamental volatility and the transitory noise of the FTSE100 index related volatilities. Futures and American options on the FTSE100 index were introduced on 3 May 1984 and European options were listed on 1 February 1990. We are not able to show

the effects of the introduction of futures and American options on the FTSE100 index volatility, since the impact of introducing two derivatives at the same time can not be separated and the number of daily observations before the introduction of the derivatives is relatively small (i.e., 85 observations). However, we find that introducing European options reduced fundamental volatility, while the transitory noise in the underlying and futures markets did not show significant changes. On the basis of the evidence, we conclude that, for the FTSE100 index, introducing an options market stabilised the other financial markets (that is, underlying and derivative markets).

2. Fundamental and Noise Components of Volatility

An observed volatility series may be regarded as a combination of transitory “noise” and permanent fundamental volatility. Empirical studies such as Shiller (1981), French and Roll (1986), and Schwert (1989) show that changes in the fundamental value cannot explain all of the price movements in financial markets. That is, the observed volatility series has noise. We define the volatility caused by information as fundamental volatility and the volatility caused by noise trading as temporary noise. Observed volatility series may be regarded as a combination of transitory noise and permanent fundamental volatility.

On a given day many different volatilities which are related to one underlying asset can be calculated, e.g., underlying asset return volatility (RV), futures price RVs, option implied volatilities (IVs). When information arrives, permanent components of all volatilities will move in the same way. On the other hand, transitory components of volatilities caused by noise trading, for example, may not behave in the same way. We shall assume that there is only one true permanent component for the many volatilities which are related to one underlying asset, while there are multiple transitory noises. Our

intention is to study how these measures behave.

Let us consider option IV. We expect the IVs of any set of options on the same underlying asset to be identical. However, when the Black and Scholes (1973) (BS) option pricing formula is used, many different IVs can be observed on the underlying asset for different time-to-maturities and exercise prices.¹ The inconsistency between theory and empirical findings may be explained by the invalidity of BS option pricing model. It might be argued that IVs from stochastic volatility models appear less biased than the IVs from BS models and thus, more appropriate than the IVs from BS models.² However, stochastic volatility option pricing models also need an assumption about an explicit volatility process such as a mean-reverting AR(1) specification which may not be the true process. Therefore, the volatilities inferred from a stochastic volatility model also may be biased due to misspecification in the underlying stochastic processes. Other option pricing models have a similar model specification problem in calculating IVs.³

In this sense, any option pricing model other than the true model can not give us

¹ Hull and White (1987) show that in the Black and Scholes (1973) (BS) option pricing formula, the longer the time to maturity, the lower the IV. This is a misspecification bias that comes from the assumption of constant volatility in the BS model. The maturity-specific variation also reveals the term structure of IV; see Canina and Figlewski (1993), Resnick, Sheikh, and Song (1993), and Xu and Taylor (1994). For the different IVs across exercise prices, several alternative weighted average methods that are designed to aggregate the different IVs into a single IV have been used; see Latane and Rendleman (1976), Chiras and Manaster (1978), Schmalensee and Trippi (1978), Beckers (1981) and Whaley (1982). Recently, at-the-money IV tends to be used more frequently; see Bates (1995) for a summary.

² See pp. 377-382, Campbell, Lo, and MacKinlay (1997) and Bates (1995) for further discussions on the BS option pricing model and the stochastic volatility model.

³ We appreciate a referee for the comments discussed here.

the true volatility process implicit in option prices. In this study we use IVs inferred from the BS option pricing model. We acknowledge that the BS option formula is at best a convenient heuristic, but all we need in this study is a measure of IV which is a proxy of volatility dynamics and the IVs from BS option pricing formula are one of the proxies, see Bates (1995). In any case, the IV reported by option exchanges such as LIFFE is based on BS and is the statistic understood and acted upon by traders.

Besides the problems in the identification of the true option pricing model, we also have measurement errors in IV: inappropriate use of risk-free interest rates, dividends and early exercise in American options, non-simultaneous option and stock price, bid/ask price effect, infrequent trading of the index, etc. For discussion on data limitations, see Harvey and Whaley (1991, 1992). Finally, we note the suggestion of Brenner and Galai (1984) that the IV based on the last daily observations may be unreliable.

Noting the above caveats, we assume that at time t an IV of an underlying asset has the following relationship with unobserved fundamental volatility (FV)

$$IV_t = FV_t + Noise_{IV,t} \quad (1)$$

The underlying asset return volatility has different properties from the implied volatility. Observed implied volatility is larger than underlying asset return volatility and implied volatility is smoother than underlying asset return volatility; see section 3. Latane and Rendleman (1976) show that the correlation between implied volatility and underlying asset return volatility is not close to 1. In addition, French and Roll (1986), using the difference in equity volatility between trading and non-trading hours, show that a significant portion of daily variance is caused by mispricing. Therefore, we represent the return volatility of an underlying asset at time t , RV_t , as

$$RV_t = FV_t + Noise_{RV,t} \quad (2)$$

Notice that implied volatility has the interpretation of an *ex ante* market expected return volatility to option maturity, if the option pricing assumptions are correct. However, since the unobserved fundamental volatility in the implied volatility reflects information which affects the fundamentals of the underlying asset, we suggest that the unobserved fundamental volatility in the return volatility is the same as the unobserved fundamental volatility in the implied volatility. That is, unobserved fundamental volatilities are assumed to be the same across the underlying asset and its options.

Now, let us consider the relationship between the return volatility of an underlying asset and that of futures. The no-arbitrage futures price can be denoted as $F_t = S_t e^{(r_{f,t} - d_t)\tau}$, where F_t is the futures price at time t , S_t is the underlying asset price at time t , d_t is the dividend yield, $r_{f,t}$ is the risk-free rate at time t , and τ is the time-to-maturity. Then, upon taking logarithms of the no-arbitrage futures price equation and differencing, futures return volatility (squared return) at time t , $RV_{futures,t}$, and the underlying asset return volatility (squared return) at time t , RV_t , have the following relationship:

$$\begin{aligned} RV_{futures,t} &= RV_t + \sigma_{r_{f,t}}^2 + \sigma_{d,t}^2 + Cov_t \\ &= FV_t + Noise_{futures,t} \end{aligned} \quad (3)$$

where $\sigma_{d,t}^2$ is the volatility of changes in dividend yield, $\sigma_{r_{f,t}}^2$ is the volatility of changes in the risk-free interest rate, Cov_t is the sum of the covariance items between underlying asset returns, changes in dividend yield, and changes in the “risk-free” interest rate, and $Noise_{futures,t} = \sigma_{d,t}^2 + \sigma_{r_{f,t}}^2 + Cov_t + Noise_{RV,t}$. Therefore, in this case, $RV_{futures,t}$ has

the same common unobserved fundamental volatility as in (1) and (2). Furthermore, we would expect the two noise terms to be correlated as the futures noise would contain elements of underlying asset noise.

The explanation above assumes that for an underlying asset, we can identify only one unobserved fundamental component but multiple transitory noises from many observable volatilities of the underlying asset across different markets. The setting requires us to use multivariate models rather than univariate models. More formally, k observed volatilities related to one underlying asset can be assumed to have one FV as follows:

$$\mathbf{V}_t = FV_t \mathbf{e} + \boldsymbol{\varepsilon}_t \quad (4)$$

where $\mathbf{V}_t = [V_{1,t} V_{2,t} \cdots V_{k,t}]'$ is a vector of observed volatilities which are related to one underlying asset, $\mathbf{e} = [1 \ 1 \ \cdots \ 1]'$, and $\boldsymbol{\varepsilon}_t = [\varepsilon_{1,t} \varepsilon_{2,t} \cdots \varepsilon_{k,t}]'$ is a vector of transitory noises of observed volatilities. Equation (4) is a multivariate model but with only one unobserved process. The model is essential to our perspective, since it isolates our scalar risk measure, i.e., FV_t .

Factor models could be used to control other significant changes in economy; any effect we find on volatility may be due to macroeconomic factors.⁴ In the GARCH class of models, factors can be included as in Engle (1987). However, the factor GARCH models have a large number of parameters, resulting in computational problems. Engle, Ng, and Rothschild (1990) and Bollerslev and Engle (1993) suggest simpler methods to avoid the problem. In SVMs, factors can be included as in Harvey, Ruiz, and Shephard (1994), see

⁴ We would like to thank the referee for suggesting that we discuss this approach as a possible extension to our procedure.

Section 8.5, Harvey (1989) and Ruiz (1992) for detailed discussion. Leaving aside the computational issues, we turn next to a discussion of macroeconomic data. Although the above suggestion would in principle allow us to relate volatility directly to informational announcements, we would need to compile a database of macroeconomic announcement over the relevant period. Using macroeconomic information without considering the announcement effects introduces new problems of frequency; daily returns and quarterly macroeconomic measures.

3. Data

Four daily volatility series which are related to the FTSE100 stock index are used in this study⁵: FTSE100 stock index return volatility, futures return volatility, American call option implied volatility, and European call option implied volatility. To investigate the possible changes in the unobserved fundamental volatility and transitory noise resulting from the introduction of derivatives, we divide the entire sample period into three sub-periods: before the introduction of derivatives (the first sub-period, from 1 January 1984 to 2 May 1984), after the introduction of American options and futures but before the introduction of European options (the second sub-period, from 3 May 1984 to 31 January 1990), and after the introduction of all three derivatives (the third sub-period, from 1 February 1990 to 29 March 1996).

FTSE100 stock index option data (both American and European) from March 1992 are provided by the London Financial Options and Futures Exchange (LIFFE).

⁵ The FTSE100 FLEX(r) (European style option), which was introduced on 30 June 1995, is not used in this study. The implied volatility of the option is difficult to obtain because of the flexibility of the option.

American option price data from May 1984 to March 1992 and European option price data from February 1990 to March 1992 are obtained from the Stock Exchange Daily Official List.

The implied volatilities of both American and European options are calculated from the Black (1976) pricing formula for options on futures. Two distinct benefits come from using Black's option pricing formula on futures. Firstly, futures and options on the FTSE100 stock index have the same closing time and thus the nonsimultaneous price problem (see Harvey and Whaley, 1991), arising from the difference in closing times between the stock market and the derivative market, becomes trivial. Secondly, the expected market dividend rate embedded in futures prices is used instead of the widely used ex-dividend rate. Harvey and Whaley (1992) report large pricing errors in American options when continuous dividends are assumed in the S&P 100 index, suggesting that discrete and seasonal dividend payments should be considered. However, using the futures price on the FTSE100 rather than the FTSE100 index itself removes these pricing errors. Therefore, implied volatility using futures prices is likely to be closer to the expected market implied volatility, if such a concept is well defined.

Bates (1995) suggests at-the-money implied volatilities as relatively robust estimates of expected average variances under a stochastic variance process. However, even though at-the-money implied volatility is used, the term structure of implied volatility is difficult to remove, unless there are many available at-the-money options of different maturities. Usually in this case, the volume is so low that the prices are no longer trustworthy. To minimize the term structure effect of implied volatility, the options with the shortest maturity but with at least 15 working days to maturity are used, as in Harvey

and Whaley (1991, 1992)⁶. Options which have the March cycle - March, June, September, and December - are used. The Newton-Raphson algorithm on Black's model is used to calculate implied volatility. We use the three month UK Treasury Bill for the risk-free interest rate.

The FTSE100 index futures series was provided by LIFFE and the daily FTSE100 index series was obtained from Datastream. As with implied volatility, the March cycle of futures prices is used and, to remove possible term structure effects in futures, futures prices with the shortest maturity, but with at least 15 working days to maturity are used. Therefore, all derivatives used in this study have the same maturity. The actual return volatilities of the FTSE100 index and futures are calculated by squaring the log-returns of the index and futures prices multiplied by 250 to convert to an annualized amount⁷. We emphasize that we use variances, and hence squared returns rather than standard deviations⁸.

Table 1 reports the statistical properties of each logarithmic volatility series. Note that zero volatilities should be converted to positive numbers when applying logarithms. The zero volatilities were converted to -15 for index return logarithmic volatility (log-RV)

⁶ However, the effects of the term structure of implied volatility cannot be removed completely. This is a weakness in this study, although we attempt to minimize its impact. By working with contracts of approximately the same maturity we can argue that our analysis treats maturity as fixed (cross-sectionally) at a point in time but is changing throughout the cycle.

⁷ Square of log-returns will result in larger volatilities than the square of residuals from any log-return process.

⁸ This is for consistency with the stochastic volatility model. However, standard deviations may also be used in the stochastic volatility model, as suggested in Fornari and Mele (1994).

and -12 for futures log-RV, which are the minimum log-RVs when zero volatilities are excluded from each log-RV series. As expected, logarithmic volatilities decrease kurtosis and skewness.⁹ However, futures and index log-RVs show negative skewness because of close-to-zero return volatilities. Although logarithmic implied volatilities (log-IVs) of the third sub-period are far from normal (for the normality test, a critical value of 5.99 at 5% significance can be used for the Jarque and Bera (1980) (J&B) statistics in the table), application of logarithms make the raw volatility series closer to normality. Therefore, the statistical properties in Table 1 suggest that log-volatilities might be better used in a linear modelling framework than volatilities themselves.

Some interesting differences between log-volatilities are found in Table 1. First of all, the mean of the log-RVs is smaller than that of the log-IVs. This means that the actual options prices are higher than the option prices obtained by using index return volatility as a volatility measure. The overpricing phenomenon is found over all sub-periods. Another interesting point is that the mean value of the futures log-RV is larger than that of the index log-RV. The covariance in equation (3) is not large enough to offset the volatility of changes in the risk-free rate and the dividend yield. On the other hand, the two log-IVs have almost the same statistical properties. As expected, the log-IVs are strongly autocorrelated and their standard deviations are relatively small. The statistical properties are quite different to those of log-RVs. This can be explained by Hull and White (1987) who argue that Black-Scholes implied volatility can be regarded as an ex ante averaged volatility to maturity. The averaging procedure removes a large portion of noise, increases

⁹ Although it is not reported, all return volatilities are positively skewed, leptokurtic, and fail to show signs of normality.

the autocorrelation, and makes the averaged process smoother than the unaveraged one.

4. Stochastic Volatility Model

Decomposition of volatilities into one fundamental volatility and noises can be carried out with GARCH models or stochastic volatility models (SVMs).¹⁰ We expect that there is no significant difference in our analysis between the two models since consistent estimates of a stochastic volatility model can be obtained with GARCH models under certain conditions, see Nelson and Foster (1994), Nelson (1996). However, the two models are different in the sense that the SVM has been developed in terms of information arrival and is known to be consistent with diffusion models for volatility, while the GARCH model has been predominantly used to describe some stylised facts of volatility, see Taylor (1994) and Ghysels, Harvey, and Renault (1996). Note that SVM is a discrete-time structural model of the geometric diffusion process used by Hull and White (1987), where they generalise the Black-Scholes option pricing model to allow for stochastic volatility.

In this study, the SVM developed by Harvey and Shephard (1993, 1996) and Harvey, Ruiz, and Shephard (1994) is used to decompose observed volatility into unobserved fundamental volatility and transitory noise as represented in section 2. As explained above, we explain volatility in terms of information arrivals in this study. In addition, changes in the level of the fundamental volatility which are used for the investigation of the effects of introduction of derivative markets, are hard to identify in GARCH models, because a non-negative time trend included in the conditional volatility equation of GARCH models is usually not significantly different from zero.

The SVM suggested by Harvey and Shephard (1993) may be represented by

¹⁰ See Taylor (1994) for a comparative study on these two models.

$$u_t = \sigma \xi_t e^{0.5 FVP_t}$$

$$FVP_t = \phi FVP_{t-1} + \eta_t$$

where u_t represents observed random residuals of a series (e.g., log-return series), σ is a positive scale factor, ξ_t is an independent, identically distributed random disturbance series, FVP_t is unobserved fundamental volatility process, and η_t is a series of independent disturbances with mean zero and variance σ_η^2 . When we take logarithms of the squared residuals, the SVM can be represented as¹¹

$$\begin{aligned} \log(u_t^2) &\equiv V_t = \log(\sigma^2) + FVP_t + \log(\xi_t^2) \\ &= \mu + FVP_t + \varepsilon_t \end{aligned} \quad (5)$$

$$FVP_t = \phi FVP_{t-1} + \eta_t$$

where V_t is a logarithmic value of the squared residual at time t , $\mu = \log \sigma^2 + E(\log \xi_t^2)$, and $\varepsilon_t = \log \xi_t^2 - E(\log \xi_t^2)$ is a zero mean white noise. The disturbance term, ε_t , in (5) is not normal unless ξ_t is log-normal. When ξ_t is standard normal, the mean and variance of $\log \xi_t^2$ are -1.27 and 4.93. In general, the distribution of ε_t is not known, and it is not possible to represent the likelihood function in closed form. However, quasi-maximum likelihood (QML) estimators of the parameters in (5) can be obtained using the Kalman filter by treating ε_t and η_t as normal. Ruiz (1994) suggests that for the kind of data typically encountered in empirical finance, the QML for the SVM has good finite-sample properties.

Equation (5) assumes that the fundamental volatility process follows an AR(1) process without a trend. Instead of a trend, we introduce a constant, μ , which represents

¹¹ We use the time invariant SVM in this study. The time invariant SVM is a SVM which has time invariant parameters, but whose value changes through time.

the level of expected volatility in the measurement equation. This should not be misinterpreted as an assumption of constant fundamental volatility. As mentioned by a referee, the fundamental volatility may include a trend. Although our model does not accommodate this since equation (5) only provides levels, it is estimated over sub-periods which allow changes in the level. The changing volatility levels over sub-periods can partly accommodate a trend in volatility level. In addition, the impacts of the introduction of derivative markets on the financial markets can also be investigated with changes in volatility levels over sub-periods.

Therefore, the fundamental volatility (FV_t) in section 2 can be further decomposed into a ‘volatility level (μ)’ and a ‘fundamental volatility (mean zero) process (FVP_t)’ as in equation (5). Note that we have only one fundamental volatility process in each period, while volatility levels are different across the four volatility series used in this study. Precise mathematical details of our SVM processes (i.e., multivariate SVMs and identifiability of the models) are given in Appendix. We present results for AR(1), AR(2), and ARMA(2,1) extensions of equation (5).

It is assumed throughout this paper that FVP_t and ε_t are uncorrelated. A referee has raised the point that in reality the correlation between these two would be non-zero and probably positive. We note that in these structural time series models, it is possible to consider this case, see chapter 3 of Harvey (1989). Interestingly, Harvey (1989) presents a transformation procedure which allows one to redefine transformed signal and noise that are uncorrelated. If correlation is present, we interpret our signal and noise as being these transformed variables, since our variables are unobservable. (We thank the referee for clarifying this point).

5. Empirical Results

5.1 Estimates of the SVM

Estimated SVMs using the FTSE100 stock index log-RV (univariate model) are in panel A of Table 2.¹² The first sub-period shows quite a different fundamental volatility process compared with those of sub-periods 2 and 3. The fundamental volatility process before the inception of derivatives shows mean-reversion, while after the inception of derivatives, the process is highly persistent. In addition, transitory noises in sub-periods 2 and 3 are relatively larger than the permanent innovation and thus, the signal-to-noise (STN) ratios for the AR(1) model are 0.006 and 0.001 in sub-periods 2 and 3, respectively¹³. On the other hand, in the first sub-period, the STN ratios are quite different for the models used. The unstable STN ratios seem to come from the small sample (85 observations) in the first sub-period.

Panels B and C of Table 2 represent the estimated multivariate SVM during sub-periods 2 and 3. Three log-volatilities (i.e., FTSE100 index log-RV, futures log-RV, and American call options log-IV) for the second sub-period and four volatilities (i.e., FTSE100 index log-RV, futures log-RV, American and European call options log-IVs) for the third sub-period are used in the multivariate SVM of equation (A2) in the Appendix. Although the coefficients of the fundamental volatility processes in the multivariate SVMs are different from those of the univariate SVM of panel A, all fundamental volatility

¹² We also used volatility series in the state-space form under the assumption of an additive process. As expected in the previous section, using volatility rather than log-volatility in state-space models is not preferable. Skewness, kurtosis, and portmanteau statistics are poor compared with those obtained by using the SVM.

¹³ The signal-to-noise (STN) ratio is defined as $STN = \sigma_{\eta}^2 / \sigma_{\varepsilon}^2$.

processes except the first sub-period have strong persistence. However, the STN ratios are different between the volatilities.¹⁴ During the second sub-period, the STN ratios are 0.003, 0.003, and 1.963 for the FTSE100 index, Futures, and American options, respectively. In addition, in the third sub-period, the STN ratios are 0.001, 0.001, 4, and 3 for the FTSE100 index, Futures, American options, and European options, respectively. Our results suggest that log-IVs have relatively more signal than noise, while log-RVs have relatively more noise than signal. Notice that maximum likelihood values are not significantly different between models over all sub-periods. Therefore, an AR(1) model will be used for the state equation for the rest of this study.

5.2 Properties of Fundamental Volatilities and Relationship between Transitory Noises of Different Volatilities

We now investigate the changes in the unobserved fundamental volatility resulting from the introduction of derivatives. The decomposition of observed volatility into fundamental volatility and transitory noise gives a new perspective on the investigation of the effect of derivative listing on volatility. To obtain the unobserved fundamental volatility, FV^i , we use a smoothing algorithm¹⁵. An inference about FV^i using the full set of information, defined as $FV_{t/T}^i$, is called the smoothed estimate of FV^i , which can be represented as

$$FV_{t/T}^i = E(FV_t^i / \Psi_T^i) \quad (6)$$

where $\Psi_T^i = (V_{i,T}^i, V_{i,T-1}^i, \dots, V_{i,1}^i)'$ and $i = \text{FTSE100, Futures, American options, and European options}$.

¹⁴ The standard deviation of transitory noises, σ_η , can be inferred from the STN ratios, since σ_η is given in panels B and C of Table 2.

¹⁵ This is a fixed-interval smoothing algorithm; see Harvey (1989), p149-155.

Using the smoothing technique for the AR(1) plus noise model, we obtain smoothed estimates of FV^i for each sub-period, and thus a transitory noise series. Figure 1 shows the unobserved fundamental standard deviation of FV^{FTSE} (i.e., $\exp(0.5\mu_{FTSE}+0.5FVP_t)$, where μ_{FTSE} is the level of FTSE100 stock index volatility).¹⁶ The fundamental volatility process shows strong persistence in the second and third sub-periods and a random walk may be the true process for the fundamental volatility. Smoothed fundamental volatility process was re-estimated using an AR(1) model for each sub-period. Dickey-Fuller tests reject the hypothesis of a unit root at the 1% level for all three sub-periods¹⁷. Therefore, the fundamental volatility in all three sub-periods seems to be highly persistent but not an integrated process¹⁸.

Table 6 reports correlation matrices for observed log-volatilities and transitory noises. As expected, the correlation between observed volatilities is positive. In particular, the correlation between the FTSE100 index and futures return volatilities is high. We also find high correlation between the American and European call option implied volatilities. However, the correlation between return volatilities and implied volatilities is relatively

¹⁶ Note that the FTSE100 index and futures return volatilities, and American and European options implied volatilities have the same fundamental volatility process, $FVP_t = \phi FVP_{t-1} + \eta_t$, but the levels of the fundamental volatility, μ_i , are different across the four volatility series. See equation (5) for further discussion.

¹⁷ Dickey-Fuller statistics (critical values at 1% level) of the smoothed fundamental volatility for the first, second and third sub-periods are -23.96 (-13.2), -26.01 (-13.8), and -20.73 (-13.8), respectively.

¹⁸ We should pay attention to the interpretation of the Dickey-Fuller test results. Harvey, Ruiz, and Shephard (1994) argue that the Dickey-Fuller tests are poor when the autoregressive parameter is close to 1 and the STN ratio is very small as in our study. In this case, the Dickey-Fuller tests reject the null hypothesis of a unit root too often.

low. Panel B of Table 6 reports the correlation between transitory noises of volatilities. The transitory noises of return volatilities are highly correlated and transitory noises of implied volatilities are highly negatively correlated, but transitory noises between return volatilities and implied volatilities do not seem to be correlated. Therefore, transitory noises may be grouped into two major factors: a noise factor in return volatility and a noise factor in implied volatility. Interestingly, transitory noises in American and European option implied volatilities are strongly negatively correlated (-0.906), while observed American option implied volatility is highly positively correlated (0.987) with observed European option implied volatility.

5.3 Effects of the Introduction of Derivative Markets on the Volatility of the FTSE100 Index and Its Derivatives

In traditional pricing theories such as the Black-Scholes, derivatives are redundant. They can be replicated with the underlying asset and a riskless bond. However, outside the frictionless non-arbitrage world, the introduction of derivatives may have two opposing effects on the underlying market: stabilising and destabilising effects. Theoretical and empirical investigations of the effects of a futures listing on the underlying asset are inconclusive¹⁹. Recent studies such as Lee and Ohk (1992) and Antoniou and Holmes (1995) claim that the underlying market becomes more efficient as a result of the introduction of the futures market.

On the other hand, theoretical and empirical studies on the effects of an option listing refer to an increase in the underlying asset price and a decrease in the volatility of the underlying asset return. Detemple and Selden (1991) undertake theoretical analysis of the effects of the introduction of an option in an incomplete market with a stock, a call

¹⁹ See Board and Sutcliffe (1993) for a summary.

option on the stock, and a riskless bond. They show that the introduction of the option results in an increase in the stock price and a decrease in the volatility of the stock rate of return because of investors' different assessments about the downside potential of the stock in a quadratic utility setting. Most empirical studies support the theoretical results; see Trennepohl and Dukes (1979), Skinner (1989), Conrad (1989), Detemple and Jorion (1990), Damodaran and Lim (1991), Haddad and Voorheis (1991), Watt, Yadav and Draper (1992), Chamberlain, Cheung and Kwan (1993), and Gjerde and Sættem (1995)²⁰. Some empirical studies use market models and find that the systematic risk of the underlying asset changes little, while unsystematic risk decreases. In addition, option trading seems to make the underlying asset adjust more rapidly to new information, and trading volume tends to be increased by option trading.

Table 1 shows that there are changes in observed volatilities between sub-periods. By decomposing observed volatility into fundamental volatility and noise, we can further analyze changes in volatility resulting from the introduction of derivatives. As a preliminary test, the T-test and the Mann-Whitney-Wilcoxon test are used. Panel A of Table 3 shows the t-test results. The FTSE-100 index return volatility, the futures return volatility, and the American option implied volatility show significant changes coinciding with the listing of European options. However, since volatilities have a long tail, a non-parametric test seems to be more appropriate. For this purpose, the Mann-Whitney-Wilcoxon test results are reported in panel B of Table 3. The results of the t-test and the Mann-Whitney-Wilcoxon test are similar. The FTSE100 index return volatility and the

²⁰ Chamberlain, Cheung and Kwan (1993) and Gjerde and Sættem (1995) report little change in underlying asset volatility.

American option implied volatility are changed by the listing of European options, while there is no significant change in the FTSE100 index return volatility with the introduction of the FTSE100 futures and the American options.

The effects of the introduction of derivatives on fundamental volatility are reported in Table 4. The introduction of American options and futures significantly increases FV^{FTSE} and the AR coefficient in the fundamental volatility process. On the other hand, the introduction of European options significantly decreases all three FV^{FTSE} , $FV^{futures}$, and $FV^{American}$, while it does not change the fundamental volatility process. Table 5 reports the changes in the transitory noises. The transitory noise of the FTSE100 index return volatility is decreased significantly by the inception of American options and futures. The introduction of European options reduces the noise of the American option implied volatility significantly.

Our results in Tables 4 and 5 can be discussed together with Table 3. In the preliminary test, there is no significant change in the FTSE100 index return volatility as a result of the inception of the American options and futures. However, by the decomposition, we find that FV^{FTSE} increases significantly and transitory noise decreases significantly without significant impact on the observed volatility.

With the inception of the European options, the FTSE100 index return volatility and the American options implied volatility decrease significantly. The majority of the decrease seems to come from FV^{FTSE} , and $FV^{American}$, because there is little change in the transitory noise of the FTSE100 index return volatility, and the significant decrease in the transitory noise of the American option implied volatility is quite a bit smaller than the decrease of $FV^{American}$. In addition, while the futures return volatility does not show any changes with the introduction of European options, $FV^{futures}$ decreases significantly. This

means that the existing market becomes more efficient with the listing of the European options.

We cannot separate the effects of the introduction of futures from those of American options, because both derivatives were introduced at the same time. In addition, because of the small number of observations of the first sub-period, the changes in fundamental volatility and observed volatility between sub-period 1 and 2 fails to provide convincing evidence for or against a change in volatility.

6. Conclusion

Using stochastic volatility models, we decomposed four different volatilities, the FTSE100 index return volatility, the return volatility for futures on the FTSE100 index, and the FTSE100 index American and European call option implied volatilities, into what we call unobserved fundamental volatility and transitory noise. For the return volatilities such as the FTSE100 index and its futures, transitory noise is much larger than the fundamental volatility, while implied volatilities of European and American call options consist of fundamental volatility rather than transitory noise. In addition, transitory noises of the FTSE100 index return volatility and futures return volatility are correlated with each other, and transitory noises of FTSE100 American and European call option implied volatilities are also correlated with each other. However, transitory noises of return volatilities are not correlated with those of implied volatilities, suggesting that trading noise in options markets is different from that in an underlying market or futures market.

We have obtained two types of volatility changes: changes in levels, and changes in the underlying dynamic process which correspond to a change in overall persistence of all the markets. Whilst both are interesting to asset managers or regulators, we feel that

large changes in the latter should be of particular interest as they reflect the fact that shocks may accumulate rather than die away. Unfortunately, we cannot reach a firm conclusion on the effect of the introduction of the futures or American options on the fundamental volatility and transitory noise, since there is only a small number of observations prior to the American options and futures on the FTSE100 index and their simultaneous introduction. The finding that persistence increases as a result of the introduction of derivatives needs to be supported by more data and analysis in other markets. This may reflect better risk management whereby anticipated shocks are spread out over longer periods through the use of derivatives. However, following the introduction of European options, we find that the level of fundamental volatility is reduced but there is no significant change in the fundamental volatility process. Furthermore, the transitory noise of American call options decreased significantly, while other transitory noises do not show significant change.

Our study proposes that fundamental volatility may be the correct measure of risk for the total market. Changes in fundamental volatility rather than observed volatility may be more appropriate for market regulators when they investigate the systematic effect of the introduction of derivatives on the market or the current state of the market. Regulators who currently compute the risk-neutral density of returns implied by option prices may wish to consider our procedure as a complimentary calculation to assess changes in the riskiness of market.

Appendix

A more generalised SVM is used in this study, where the state equation in (5) is allowed to follow an ARMA(p,q) model. In this generalised model, a state-space representation for a univariate model is

$$\begin{aligned} V_t &= \mu + FVP_t + \varepsilon_t \\ FVP_t &= \phi_1 FVP_{t-1} + \phi_2 FVP_{t-2} + \dots + \phi_p FVP_{t-p} + \theta_1 \eta_{t-1} + \theta_2 \eta_{t-2} + \dots + \theta_q \eta_{t-q} + \eta_t \end{aligned} \quad (A1)$$

where the ϕ 's and θ 's are AR and MA coefficients. The autoregressive and moving average lags, defined as p and q , are allowed to take values of up to 2 in this study. Therefore, a total of nine SVMs can be considered. A multivariate k equation SVM for (4) can be represented as

$$\begin{aligned} \mathbf{V}_t &= \boldsymbol{\mu} + FVP_t \mathbf{e} + \boldsymbol{\varepsilon}_t \\ FVP_t &= \phi_1 FVP_{t-1} + \phi_2 FVP_{t-2} + \theta_1 \eta_{t-1} + \theta_2 \eta_{t-2} + \eta_t \end{aligned} \quad (A2)$$

where $\mathbf{V}_t = [V_{1,t} \quad V_{2,t} \quad \dots \quad V_{k,t}]'$, $\boldsymbol{\mu} = [\mu_1 \quad \mu_2 \quad \dots \quad \mu_k]'$, $\boldsymbol{\varepsilon}_t = [\varepsilon_{1,t} \quad \varepsilon_{2,t} \quad \dots \quad \varepsilon_{k,t}]'$,

$$\mathbf{e} = [1 \quad 1 \quad \dots \quad 1]', \quad E(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_\tau') = \begin{cases} \boldsymbol{\Omega} & \text{for } t = \tau \\ \mathbf{0} & \text{for } t \neq \tau \end{cases}, \quad E(\eta_t \eta_\tau') = \begin{cases} \sigma_\eta^2 & \text{for } t = \tau \\ 0 & \text{for } t \neq \tau \end{cases}, \quad \text{and}$$

$E(\boldsymbol{\varepsilon}_t \eta_\tau) = 0$ for all t and τ . Notice that even though \mathbf{V}_t is multivariate, FVP_t is univariate.

Unobserved FVP_t which is related to the underlying asset can be obtained by considering all volatility series related to that asset. Although the fundamental volatility process is assumed to follow only one unobserved process, we allow via the vector $\boldsymbol{\mu}$ different volatility levels for each volatility to reflect the different volatility levels in Table 1. Therefore, the fundamental volatility of the observed volatility i , FV^i , is the sum of the fundamental volatility process and the volatility level of the observed volatility i . The above SVM can be represented as

$$\begin{aligned} V_t &= \boldsymbol{\mu} + \boldsymbol{\Theta}' FVP_t + \boldsymbol{\varepsilon}_t \\ FVP_t &= \boldsymbol{\Theta}' FVP_{t-1} + \boldsymbol{\Xi}_t \end{aligned} \quad (\text{A3})$$

where $FVP_t = [FVP_t, FVP_{t-1}, FVP_{t-2}]'$, $\boldsymbol{\Theta} = [1, \theta_1, \theta_2]'$, $\boldsymbol{\Phi} = \begin{bmatrix} \phi_1 & \phi_2 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$, and

$\boldsymbol{\Xi}_t = [\eta_t, 0, 0]'$. Note that the matrix representation of SVM in (A3) can be applied to the univariate SVM as well as the multivariate SVM; for the univariate SVM (i.e., $k=1$), $V_t = [V_{1,t}]$, $\boldsymbol{\mu} = [\mu_1]$ and $\boldsymbol{\varepsilon}_t = [\varepsilon_{1,t}]$.

We now address the issue of identifiability of the state-space models, see pp450-451, Harvey (1989). When there exists any non-singular 3×3 matrix \mathbf{H} which can satisfy the following state-space model, we say that the FVP is not identifiable.

$$\begin{aligned} V_t &= \boldsymbol{\mu} + \boldsymbol{\Theta}^* FVP_t^* + \boldsymbol{\varepsilon}_t \\ FVP_t^* &= \boldsymbol{\Theta}^* FVP_{t-1}^* + \boldsymbol{\Xi}_t^* \end{aligned} \quad (\text{A4})$$

where $\boldsymbol{\Theta}^* = \boldsymbol{\Theta}' \mathbf{H}^{-1}$, $FVP_t^* = \mathbf{H} FVP_t$, $\boldsymbol{\Phi}^* = \mathbf{H} \boldsymbol{\Phi} \mathbf{H}^{-1}$, and $\boldsymbol{\Xi}_t^* = \mathbf{H} \boldsymbol{\Xi}_t$. However, to make FVP_t follow the ARMA model, all elements except θ_1^* , θ_2^* , ϕ_1^* , ϕ_2^* , and η_t^* in the $\boldsymbol{\Theta}^*$, $\boldsymbol{\Phi}^*$, and $\boldsymbol{\Xi}_t^*$ must be the same as those of $\boldsymbol{\Theta}$ and $\boldsymbol{\Phi}$ in (A3). The only matrix that satisfies this restriction is the identity matrix. Therefore, as long as the FVP follows ARMA models, there is only one FVP in the SVM of equation (A3) and the FVP is identifiable for all p and q . Note that this argument applies to both the univariate and multivariate SVMs. The non-existence conditions for a non-singular 3×3 matrix \mathbf{H} are the identifiability conditions of the FVP.

However, this does not necessarily mean that the SVMs of equations (A1) and (A2) are identifiable; although the FVP is identifiable for all p and q , there are many sets

of the parameters which make the SVM have the same FVP. We need additional conditions for the identifiability of the SVM; the order condition for identifiability requires $p \geq q+1$ under the assumption that the fundamental volatility process is stationary and invertible, see pp205-209, Harvey (1989) for further discussion. Therefore, among the nine SVMs to be considered in this study, the SVMs that satisfy these conditions for the state equation are ARMA(1,0), ARMA(2,0), and ARMA(2,1) models.

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Table 1 Summary Statistics for the Daily Logarithmic Return Volatilities of the FTSE100 Index and the FTSE100 Index Futures and the Daily Logarithmic Implied Volatilities of American and European Call Options on the FTSE100 Index

A. FTSE100 Index Log-Return Volatility

	Mean	Std. Dev.	Skewness	Kurtosis	J&B Statistics	Autocorrelations										Portmanteau Statistic	
						1	3	5	8	10	30	50	100	200	Q(10)	Q(100)	
Entire Period	-5.37	2.29	-1.36	5.70	1893.41	0.03	0.02	0.05	0.03	0.08	0.01	0.04	0.01	-0.03	98.05***	226.51***	
Sub-Period 1	-5.68	3.10	-1.59	5.25	53.11	0.02	-0.09	0.08	-0.02	-0.11	-0.05	0.06	-	-	4.76	44.46	
Sub period 2	-5.20	2.27	-1.36	5.83	931.28	0.05	0.02	0.00	0.05	0.09	-0.01	0.05	-0.01	-0.04	50.23***	88.63	
Sub period 3	-5.51	2.24	-1.31	5.39	816.09	0.01	0.01	0.09	0.01	0.09	0.02	0.03	0.04	-0.03	59.74***	203.55***	

Notes: Entire sample period : 1 January 1984 - 29 March 1996, 3098 observations. Sub-period 1 : 1 January 1984 - 2 May 1984, 85 observations. Sub-period 2 : 3 May 1984 - 31 January 1990, 1454 observations. Sub-period 3 : 1 February 1990 - 29 March 1996, 1559 observations. *** represents significance at 1 % level.

B. FTSE100 Futures Log-Return Volatility

	Mean	Std. Dev.	Skewness	Kurtosis	J&B Statistics	Autocorrelations										Portmanteau Statistic	
						1	3	5	8	10	30	50	100	200	Q(10)	Q(100)	
Entire Period	-5.10	2.24	-1.08	4.22	768.73	0.07	0.05	0.06	0.05	0.07	0.04	0.05	0.00	-0.02	132.09***	356.35***	
Sub period 2	-5.05	2.24	-0.99	4.18	322.74	0.09	0.10	0.05	0.09	0.08	0.05	0.04	0.02	-0.03	103.99***	201.39***	
Sub period 3	-5.14	2.24	-1.15	4.26	448.32	0.04	0.01	0.06	0.01	0.06	0.03	0.05	0.00	-0.01	48.07***	207.14***	

Notes: Entire sample period : 4 May 1984 - 29 March 1996, 3012 observations. Sub-period 2 : 4 May 1984 - 31 January 1990, 1453 observations. Sub-period 3 : 1 February 1990 - 29 March 1996, 1559 observations. *** represents significance at 1 % level.

C. Logarithmic Implied Volatility of American Call Options on the FTSE100 Index

	Mean	Std. Dev.	Skewness	Kurtosis	J&B Statistics	Autocorrelations										Portmanteau Statistic	
						1	3	5	8	10	30	50	100	200	Q(10)	Q(100)	
Entire Period	-3.56	0.48	1.34	7.16	3074.30	0.96	0.91	0.88	0.84	0.81	0.59	0.48	0.21	0.00	23323.25***	69582.39***	
Sub period 2	-3.45	0.53	1.59	7.31	1732.74	0.94	0.88	0.84	0.79	0.77	0.52	0.39	0.14	-0.06	10372.67***	28217.15***	
Sub period 3	-3.66	0.40	0.41	2.90	43.99	0.98	0.95	0.93	0.89	0.87	0.66	0.57	0.25	-0.10	13323.35***	43051.43***	

Notes: Entire sample period : 3 May 1984 - 29 March 1996, 3013 observations. Sub-period 2 : 3 May 1984 - 31 January 1990, 1454 observations. Sub-period 3 : 1 February 1990 - 29 March 1996, 1559 observations. *** represents significance at 1 % level.

D. Logarithmic Implied Volatility of European Call Options on the FTSE100 Index

	Mean	Std. Dev.	Skewness	Kurtosis	J&B Statistics	Autocorrelations										Portmanteau Statistic	
						1	3	5	8	10	30	50	100	200	Q(10)	Q(100)	
Entire Period	-3.69	0.39	0.36	2.87	33.84	0.98	0.95	0.92	0.88	0.86	0.63	0.56	0.24	-0.12	13128.30***	41257.73***	

Notes: Entire sample period : 1 February 1990 - 29 March 1996, 1559 observations. *** represents significance at 1 % level.

Table 2 Estimates of Stochastic Volatility Models for FTSE100 Stock Index Volatility

A. FTSE100 Stock Index

Periods	Sub-Period 1 (1 January 1984 - 2 May 1984)			Sub-Period 2 (4 May 1984 - 31 January 1990)			Sub-Period 3 (1 February 1990 - 29 March 1996)		
	AR(1)	AR(2)	ARMA(2,1)	AR(1)	AR(2)	ARMA(2,1)	AR(1)	AR(2)	ARMA(2,1)
μ	-5.68 (0.36)	-5.69 (0.37)	-5.68 (0.37)	-5.19 (0.11)	-5.19 (0.11)	-5.20 (0.10)	-5.52 (0.19)	-5.52 (0.18)	-5.46 (0.19)
θ_1	-	-	0.28 (0.23)	-	-	0.41 (0.31)	-	-	-0.81 (0.09)
ϕ_1	0.44 (0.49)	0.02 (0.09)	-0.26 (0.26)	0.95 (0.03)	0.04 (0.05)	-0.02 (0.04)	0.99 (0.01)	0.17 (0.08)	0.47 (0.15)
ϕ_2	-	0.09 (0.12)	0.11 (0.11)	-	0.87 (0.09)	0.92 (0.04)	-	0.81 (0.08)	0.51 (0.15)
Standard Deviation of Transitory Noise (σ_ε)	2.98 (0.50)	0.01 (0.12)	0.01 (0.05)	2.20 (0.07)	2.18 (0.07)	2.18 (0.07)	2.18 (0.06)	2.17 (0.06)	2.07 (0.09)
Standard Deviation of Permanent Error (σ_η)	0.77 (1.09)	3.09 (0.35)	3.08 (0.34)	0.17 (0.05)	0.30 (0.11)	0.24 (0.08)	0.07 (0.02)	0.14 (0.04)	0.62 (0.22)
Maximum	-216.82	-216.52	-216.39	-3243.65	-3242.03	-3241.38	-3446.02	-3445.85	-3443.79
AIC	441.64	443.03	444.78	6495.30	6494.05	6494.75	6900.04	6901.70	6899.58
BIC	451.41	455.24	459.44	6516.42	6520.46	6526.44	6921.45	6928.46	6931.69
Skewness	-1.60	-1.58	-1.56	-1.43	-1.42	-1.42	-1.31	-1.31	-1.32
Kurtosis	5.28	5.20	5.11	6.05	6.06	6.03	5.34	5.35	5.40
Normality	53.96	52.00	49.84	1054.11	1057.35	1044.65	802.37	803.62	825.53
Q(10)	4.89	4.44	4.27	16.51*	13.13	12.64	18.56**	18.13**	14.81
Q(50)	44.59	42.33	41.47	52.41	48.08	46.26	70.11**	69.57**	62.35

Notes: The table reports the Quasi-Maximum Likelihood estimates of stochastic volatility models for the daily FTSE100 Index log-variance. Estimates are obtained using the BFGS optimisation algorithm provided by GAUSS. Numbers in parentheses are robust standard errors. State equations are assumed to follow ARMA(p,q) models. The state-space representation is

$$V_t = \mu + FV_t + \varepsilon_t$$

$$FV_t = \phi_1 FV_{t-1} + \phi_2 FV_{t-2} + \eta_t + \theta \eta_{t-1}$$

where V_t and FV_t are observed and unobserved fundamental volatilities, μ is level of fundamental volatility, and ε_t and η_t are the transitory noise and permanent error, respectively. Q(10) and Q(50) are the Box-Ljung statistics of standardised residuals for numbers in parantheses. The normality test is the Jarque and Bera (1980) statistic, which has a Chi-square distribution with 2 degrees of freedom in large samples.

* represents significance at 10% level and ** represents significance at 5% level.

B. Sub-Period 2 (4 May 1984 - 31 January 1990, 1453 Observations)

State Equation	AR(1)			AR(2)			ARMA(2,1)		
Observed Volatilities	FTSE100	FTSE100 Futures	FTSE100 American Options	FTSE100	FTSE100 Futures	FTSE100 American Options	FTSE100	FTSE100 Futures	FTSE100 American Options
μ	-5.19 (0.12)	-5.05 (0.12)	-3.45 (0.11)	-5.20 (0.13)	-5.06 (0.13)	-3.46 (0.11)	-5.19 (0.12)	-5.04 (0.12)	-3.44 (0.11)
θ_1		-			-			0.98 (0.01)	
ϕ_1		0.97 (0.01)			1.00 (0.02)			-0.02 (0.01)	
ϕ_2		-			-0.03 (0.02)			0.96 (0.01)	
Standard Deviation of Permanent Error (σ_η)		0.13 (0.04)			0.12 (0.04)			0.13 (0.04)	
Maximum		-3002.57			-3002.48			-3002.20	
AIC		6027.15			6028.95			6030.40	
BIC		6097.33			6105.51			6113.34	

Notes : The table reports the Maximum Likelihood estimates of multivariate stochastic volatility models for the FTSE100 Index, futures, and American option implied variance from 4 May 1984 through 31 January 1990 for a total of 1453 observations. Estimates are obtained using the BFGS optimisation algorithm provided by GAUSS. Numbers in parentheses are robust standard errors. State equations are assumed to follow ARMA(p,q) models. The state-space representation is

$$V_t = \mu + FV_t + \varepsilon_t$$

$$FV_t = \phi_1 FV_{t-1} + \phi_2 FV_{t-2} + \eta_t + \theta \eta_{t-1}$$

where V_t and FV_t are observed and unobserved fundamental volatilities, μ is level of fundamental volatility, and ε_t and η_t are the transitory noise and permanent error, respectively. Note that V_t , μ , and ε_t are 3 by 1 vectors.

C. Sub-Period 3 (1 February 1990 - 29 March 1996, 1559 Observations)

State Equation	AR(1)				AR(2)				AR(2,1)				
Observed Volatilities	FTSE100	FTSE100	FTSE100	FTSE100	FTSE100	FTSE100	FTSE100	FTSE100	FTSE100	FTSE100	FTSE100	FTSE100	FTSE100
	Futures	American	European	Options	Futures	American	European	Options	Futures	American	European	Options	Options
μ	-5.51 (0.12)	-5.14 (0.12)	-3.67 (0.11)	-3.70 (0.11)	-5.51 (0.12)	-5.14 (0.12)	-3.67 (0.11)	-3.70 (0.11)	-5.53 (0.13)	-5.16 (0.13)	-3.69 (0.11)	-3.71 (0.11)	
θ_1			-				-				0.91 (0.08)		
ϕ_1			0.98 (0.01)				0.98 (0.02)				0.16 (0.11)		
ϕ_2			-				0.00 (0.01)				0.82 (0.11)		
Standard Deviation of Permanent Error (σ_η)			0.07 (0.01)				0.07 (0.01)				0.06 (0.01)		
Maximum			1851.67				1851.67				1854.99		
AIC			-3671.34				-3669.34				-3673.99		
BIC			-3563.53				-3554.79				-3552.70		

Notes : The table reports the Maximum Likelihood estimates of multivariate SVMs for the FTSE100 Index, futures, American and European option implied variances from 1 February 1990 through 29 March 1996 for a total of 1559 observations. Estimates are obtained using the BFGS optimisation algorithm provided by GAUSS. Numbers in parentheses are robust standard errors. State equations are assumed to follow ARMA(p,q) models. The state-space representation for a ARMA(2,1) model is

$$\mathbf{V}_t = \boldsymbol{\mu} + FV_t + \boldsymbol{\varepsilon}_t$$

$$FV_t = \phi_1 FV_{t-1} + \phi_2 FV_{t-2} + \eta_t + \theta \eta_{t-1}$$

where \mathbf{V}_t and FV_t are observed and unobserved fundamental volatilities, $\boldsymbol{\mu}$ is level of fundamental volatility, and $\boldsymbol{\varepsilon}_t$ and η_t are the transitory noise and permanent error, respectively. Note that \mathbf{V}_t , $\boldsymbol{\mu}$, and $\boldsymbol{\varepsilon}_t$ are 4 by 1 vectors.

**Table 3 Preliminary Tests of the Effects of the Introduction of the FTSE100 Index Derivatives
on FTSE100 Index Related Observed Volatilities**

A. t - Test Results

	FTSE100 Index	FTSE100 Futures	FTSE100 American Options
The probability that the variances between Sub-Period 1 (1 January 1984 - 2 May 1984) and Sub-period 2 (4 May 1984 - 31 January 1990) are changed.	0.87	-	-
The probability that the variances between Sub-Period 2 (4 May 1984 - 31 January 1990) and Sub-period 3 (1 February 1990 - 29 March 1996) are changed.	1.00	0.98	1.00

B. Mann-Whitney-Wilcoxon Test Results

	FTSE100 Index	FTSE100 Futures	FTSE100 American Options
Mann-Whitney-Wilcoxon test statistic between Sub-Period 1 (1 January 1984 - 2 May 1984) and Sub-period 2 (4 May 1984 - 31 January 1990)	0.45	-	-
Mann-Whitney-Wilcoxon test statistic between Sub-Period 2 (4 May 1984 - 31 January 1990) and Sub-period 3 (1 February 1990 - 29 March 1996)	-4.54***	-0.80	-10.76***

Notes: Normal approximation can be applied for the statistics, and *** represents significance at 1 % level. Probabilities of 1 in panel A are rounded to the nearest 2 digits.

Table 4 The Effects of the Introduction of the FTSE100 Index Derivatives on the Unobserved Fundamental Volatilities

A. Changes in Volatility Level

		μ	d
FTSE100 Fundamental Volatility	Between Subperiod 1 (1 January 1984 - 2 May 1984) and Subperiod 2 (4 May 1984 - 31 January 1990)	-5.68 (0.03)	0.48*** (0.03)
	Between Subperiod 2 (4 May 1984 - 31 January) and Subperiod 3 (1 February 1990 - 29 March 1996)	-5.20 (0.01)	-0.31*** (0.02)
FTSE100 Futures Fundamental Volatility	Between Subperiod 2 (4 May 1984 - 31 January) and Subperiod 3 (1 February 1990 - 29 March 1996)	-5.05 (0.01)	-0.08*** (0.02)
FTSE100 American Options Fundamental Volatility	Between Subperiod 2 (4 May 1984 - 31 January) and Subperiod 3 (1 February 1990 - 29 March 1996)	-3.45 (0.01)	-0.21*** (0.02)

Notes: As explained in section 4, the fundamental volatility (FV_t) is decomposed into a volatility level (μ) and a fundamemtal volatility process (FVP_t). Note that the volatility levels are different across the four volatility series used in this study, although we have only one fundamental volatility process.

Panel A investigates the effects of the introduction of derivative markets on the level of the fundamental volatility using the following intervention model;

$$FV_t = \mu + dD_t$$

where D_t is a dummy variable which is 0 before the listings of derivatives and 1 after the listings of derivatives. Numbers in parentheses are robust standard errors. *** represents significance at 1% level.

B. Changes in Fundamental Volatility Process

	ϕ	d
Between Subperiod 1 (1 January 1984 - 2 May 1984) and Subperiod 2 (4 May 1984 - 31 January 1990)	0.72*** (0.08)	0.26*** (0.08)
Between Subperiod 2 (4 May 1984 - 31 January) and Subperiod 3 (1 February 1990 - 29 March 1996)	0.98*** (0.01)	0.00 (0.01)

Notes: Panel B reports the results on the effects of the introduction of derivative markets on the fundamemtal volatility process (FVP_t). The intervention model on fundamental volatility process are

$$FVP_t = \phi FVP_{t-1} + dD_t FVP_{t-1} + \eta_t$$

where D_t is a dummy variable which is 0 before the listings of derivatives and 1 after the listings of derivatives. Numbers in parentheses are robust standard errors. *** represents significance at 1% level.

Table 5 The Effects of the Introduction of the FTSE100 Index Derivatives on the Transitory Noises

		μ	d
FTSE100 Transitory Noise	Between Subperiod 1 (1 January 1984 - 2 May 1984) and Subperiod 2 (4 May 1984 - 31 January 1990)	2.14 (0.21)	-0.48** (0.21)
	Between Subperiod 2 (4 May 1984 - 31 January) and Subperiod 3 (1 February 1990 - 29 March 1996)	1.65 (0.04)	0.01 (0.05)
FTSE100 Futures Transitory Noise	Between Subperiod 2 (4 May 1984 - 31 January) and Subperiod 3 (1 February 1990 - 29 March 1996)	1.65 (0.04)	0.01 (0.05)
FTSE100 American Options Transitory Noise	Between Subperiod 2 (4 May 1984 - 31 January) and Subperiod 3 (1 February 1990 - 29 March 1996)	0.04 (0.001)	-0.02*** (0.001)

Notes: Transitory noises of observed volatility are obtained by applying the Stochastic Volatility Model. The above table reports the effects of the introduction of the derivative markets on the transitory noise using the following intervention model

$$|\varepsilon_t| = \mu + dD_t + v_t$$

where D_t is a dummy variable which is 0 before the listings of derivatives and 1 after the listings of derivatives. Numbers in parentheses are standard errors. *** represents significance at 1% level and ** represents significance at 5% level.

Table 6 Correlation Matrix of Observed Volatilities and Transitory Noises

A. Correlation of Observed Volatilities

1. Sub-Period 2 (4 May 1984 - 31 January 1990, 1453 Observations)

	FTSE100	FTSE100 Futures	FTSE100 American Options
FTSE100 Index	1.00		
FTSE100 Futures	0.56	1.00	
FTSE100 American Options	0.20	0.24	1.00

2. Sub-Period 3 (1 February 1990 - 29 March 1996, 1559 Observations)

	FTSE100	FTSE100 Futures	FTSE100 American Options	FTSE100 European Options
FTSE100 Index	1.00			
FTSE100 Futures	0.70	1.00		
FTSE100 American Options	0.20	0.21	1.00	
FTSE100 European Options	0.19	0.21	0.99	1.00

Notes: These correlations refer to correlations of observed volatilities, V_t in equation (5).

B. Correlation of Transitory Noises

1. Sub-Period 2 (4 May 1984 - 31 January 1990, 1453 Observations)

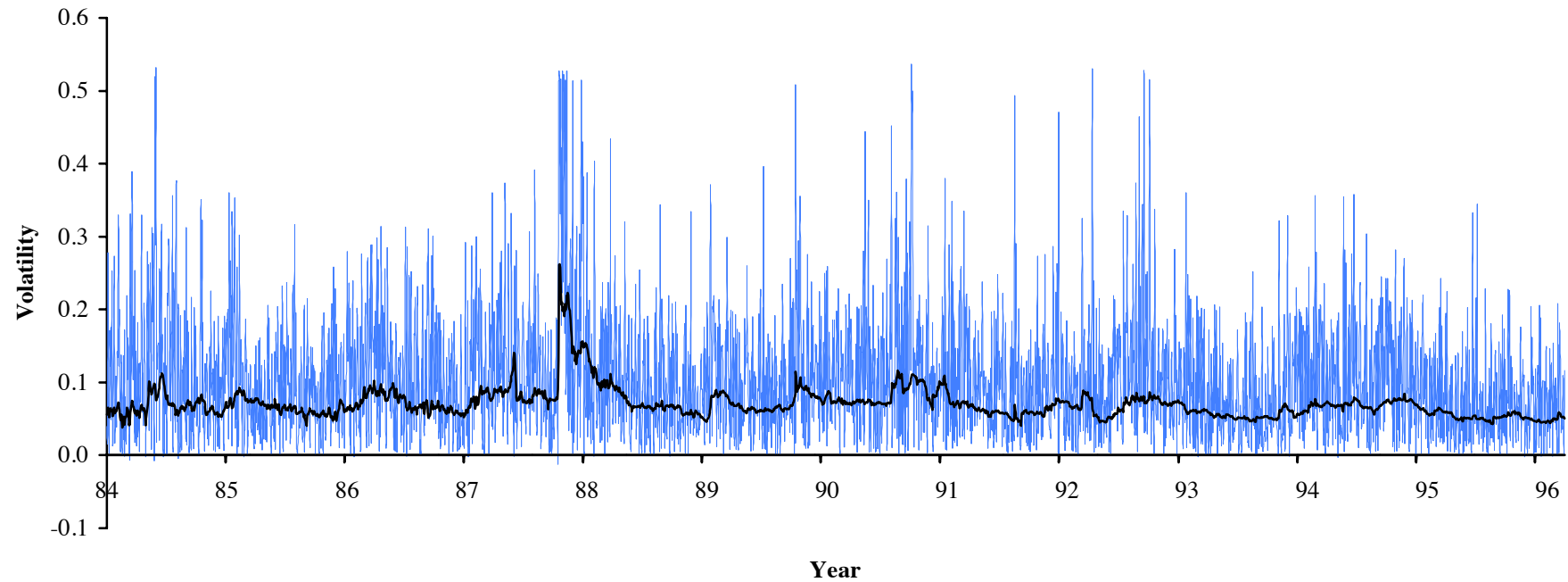
	FTSE100	FTSE100 Futures	FTSE100 American Options
FTSE100 Index	1.00		
FTSE100 Futures	0.54	1.00	
FTSE100 American Options	-0.02	-0.15	1.00

2. Sub-Period 3 (1 February 1990 - 29 March 1996, 1559 Observations)

	FTSE100	FTSE100 Futures	FTSE100 American Options	FTSE100 European Options
FTSE100 Index	1.00			
FTSE100 Futures	0.69	1.00		
FTSE100 American Options	0.06	0.09	1.00	
FTSE100 European Options	-0.02	0.00	-0.91	1.00

Notes: These correlations refer to correlations of transitory noises, ε_t in equation (5).

Figure 1 FTSE100 Stock Index Daily Volatility and Its Unobserved Fundamental Daily Volatility (Smoothed Value)



— FTSE100 Observed Volatility — FTSE100 Fundamental Volatility

Notes: The figure shows FTSE100 Index annualised daily volatility (lu_t) and its unobserved fundamental annualised daily volatility, i.e., $\exp(0.5FV_t^{FTSE})$, see equation (5) and section 5.2 for further explanation. This is calculated from 3 January 1984 through 29 March 1996 for a total of 3097 observations (except for 3 May 1984 when the volatility of the FTSE100 futures is not available). As defined, FV_t^{FTSE} is unobservable and the filtered value of u_t . Extreme FTSE-100 index volatilities are not shown for reasons of scaling.

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