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THE SWEDISH EXPECTED VOLATILITY INDEX
- CONSTRUCTION AND PROPERTIES -

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ABSTRACT

In this paper we construct an index, SVIX, measuring the expected 30 calendar day volatility on the Swedish stock market for the time period January 1993 to June 2006. SVIX is constructed from OMX index option prices using the same method as used by the Chicago Board Options Exchange (CBOE) in calculating the CBOE Volatility Index, VIX, and is independent of any option pricing model. The overall results from the examination of the properties of SVIX indicate that the index behaves largely as existing foreign volatility indices. We find that SVIX has a non-normal distribution, exhibits both volatility clustering and mean reversion, has a negative, albeit not asymmetric, relationship with the returns of the underlying OMX index and is affected by the expected volatility both on the US and Eurozone markets. Most interestingly, SVIX displays good forecasting ability and although we find it to provide a slightly biased forecast of future realized volatility, it is nevertheless efficient and completely subsumes the information content of historical volatility.

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1 INTRODUCTION

The uncertain nature of asset returns has for a long time captured the interest of many academic researchers as well as practitioners operating on the financial markets. One way to quantify this uncertainty is to consider the asset return volatility. Even if volatility is not the same as risk it can, when interpreted as uncertainty, serve as a simple risk measure.[1] This has led volatility to become a key element in modern asset pricing theory, derivative pricing models, portfolio allocation problems and risk management. In combination with the fundamental implications between risk and return, the interest for understanding the behavior of volatility is well motivated and has resulted in an extensive literature on the subject.

In response to this attention several ways to measure and forecast volatility have been proposed. These methods range from time-series models, which make use of information contained in historical realized volatility, to models that derive the volatility implied in current option prices, often using an option pricing model such as Black&Scholes (BS). A growing body of literature also concerns implied volatility indices, i.e. indices that basically extract volatility information from a number of options with different strike prices as well as maturities and weigh it together according to a certain scheme to arrive at a more reliable measure of the market's expected volatility. The most recognized volatility index is the Chicago Board Options Exchange (CBOE) Volatility Index, VIX, which is based on S&P 500 stock index options and widely regarded as the benchmark for the expected 30 (calendar) day US stock market volatility. VIX, as most other volatility indices disseminated by various options and futures exchanges, has recently shifted to use a new method which is independent of the validity of any specific option pricing model, such as BS, to reduce potential biases induced by model dependence. In short, the new method prescribe that specific options are included into a portfolio according to a certain weighting scheme so that the portfolio provides a stable exposure to the variance of the underlying stock index. Based on a non-arbitrage argument the value of this portfolio is then used to derive the price of volatility, and thereby the volatility index level.

The purpose of this paper is to construct a volatility index for the Swedish market, SVIX, by employing the method used for the VIX calculation. Specifically, SVIX will be based on OMX stock index options and aims to measure the expected 30 (calendar) day volatility on the Swedish market.[2] We construct SVIX with a daily frequency for the time period January 1993 through June 2006, to discern long term trends and enhance comparison possibilities with existing volatility indices. The choice of 1993 as a starting point is due to rather poor liquidity during the first years after the introduction of OMX index options in 1986 (OMX, 2002). The usefulness of SVIX as an indicator of the expected Swedish stock market volatility depends on its characteristics and hence, a second

[1] In this paper we let volatility denote the (annualized) standard deviation of the underlying stock (index) return, unless otherwise specified.
[2] We let OMX denote the OMXS30 (OMX Stockholm 30) index, disregarding name changes during the years.

objective of this paper is to examine how the SVIX index behaves in regards to certain well known properties of volatility. In order to gain a broad overview of the index' functionality, we will briefly examine several selected features of volatility instead of focusing more in depth on one specific property. Firstly, we assess several stylized facts that have been documented about volatility in financial time series; such as a non-normal distribution, volatility clustering and mean reversion. Furthermore, we examine co-movements of SVIX and price movements of the underlying OMX index, the ability of the SVIX index to forecast future realized volatility of the OMX index, and finally, international co-movements of volatility.

The motivations for this study and the possible contributions that can come out of it are twofold. Firstly, concerning the construction of SVIX, there is at present no publicly available index measuring the expected volatility on the Swedish stock market. One of few volatility indices that do exist is SIXVX, disseminated by SIX. However, SIXVX is, as opposed to SVIX, calculated using an option pricing model (BS), and SVIX might therefore, due to its non-model dependence provide a better estimate of expected volatility. Moreover, SIXVX is only available since 2004, whereas we are able to calculate the SVIX index for a substantially longer time period, enabling historical evaluation and facilitating comparisons with other indices. Furthermore, since implied volatility indices compare very favorable with more complex econometric models that use historical returns, e.g. Giot (2002) argues that options and futures exchanges should develop and compute implied volatility indices and make them publicly available to investors. Our construction of SVIX is a step in this direction by evaluating whether it would be possible to construct such an index for the Swedish stock market.

Secondly, concerning the assessment of the SVIX index' properties, there does not (to our knowledge) exist any previous studies evaluating an index (model or non-model-dependent) which aim to measure the expected volatility on the Swedish market. Moreover, the research on volatility indices on smaller stock markets is overall very scarce; one of few exceptions is Skiadopoulos (2004) who construct a volatility index, GVIX, for the emerging Greek derivatives market. Hence, we will with this paper add to this field by considering whether SVIX shares the properties of the volatility indices calculated for larger markets. Finally, if SVIX is found to possess the common properties of volatility it could, as an indicator of expected volatility, be used for several financial purposes, e.g. as a market sentiment indicator predicting the forthcoming direction of the market, as an input variable in derivatives pricing, for risk management purposes, and it could also be used in various trading strategies and applications.[3]

The remainder of this paper is organized as follows. Part 2 gives a brief background to volatility indices and is followed by part 3 outlining relevant findings in previous research. Thereafter, the data

[3] Concerning general volatility trading see e.g. Carr and Madan (1998), for specific trading strategies based on VIX see e.g. Connors (1999a,b, 2002), Copeland and Copeland (1999) and Larsen (2004), for trading of VIX futures and options see e.g. Tan (2004, 2006) and Mehta (2004). Concerning pricing of VIX futures and options see e.g. Daouk and Guo (2004) and Zhu and Zhang (2005).

is presented in part 4 and the method of the SVIX calculation and practical problems associated with this approach in part 5. The empirical results are presented in part 6; beginning with a description of the SVIX index followed by an evaluation of basic properties, the relationship between the SVIX and OMX indices, the forecasting ability of SVIX and finally, volatility transmission across the Swedish, Eurozone and US markets. The paper is concluded in part 7 with our overall conclusions and finally, part 8 provides our suggestions for further research.

2 BACKGROUND TO VOLATILITY INDICES

In several occasions, such as investment decisions, a high-quality forecast of the future stock (index) volatility is of outmost importance. Realized historical volatility, defined as the annualized standard deviation of the underlying index' return over a certain time period, may in those instances be disadvantageous since it is based only on historical data which is backwards looking and not necessarily a good indicator of future developments. One way to obtain a forwards looking estimate is to use the volatility information conveyed by current option prices. Implied option volatility is generally believed to represent the market's best expectation of future volatility, however, if it is backed out using a specific option pricing model, it will depend on the assumptions of that model. In case of the widely used BS model, empirical research has questioned the assumptions of a normal distribution of the underlying asset's return and a constant volatility until expiration. The implied volatility has been found to differ among options of varying strike prices (the 'skew' pattern) and to exhibit significant random elements, signaling that the underlying return process is mis-specified (CFE, 2007).

A more robust measure of expected future volatility was achieved when CBOE introduced its volatility index, VIX, in 1993. VIX was then based on a weighted average of BS implied volatilities for eight near-the-money S&P 100 index options for the two closest maturities. Specifically, the volatilities were weighted so that, at any given time, VIX represented the implied volatility of a hypothetical at-the-money option with 30 days to maturity[4] and several exchanges adopted similar approaches to compute volatility indices for other markets. However, even if this approach might provide an estimate that is superior to the volatility implied by a single option, it remains dependent on the validity of the BS model.

To incorporate the latest developments in how academics and practitioners view volatility, CBOE revised the VIX method in 2003. The new method still produces a measure of the market's expectation of the 30 day volatility, but derives it directly from prices of a weighted strip of options, i.e. without using any option pricing model, and the theoretical objections against the old VIX (henceforth called

[4] For further information about the old VIX calculation see e.g. Whaley (2000) and Fleming et al. (1995).

VXO, its ticker symbol after the method shift) are therefore circumvented.[5] The new VIX (henceforth called VIX) can be seen as more robust, since it by using a wider range of options, not only those near-the-money, pools more information and takes the skew into account. It is also simpler, since it does not require using the BS model to back out implied volatilities. The new method also enables static replication of VIX squared, which makes it easier to base products on the index, since it facilitates hedging and arbitrage of VIX products.[6] Moreover, when changing the method, CBOE shifted the underlying index from the S&P 100 index to the S&P 500 index, which has additional practical appeal due to more liquid options (CBOE, 2003).[7] Subsequent to CBOE's change in method, several other indices also shifted to the new method. For a brief overview of other volatility indices see *table A.1*, appendix A.

3 PREVIOUS RESEARCH

This part provides a brief introduction to the research done in areas relevant to our study. The presentation is divided into four sections concerning (1) the general properties of volatility, (2) the relationship between volatility and its underlying asset, (3) forecasting of future realized volatility and (4) international volatility transmission. Since our purpose is to evaluate whether properties of existing volatility indices apply also to the SVIX index, and not to evaluate potential underlying reasons for a specific feature, this presentation will only comprise a broad overview. The reader should note that since the current VIX method is rather new, most studies have investigated the behaviour of volatility indices based on the BS method, and few studies have yet been carried out on non-BS-dependent volatility indices. Nevertheless, also studies relating to BS-based volatility indices should be of interest since the fundamental nature of VXO / VIX did not change when the calculation method was revised (CBOE, 2003) and additionally, VXO and VIX are highly correlated, see e.g. Carr and Wu (2006).

3.1 Basic Properties of Volatility

As already mentioned, there are certain well established stylized properties of volatility, including a non-normal distribution, positive autocorrelation, mean-reversion and clustering. These properties have later been shown to apply also to volatility indices; concerning non-normality see e.g. Aboura (2003) and Carr and Wu (2006), autocorrelation see e.g. Carr and Wu (2006), mean-reversion see e.g. Skiadopoulos (2004) and Fleming et al. (1995), and clustering see e.g. CFE (2007). Moreover, a number of studies have examined stationarity of volatility indices. These results are however, mixed and depend both on the index and time period considered, see e.g. Aboura (2003) and Skiadopoulos (2004). Lastly, also expiration and weekday effects have been examined, and e.g. Fleming et al.

[5] A more comprehensive description of the (new) VIX method follows in part 5.
[6] Currently options and futures on VIX are traded on CBOE and CFE (CBOE Futures Exchange), respectively.
[7] For differences between the (new) VIX and (old) VXO see also e.g. Carr and Wu (2006).

(1995) account for some evidence of increased volatility index levels surrounding expiration days but do not find any substantial weekday effects.

3.2 The Relationship between Volatility and Index Returns

The negative relationship between volatility and contemporaneous stock (index) prices has been widely documented, however, the research concerning its causes has this far reached inconclusive results.[8] One of the first to investigate the relationship was Black (1976) who, for individual US stocks, explained it as a 'leverage effect'; when stock prices fall (given a fixed debt level) the leverage increases which causes an increase of the risk and hence, volatility. This explanation has been questioned in subsequent literature and another main hypothesis relating to systematic market-wide influences and volatility feedback has been advanced (Dennis et al., 2006). Volatility feedback implies that if volatility (as a risk measure) is priced, then news changing the price of a stock causes increased volatility, leading to an upwards revision of risk premiums and a higher required return on equity, which brings about an immediate stock price decline (Bekaert and Wu, 2000). Although most recent studies seem to favor the later hypothesis over the leverage effect,[9] many note that there may be some other explanation altogether. In addition to the negative relation, an asymmetric pattern has been documented; stock price decreases associated with a volatility increase is greater (in absolute value) than stock price increases associated with a volatility decrease of the same magnitude, see e.g. Cho and Engle (1999), Engle and Ng (1993) and Wu (2001).

A number of studies confirm that the negative relationship exists also for volatility indices and their underlying stock index, and moreover, an asymmetric effect is found for most volatility indices, see e.g. Fleming et al. (1995), Skiadopoulos (2004) and Carr and Wu (2006), however, it does not apply to all, see e.g. Giot (2005). The asymmetric relation is strong for VIX, and the index has consequently been dubbed the 'investor fear gauge', since "VIX is more a barometer of investors' fear of the downside than it is a barometer of investors' excitement (or greed) in a market rally" (Whaley, 2000, p. 17). Whaley also notes that a possible explanation of the asymmetry is a surge in the demand for put options (often used as portfolio insurance) when markets fall. The increased demand drives up the option prices and thereby the volatility index level. Further, Giot (2005) provides proof of a stronger asymmetric effect in low volatility environments and suggests that the reason could be that option traders react more aggressively to negative stock returns in such environments. Conversely, in high volatility environments traders might be unwilling to bid up the price of volatility (options) much

[8] An investigation of the causes of this negative relationship is beyond the scope of this paper and we refer the reader to Bekaert and Wu (2000) and Dennis et al. (2006) for a literature review on the subject. See Figlewski and Wang (2000) for a good explanation of the leverage effect and Dean and Faff (2004) about the feedback effect, see also Haugen et al. (1991).

[9] One approach that has been suggested to distinguish between the two hypotheses is to consider the causality of the relationship; the leverage effect implies causality from negative stock returns to increased volatility whereas the opposite is true for the volatility feedback effect (Bekaert and Wu, 2000).

higher, even if markets fall, since options are already rather expensive. An alternative explanation is that in low volatility environments, large volatility shocks may lead to proportionally much higher discount rates for equity markets, implying lower stock prices (Giot, 2005).

3.3 Forecasting Future Realized Volatility

The two primary methods employed to predict future volatility are time-series models using historical return information (e.g. simple past standard deviation measures and complex GARCH models) and implied volatility derived from option prices. Implied volatility is often considered superior since it is viewed as the market consensus estimate of future stock market volatility and "if option markets are efficient, implied volatility should be an efficient forecast of future volatility, i.e. implied volatility should subsume the information contained in all other variables in the market information set in explaining future volatility" (Christensen and Prabhala, 1998, p. 126). Previous literature however, presents somewhat mixed results concerning which type of model that provides the best forecasts, yet, an extensive survey of Poon and Granger (2003) indicates that implied volatility has better predictive ability and contains more information about future volatility than historical volatility measures. Papers reaching contrasting conclusions are mostly earlier ones. Canina and Figlewski (1993) find that implied volatility is a poor forecast of future volatility and further, Day and Lewis (1992) and Lamoureux and Lastrapes (1993) conclude that past volatility contains information incremental to that of implied volatility.

These early studies have however, been criticized for using overlapping data and that they suffer from a maturity mismatch problem.[10] When correcting for these problems e.g. Christensen and Prabhala (1998), Christensen and Strunk Hansen (2002) and Fleming (1998) conclude that implied volatility outperforms historical volatility, which moreover is found to have little or no incremental explanatory power. Additionally, although Fleming finds implied volatility to be a biased forecast overstating future volatility, Christensen and Strunk Hansen (and in some specifications also Christensen and Prabhala) find it to be both unbiased and efficient.

All studies mentioned this far have used the BS model to back out implied volatilities from individual options, a procedure that can cause an error in variable (EIV) problem, which might induce a bias in the forecast.[11] Christensen and Prabhala (1998), Christensen and Strunk Hansen (2002) and Fleming (1998) use an instrumental variable approach to overcome this problem. However, another solution that has been put forward to reduce the EIV problem is the use of a weighted average of implied volatilities for options with different strike prices, e.g. Blair et al. (2001) suggest use of a volatility

[10] Overlapping data can cause autocorrelation in the error terms, inefficient slope estimates, spurious explanatory power and also tends to overstate the explanatory power of past volatility. Also maturity mismatch, i.e. different volatility measures are not calculated for the same time horizon, may impact the comparison of various models.
[11] The EIV problem (i.e. measurement errors in the implied volatility estimate) is attributed to e.g. non-synchronous measurement of index level and option prices, use of American options which allow early exercise and a disregard of dividends in the BS formula, see e.g. Christensen and Prabhala (1998).

index since it by construction mitigates mis-measurement and 'smile' effects. Several studies have used volatility indices as measures of implied volatility when evaluating different forecasting models and even if the results are not conclusive, see e.g. Bluhm and Yu (2001) for contrasting evidence, most studies find that volatility indices have better predictive ability than historical volatility, even though their forecasts are found to be biased, see e.g. Blair et al. (2001), Giot (2002), Corrado and Miller (2005) and Aboura and Villa (1999). This general conclusion is confirmed also for a non BS-dependent volatility index by Carr and Wu (2006), who find that the VIX index has better predictive ability than a time series model, which moreover does not provide much additional information.

An upwards bias is often found for implied volatility predictors, which according to Poon and Granger is not likely to be caused by either measurement errors in option prices or noise in estimating the actual volatility, since those do not imply a certain direction of the bias. Instead they attribute the bias to a variance risk premium.[12] If the variance risk is not priced in the market, then the average realized volatility should equal the expected volatility as measured by e.g. a volatility index (Carr and Wu, 2004 and 2006).[13] However, Carr and Wu find a significantly negative average risk premium implying that investors are willing to pay a premium to hedge against increasing volatility, inducing an upwards bias of implied volatility. Furthermore, they find the risk premium to be time varying, a conclusion shared by Lamoureux and Lastrapes (1993).

3.4 International Volatility Transmission

Evidence of volatility linkages internationally across different stock markets has been found by several authors. Cifarelli and Paladino (2001) find volatility transmission between Europe, Asia, South and North America, and attribute it mainly to trade and financial flows between markets and that news about fundamentals in one country may have implications for other countries. Further, they argue that the European market is highly sensitive to news from the US because of its large share of the world market capitalization and its crucial influence on international financial markets. However, they also claim that countries in the same geographical area are relatively more interconnected, which is in line with evidence put forward by Eun and Shim (1989), who conclude that intra-regional patterns make integrated markets more correlated, since they tend to react simultaneously and in the same way to new information. Further, Baele (2003) notes that the increased economic, monetary, and financial integration within the EU has contributed to increased European shock spillover intensity over time.

Previous studies have also found that the volatility interdependence depends on the volatility level. Specifically, links between stock markets have been found to increase in high volatility regimes, see e.g. King and Wadhwani (1990) for evidence relating to the US, UK and Japanese stock markets and

[12] Investors face two sources of uncertainty, the uncertainty about the return (return variance), and the uncertainty about the return variance itself i.e. the 'variance of variance', which is captured by the variance risk premium.
[13] To be precise, this is only true under a certain probability measure, see Carr and Wu (2004 and 2006).

Baele (2003) for the US and European markets. Additionally, Baele finds evidence of stronger correlations in falling markets than in rising markets, which also is confirmed by Koutmos and Booth (1995) for the US, UK and Japanese stock markets. Cifarelli and Paladino (2001) moreover, conclude that larger markets become more influential in times of financial turbulence, a finding they attribute mainly to a stronger herding effect (investors in secondary markets imitate their counterparts in leading markets) and that assets in uncertain markets are passed from one portfolio to another during financial turmoil.

The papers accounted for above all concern general spillover of volatility across markets whereas the topic of implied volatility transmission has not been widely addressed. One of few studies is Aboura (2003), who examines volatility indices and finds that the (intra-regional) French and German volatility indices are less correlated with each other than with an US index. This is in contrast to earlier studies (not using implied volatility) such as Eun and Shim (1989). Aboura also finds that information originating in the US market is transferred on the same day to France while it is diffused over two days to Germany. However, the US index cannot unambiguously be shown lead the other indices, since all three indices (Granger) cause each other. Moreover, concerning emerging derivatives markets, Skiadopoulos (2004) finds the cross-correlations between changes in US and Greek volatility indices are almost zero and attribute this to the emerging status of the Greek derivatives market.

4 DATA

This part describes the data needed for the SVIX calculation and / or for examination of the features of the SVIX index. Consecutively, we go through the OMX index, the OMX index options, the interest rate and the VIX, VSTOXX and SIXVX indices. The part ends with a short note on data reliability.

The OMX index is a market-weighted price index based on the 30 most actively traded stocks on the Stockholm Stock Exchange (OMX, 2007a) and hence, by using the OMX index as underlying for SVIX we should capture the expected volatility of the Swedish market.[14] We obtain index close prices from the OMX group for the period January 4, 1993, to June 30, 2006, since even if the OMX index does not enter into the SVIX calculation, it is used when examining properties of SVIX and in procedures to detect erroneous option prices. [15] The base date for the OMX index is September 30, 1986, with a base value of 500 and the index was subsequently split 4:1 April 27, 1998 (OMX, 2007a).[16] In this paper we mostly use a split-adjusted series, and a graphical representation is provided (alongside the SVIX index) in *figure 2*, section 6.1, and summary statistics are provided in *table B.1*, appendix B.

[14] More detailed information about the OMX index can be found at http://omxgroup.com/nordicexchange.
[15] Observations for Nov to Dec 1992 and Aug to Sept 2006 are also collected to calculate realized volatility.
[16] At the date of the split, the strike prices of the outstanding options were divided by four and the option prices adjusted accordingly, hence the split does not impact the SVIX index.

The main input for the SVIX calculation is OMX index option prices. The (European style) OMX index options were introduced in December 1986 (OMX, 2002) and we obtain daily (end of the day) observations on bid, ask and close prices as well as option trading volume for all OMX options for the period January 4, 1993, until June 30, 2006, from the OMX group.[17] An overview of the amount of options used for the SVIX calculation is provided in *table B.2*, appendix B. The amount of available bid and ask prices substantially exceeds the amount of close prices. Furthermore, *figure B.1*, appendix B, shows that the yearly option trading volume has fluctuated around 5 million contracts for most of the sample, but has risen substantially during the last three years.

The other necessary input for the SVIX calculation is the risk free interest rate and as a proxy we use the one month Stockholm Interbank Offered Rate, STIBOR 1M. We obtain observations for the period January 4, 1993, to June 30, 2006, from the Swedish Riksbank (www.riksbank.se). The development of the interest rate, in its continuously compounded form (R), can be seen in *figure B.2*, and summary statistics are given in *table B.1*, appendix B.

Moreover, data for existing volatility indices is collected to enable later analysis. Firstly, we collect daily close price observations on the VIX index from CBOE (www.cboe.com) for the period January 4, 1993, to June 30, 2006. The VIX index is based on prices for options on the S&P 500 index, which is a market-value-weighted index based on 500 US stocks and is "widely regarded as the best single gauge of the U.S. equities market" (S&P, 2007). Secondly, we obtain daily close observations on the VSTOXX index for the period January 4, 1999, to June 30, 2006, from STOXX (www.stoxx.com). VSTOXX is calculated in a similar way as VIX, and measures the expected 30 day volatility in the Eurozone market.[18] The underlying stock index for VSTOXX is the Dow Jones EURO STOXX 50 index, which is based on the 50 largest sector leaders in the Eurozone market. VSTOXX was introduced April 20, 2005, and historical observations are available from January 4, 1999 (STOXX, 2007). Thirdly, we obtain close price data for the SIXVX index from SIX for the longest period available, May 7, 2004, to June 30, 2006. Also SIXVX sets out to capture 30 days expected volatility, in this case of the Swedish stock market by use of OMX index options. However, SIXVX is based on implied volatilities extracted from option prices by use of the BS 73 formula (SIX, 2006).[19] *Figure D.3* (VIX) and *D.4* (VSTOXX) appendix D5.1, and *D.2* (SIXVX), appendix D1.5, show the development of the indices, complemented with summary statistics in *table B.1*, appendix B.

To increase reliability the data has been gathered from primary sources and to certify that the data is as error free as possible we conduct graphical inspections of the OMX, STIBOR 1M, VIX, VSTOXX

[17] By close price we mean the transaction price relating to the last trade made during the day, bid and ask prices relate to the prices quoted at the end of the day.
[18] The Eurozone market covers countries with EURO as currency. For details about the VSTOXX calculation see STOXX (2007).
[19] For a more thorough method description the reader is referred to SIX (2006).

and SIXVX series (the options data is considered in section 5.3). Manual inspections show few cases of missing observations and reveal no obvious problems with the datasets (e.g. no large amount of missing observations or clear outliers). [20] However, for the VSTOXX series we choose to remove the first three observations (of 18, 29 and 25) since they are clearly different from the closest following observations (well above 30). Even if they might not be wrong per se, we exclude them due to their outlier quality, in order to ensure that they will not influence the results.

5 CONSTRUCTION OF THE SVIX INDEX

This part is devoted to provide an understanding of how the SVIX index is constructed. In the first section, a brief intuitive explanation of the mechanics behind the index construction is given, i.e. an explanation of how a volatility measure can be derived directly from option prices without use of an option pricing model and backing out implied volatilities. Then, the second section outlines the index computation method more formally step-by-step, and the last section accounts for some specific considerations concerning this construction method when applied to Swedish data.

5.1 Intuitive Explanation of the Index Construction

The general idea underlying the (new) VIX calculation method is pricing of expected volatility by use of replication technique. However, even if the objective is to capture volatility (i.e. standard deviation), it is variance that has the more fundamental theoretical characteristics since it enables creation of the most reliable replicating portfolio (Demeterfi et al., 1999). Therefore a portfolio of existing instruments is created to provide a clean exposure to the variance of the underlying stock index. Given efficient markets, the portfolio value will consequently, due to non-arbitrage reasons, equal the price of variance and finally, the volatility (index) is defined as the square root of the price of variance.[21]

The creation of a variance replicating portfolio is built on the theoretical framework of how to price a variance swap. A variance swap is in reality a forward contract with a payoff linked to the realized variance of the underlying asset. On the payment date one side pays a notional (N), e.g. \$1000 per variance point, times realized variance during the period (σ_R^2), while the other side pays the notional times a pre-specified variance level, the 'swap rate' or delivery price (K_{var}). Hence, the payoff function is $N \times \left(\sigma_R^2 - K_{\text{var}}\right)$. As with all forward or swap contracts, the 'swap rate' is at inception set so that the (initial) value of the contract is zero and hence, the swap rate equals the fair value of variance, i.e. K_{var}

[20] One missing observation for STIBOR 1M is approximated with the interest rates prevailing on the surrounding days, we also have a few missing observations for the SIXVX series, and a few days with no option prices.
[21] Note that the price of a portfolio replicating volatility is not equal to the square root of the price of a portfolio replicating variance (volatility squared). It is possible to create a portfolio replicating volatility directly, however, such a portfolio is much more difficult to hedge than the variance replicating portfolio and therefore the square root of variance has been chosen when defining the VIX index.

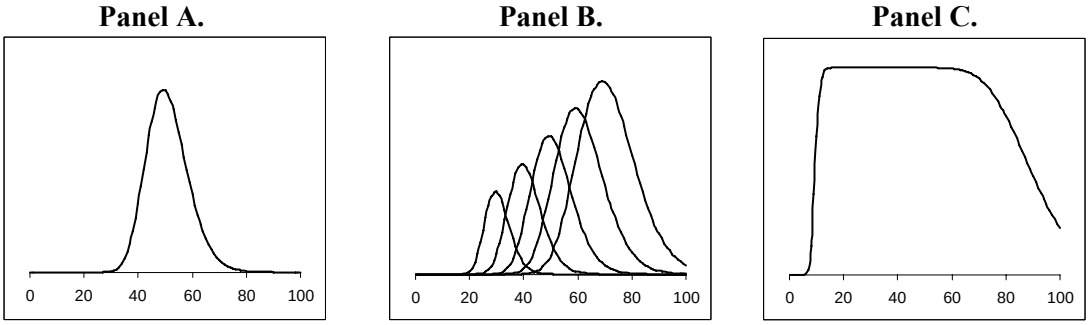
is then the risk neutral expected value of future variance (Demeterfi et al., 1999). The portfolio constructed to replicate the variance swap in order to derive the fair value of variance can be used to obtain a price of the expected future variance. We will not go into all the technical details concerning variance swaps, but will provide an intuitive explanation how a portfolio replicating variance is constructed and at the same time highlight some necessary requirements and potential problems. [22] The following section is based on Demeterfi et al. (1999) and CFE (2007).

To understand the intuition behind the variance replicating portfolio, consider a portfolio of index options (with a given time to expiration). This portfolio provides an exposure to both movements of the index (as measured by its delta) as well as the variance of the index return (measured by its vega), and hence the replication of variance is impure. To render the portfolio solely dependent on variance the price risk must be removed, something that can be achieved by delta-hedging the options using a forward (with a matching time to maturity) on the underlying index. Adding the forward makes the portfolio value sensitive only to movements in variance, but to price variance correctly, the portfolio needs to have a constant sensitivity to variance, i.e. a vega that is independent of the index price. A constant vega can be obtained by including options for a wide range of strike prices and applying a certain weighting scheme to their prices (see further below). If held until expiration, a portfolio constructed in this way will replicate the realized variance (σ_R^2), and hence, in order for the non-arbitrage restriction to be fulfilled, the initial price of this portfolio must equal the price of expected variance (K_{var}). The price of the portfolio is simply the price of the options included since a forward has a zero value initially and therefore does not contribute to the portfolio value.

As mentioned, to obtain a portfolio with a constant vega, options of varying strike prices must be combined according to a specific weighting scheme. From Panel A, *figure 1*, it is clear that a single option cannot be used to achieve a constant variance exposure since vega changes as the level of the index changes. The vega is highest when the option is at-the-money (ATM) and decreases rapidly when the index level changes and renders the option in-the-money (ITM) or out-of-the-money (OTM). Further, Panel B shows that the contribution to the aggregate portfolio vega increases as the strike price increases. Consequently, a reasonable assumption is that, in order to obtain a constant aggregate vega, the options with lower strike prices should be given a higher weight and the ones with higher strike prices a lower weight. Specifically, as shown by e.g. Demeterfi et al. (1999), each option price should be weighted by the inverse of its squared strike price. This weighing provides a constant aggregate vega for index levels inside the range of available strike prices, see Panel C. Lastly, note that since OTM options are generally more liquid than ITM options, put options are used for strike prices below an ATM forward index level and call options for strikes above the ATM level.

[22] The interested reader is referred to Demeterfi et al. (1999) and Bossu et al. (2005).

Figure 1. Variance Exposure (Vega)
Panel A shows the option vega as a function of the index level, and **Panel B** similarly, shows how the vega differs for options of different strike prices. **Panel C** shows the sum of the variance exposure for a portfolio comprised of options for strikes from 10 to 90 (spaced 1 apart) weighted with the inverse of their individual squared strike price.



This derivation of the fair value of variance is based on two main assumptions; a continuous index level evolution and availability of options for a continuum of strike prices from zero to infinity. Since in reality stock prices undergo jumps and only a finite number of options are available, Carr and Wu (2006) note that the VIX index squared approximates the variance swap rate up to a discretization error and an error induced by jumps of the index price. These effects interact with each other in a complicated manner, and the combined effect of the violations is inherently difficult to characterize and the variance replication may become imperfect (Demeterfi et al., 1999). Concerning the use of a discrete number of options, a portfolio constructed according to the weighing scheme above will still give a vega that is (virtually) independent of the index level, given that it remains within the range of available strikes and far away from the edges of that range, and provided that the strikes are closely and evenly spaced. A narrow strike range increases the probability that the index level will move outside (or very close to the edge) of the strike range during the time to expiration. If this happens the portfolio vega will no longer be constant but rather approach zero (cf. Panel C, *figure 1*). Hence, the replicating portfolio will be less sensitive to true variance changes and no longer capture the realized variance as the index level moves, i.e. the variance estimate will be lower than the fair value. Further, even if the strike range is wide and the index level is far from the edges, deviations from constant vega exposure might arise if the strikes are not evenly spaced or spaced widely apart. Also in this case the non-constant vega exposure leads to an imperfect replication of true variance.

Despite these limitations when the theoretical model is applied to actual data, the replication of variance still provides a reasonable approximation of true expected variance, as shown by Demeterfi et al. (1999). Moreover, judging from volatility indices such as VIX and VSTOXX, the replication method provides a good estimate of expected future volatility even though it, as all practical applications, calls for some simplifications. However, concerning the construction of SVIX, the somewhat poorer liquidity on the Swedish market might have an impact and therefore section 5.3 will

discuss how we proceed to mitigate these problems by imposing restrictions on the data and calculation procedure.

5.2 Method for Calculation of SVIX

This section describes the method used for the SVIX calculation, which in most aspects is identical to the one used to calculate the VIX index and any deviation will be explained specifically. The section is based on *The New VIX Calculation Step-by-Step* (CBOE, 2003) and *How is VIX Calculated? Step-by-Step* (CFE, 2007).

Formally, we define SVIX (1) as 100 times the square root of the (annualized) expected 30-calendar day variance of the OMX rate of return (σ^2).

$$SVIX = 100\sqrt{\sigma^2} \quad (1)$$

As explained previously, the expected variance of the OMX return can be extracted from prevailing OMX index option prices by choosing options with a certain time to maturity and applying a specific weighing scheme based on strike prices. In most cases options with a time to expiration of exactly 30 (calendar) days are not available, and hence, the 30-day variance needs to be inter- or extrapolated from options for two months with shorter and / or longer maturities (most often the following two expiration months). This will be done according to equation (2):

$$\sigma^2 = \left[T_1\sigma_1^2 w + T_2\sigma_2^2(1-w)\right]\frac{365}{30} \quad (2)$$

where:

- T_1 and T_2 are time to expiration (in years) for the two chosen contract months[23]
- σ_1^2 and σ_2^2 are (annualized) variances for periods of T_1 and T_2
- w and (1-w) are weights assigned to each option strip variance to obtain a 30-day variance.

  w is calculated as $w = \dfrac{T_2 - 30/365}{T_2 - T_1}$

Step 1. Selection of Contract Months

The options used to calculate the variances, σ_1^2 and σ_2^2, are usually the contracts expiring in the two nearest months, the closest in time is called near term (subscript 1) and the second is called next term (subscript 2). However, as anomalies, unrelated to pure variance, might affect option prices close to expiration, the VIX method excludes the nearest contract month and instead includes a new far term contract month when eight *calendar* days remain to expiration for the near term options.

[23] Subscript 1 denotes the closest month and subscript 2 the following month.

Correspondingly, VSTOXX (essentially based on the same method as VIX) and SIXVX (based on the same underlying as SVIX) include a new far term month two *trading* days before expiration of the front month contract (STOXX, 2007 and SIX, 2006). To decide on the proper procedure for SVIX, the tradeoff between using prices that could be affected by the short time to maturity and using far term options with poor liquidity needs to be considered. We choose to adopt the two *trading* day approach, in order to minimize the accumulation of missing observations, and hence instability, of the SVIX series around the 20th every month (when new far term series are included). For sensitivity purposes SVIX will also be calculated using the same approach as VIX to see if this choice has any substantial impact on the resulting SVIX series, see appendix D1.4.[24]

Step 2. Selection of Options to Include in Variance Calculation

The variance calculation is based on prices for options for all available strike prices, where OTM options are used since those are generally more liquid and contain more relevant information than ITM options (Demeterfi et al., 1999). Hence, to determine whether the option included for a certain strike should be the call or put option it is necessary to determine the reference point for moneyness, K_0. K_0 is defined as the first strike price below the forward index level, F, which can also be viewed as the expected ATM level at the expiration of the options. For each contract month F is derived through the put-call parity relation according to equation (3). Put and call option prices are compared for each strike level, and the *ATM strike price* is defined as the strike price where the absolute difference between call and put price is the smallest.[25]

$$F = ATM\ strike\ price + e^{RT}\left(call\ price - put\ price\right) \quad (3)$$

where:

- *ATM strike price* is the strike price where |*call price – put price*| is minimized
- R is the continuously compounded risk free interest rate[26]
- T is time to expiration (in years, i.e. *days to expiration*/365)
- *call price* is the price of the call option with strike price *ATM strike price*
- *put price* is the price of the put option with strike price *ATM strike price*

[24] The S&P 500 index options generally expire on the third Saturday each month, and the exercise settlement value is determined on the Friday preceding the expiration date (CBOE, 2007). Consequently, for VIX a new far term contract is generally included starting on the Monday the expiration week (CFE, 2007). Concerning OMX index options, the last trading day and expiration date was generally the day before the fourth Friday of each month until August 1995, and subsequently it has been the fourth Friday (OMX, 2006b). Consequently, for SVIX we also include the new contracts on the Monday for the eight *calendar* day approach (after Aug 1995), although this in effect implies that we shift the calculation seven calendar days before the expiration date.
[25] Note that the ATM strike price and hence, which options that are used, might be different for the two months.
[26] Theoretically it would be optimal to use an interest rate with the same time span as the options' time to expiration. The STIBOR rates are however, quoted with certain horizons and since interpolation to get rates with the exact same maturity as the options would increase the computational burden substantially, we use STIBOR 1 month, the impact on SVIX is negligible.

Further, denote the strike price of the i^{th} option as K_i and the price for the option selected for that strike price as $Q(K_i)$. Consequently, for strike prices below K_0 put options are chosen and for strikes above K_0 call options. For strike price K_0 both the put and call option are chosen and an average of the call and put price is used. Hence, the following option prices are included in the option strip used for the variance calculation:

$$Q(K_i) = \begin{cases} put\ price & & K_i < K_0 \\ (put\ price + call\ price)/2 & for & K_i = K_0 \\ call\ price & & K_i > K_0 \end{cases}$$

Step 3. Calculation of Variance for Each Contract Month

After the option selection the variance for each contract month is calculated according to equation (4):

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \quad (4)$$

where:

- T is time to expiration (in years)
- K_i is the strike price of the i^{th} option included in the option strip
- ΔK_i is a measure of the interval between strike prices and is defined as half the difference between the strike price on either side of K_i, except for the highest (K_{max}) and lowest (K_{min}) strike price where it is defined as the difference between K_i and the second highest / lowest strike, formally:

$$\Delta K_i = \begin{cases} K_i - K_{i-1} & & K_i = K_{\max} \\ (K_{i+1} - K_{i-1})/2 & for & K_{\max} > K_i > K_{\min} \\ K_{i+1} - K_i & & K_i = K_{\min} \end{cases}$$

- R is the continuously compounded risk free interest rate
- $Q(K_i)$ is the option price (either a put or a call or an average) selected for strike price K_i
- F is the forward index level based on index option prices as defined in (3)
- K_0 is the strike price immediately below F

As can be seen in equation (4), each option's contribution to the variance is proportional to the price of the option and to the strike price interval, and inversely proportional to the square of the options strike price. The last term, $\frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2$, is included in the variance calculation to adjust for the difference between the forward price of the index and the closest listed strike price. From equation (4) it is easy to see that, everything else equal, an increase of the option prices ($Q(K_i)$) from one day to the next will

lead to an increase in the variance. E.g. if markets become more turbulent the option prices are driven up and hence, the variance, and SVIX, will increase.

Step 4. Inter- or Extrapolation of Variances and Final Calculation of SVIX
When the variances for the two chosen contract months have been calculated according to equation (4), the 30-calendar day variance is calculated according to equation (2) and finally, SVIX is obtained by equation (1).

5.3 Considerations of Problems in Practice and Adjustments of the Calculation Method

When the VIX calculation method is applied to Swedish data some issues need to be considered, particularly since the OMX index option market is less liquid than its US equivalent, and since we use daily prices and not intra-daily as is used for VIX. This section therefore addresses specific considerations and adjustments which we find necessary to enable creation of a stable and reliable SVIX index with as few missing observations as possible. We first clarify why a SVIX observation cannot be obtained for some days, and thereafter discuss restrictions imposed on minimum number of options to ascertain reliability of SVIX. Next, we consider the choice of using bid and ask prices or close prices as input and finally, we go over the procedures used to remove erroneous and noisy input data. The impact of these choices on the resulting SVIX index will be addressed in the sensitivity analysis in appendix D1.4.

5.3.1 Basic Reason for Missing SVIX Observations

For some days no call-put differences, necessary for equation (3), can be computed, since the call and put price series are non-overlapping (i.e. no strike price corresponds to both a call and put price). Additionally, it is not certain that both a call and put price exist for strike price K_0. As a consequence SVIX cannot be calculated for all days, and we refer to this problem as 'the K_0 restriction not fulfilled'. The problem is most prevalent for options with long time to expiration, especially in the earlier part of the sample.

5.3.2 Restrictions Imposed to Stabilize SVIX: Requirements on Number of Call-Put Differences and Number of OTM Call and Put Prices

In order to make the SVIX index less affected by noise introduced by potential poor liquidity of the underlying OMX option series we impose minimum requirements on the number of call-put differences and on the number of OTM call and put options on either side of K_0. We think these restrictions are motivated even though they are not used in the VIX calculation, since the liquidity is less for OMX index options compared to S&P 500 options.

The requirement on number of call-put differences is introduced to be able to reach an acceptable minimum difference. Too few corresponding call and put options could be troublesome since it is

possible that another difference would be selected as the minimum if corresponding put and call prices existed for all strike levels. In the most extreme case where only one call-put difference can be computed, it would be used as minimum difference independent of its size. This could distort the SVIX calculation, as the options chosen would not necessarily be the actual OTM options. However, the call-put difference requirement encompasses a tradeoff as few call-put differences only pose a problem if they do not include the 'true' minimum difference, and a too strict restriction will severely reduce the number of SVIX observations.

The requirement on number of OTM call and put prices is introduced to reduce potential problems relating to a finite strike range as K_0, in the case of few OTM options, will be close to the 'edge' (cf. *figure 1*, Panel C). Additionally, a SVIX observation calculated using only one OTM put and call price would be very sensitive to those particular prices and changes in SVIX from day to day could potentially be large only due to small changes of those prices or to inclusion of a different amount of options. This restriction on number of option prices also presents a tradeoff in using tough requirements, reducing noise and stabilizing SVIX, and using weaker requirements, improving the SVIX series by enabling calculation of more SVIX observations.

For our base specification of SVIX, i.e. the series used for subsequent analysis, we apply rather weak restrictions and demand, at least, two call-put differences, and two OTM puts and calls on the respective side of K_0, to not exclude an excessive amount of SVIX observations. We consider the requirements fulfilled if they are satisfied for both the near and next term option strips; note that both problems are more exacerbated for the next term option series and when using close prices.[27]

5.3.3 Choice of Input Prices for the SVIX Calculation: Midquote of Bid- and Ask Prices or Close Prices

The main input for the SVIX calculation is option prices, however, it is not obvious whether bid and ask prices or close prices should be used. When calculating VIX CBOE uses a midquote of bid and ask prices and one reason is, as noted by e.g. Fleming et al. (1995), to avoid negative autocorrelation induced in the close prices by the bid-ask bounce. Furthermore, as stated by Lamoureux and Lastrapes (1993), bid and ask prices are always synchronous, in contrast to close prices which may relate to trades made any time during the day. Moreover, they note that close prices may potentially include price pressure effects. However, one could argue that close prices should be advantageous since they correspond to more liquid options and reflect the actual trades, conversely one can not be sure that actual trades will take place at the bid and ask. Contrary to the VIX calculation, Skiadopoulos (2004)

[27] As a robustness check we create alternative specifications of SVIX where stricter restrictions are imposed, specifically we consider cases with a minimum of three call-put differences and three or four OTM call and put options, see appendix D1.4.

chooses to base his volatility index for the Greek market on close prices, as he claims those prices to be less prone to noise compared to bid and ask prices.

We choose to construct our SVIX index from a midquote of bid- and ask prices for a number of reasons. One of the strongest is the synchronicity argument, since using stale close prices could, especially when the underlying OMX index has changed a lot during the day, add substantial noise to the input prices and thereby potentially also SVIX. Additionally, we have considerably more bid and ask price observations compared to close prices (see *table B.2*, appendix B), hence a midquote approach reduces the number of missing SVIX observations since it minimize the K_0, call-put differences and OTM call and put option problems accounted for above. Of course, more SVIX observations is not an objective per se, but we find no particular reason why the bid and ask prices should be inferior to close prices in terms of reliability. Moreover, a midquote approach could also lead to a more stable SVIX since the particular options used in the calculation will change less from day to day; close price observations only exist if there has been a trade during that day, whereas bid and ask prices (almost) always are quoted for all options.[28]

5.3.4 Removal of Errors and Noise in the OMX Option Price Series

To ascertain a high quality of the SVIX index we set out to remove potentially erroneous and very noisy input option prices. Due to the large amount of option prices (273 059 bid and ask prices and 143 185 close prices) it is not viable to manually go through all options series in search of potential wrong entries and we instead use various computerized screening methods. Even though the approaches outlined below are not flawless and might not be able to capture all wrong entries and / or might exclude some correct entries, we believe that the benefits of error removal and noise reduction outweigh the disadvantages.[29]

Screening 1.
The first step excludes all zero option price observations.

Screening 2.
The second step is a more thorough price screening where we, for the bid and ask price series, use a procedure similar to the one used by STOXX for VSTOXX. Specifically, STOXX excludes all options with bid-ask spreads exceeding the established maximum spreads for Eurex market makers (STOXX, 2007). Likewise, we consider the maximum spreads allowed for OMX options, however, since we have not been able to find a complete record of the maximum spreads since 1993,[30] this leads us to

[28] For sensitivity analysis purposes we also consider a close price approach, see appendix D1.4.
[29] For sensitivity reasons SVIX is also computed using option prices where only the first type of screening has been performed. One should note however, that the SVIX computed without the data adjustment will inevitably differ to some extent only due to inclusion of different amounts of options. For transparency reasons, the number of options excluded by each type of screening is explicitly shown in *table D.4*, appendix D1.4.
[30] For the maximum spreads prevailing today see *table D.7*, appendix D1.4.

choose a more modest approach and only exclude observations where the bid-ask spread is greater than 10 SEK.[31]

Screening 3.

The third screening is called the non-arbitrage requirement[32] as it evaluates whether the options fulfill the basic requirement that prices of call (put) options, with the same expiration date, should strictly decrease (increase) as the strike level increases, for any given day. If the requirement is not fulfilled we keep the observation closest to the contemporaneous OMX index level, since options closer to at-the-money generally are more liquid, and remove the option with strike price farther away from the index level. By employing the non-arbitrage approach errors in the option data set are reduced and noise from the option prices removed.[33] Further, a violation of the non-arbitrage requirement, e.g. due to an erroneous price, might lead to the 'wrong' minimum call-put difference being chosen (for a more extensive explanation about consequences of that, see section 5.3.2). The impact on SVIX depends on how big the deviation is from the 'true' parameter values, but it could have an impact that would make the quality of the SVIX index inferior.

6 RESULTS

This part provides an overview of the SVIX index and its features. The first section accounts for the historical index evolution and basic descriptives and additionally, includes a brief sensitivity analysis and comparison with the SIXVX index. In the second section, we perform some basic tests, such as normality, stationarity and autocorrelation, and also test for weekday and expiration effects. The third section considers the co-movements of SVIX and the underlying OMX index and the fourth section extends the analysis as to whether SVIX has some predictive power when it comes to forecasting future realized volatility of the OMX index. In the final section we examine volatility transmission between the Swedish market (SVIX), the US market (VIX) and the Eurozone market (VSTOXX).[34]

[31] For sensitivity analysis purposes an alternative specification of SVIX is calculated, performing a stricter price screening where we employ different max spreads depending on the option price level, see appendix D1.4. Moreover, since the max spread criteria cannot be used for the close price series we use the BS option pricing model to determine a theoretical price of the options and then exclude close prices with large deviations from the theoretical price (for more information about BS see e.g. Hull (2003)). We choose to tolerate a rather large deviation from the theoretical price since we as input volatility arbitrarily use 60 day historical volatility as a proxy, and the BS model does not necessarily give the 'true' option price. Specifically, we choose to accept a difference of 10 SEK.

[32] Note however, that violations of this requirement do not necessarily imply exploitable arbitrage opportunities.

[33] Concerning close prices, one reason for this kind of violation is non-synchronous data, i.e. the observations are not erroneous per se. A tradeoff exists between using all available data, which enables inclusion of more options in the variance calculation and causes less uneven strike levels, and using only observations fulfilling the non-arbitrage requirement which minimize the problem with non-synchronous data. Nevertheless, using observations not fulfilling this requirement would add noise to the SVIX calculation.

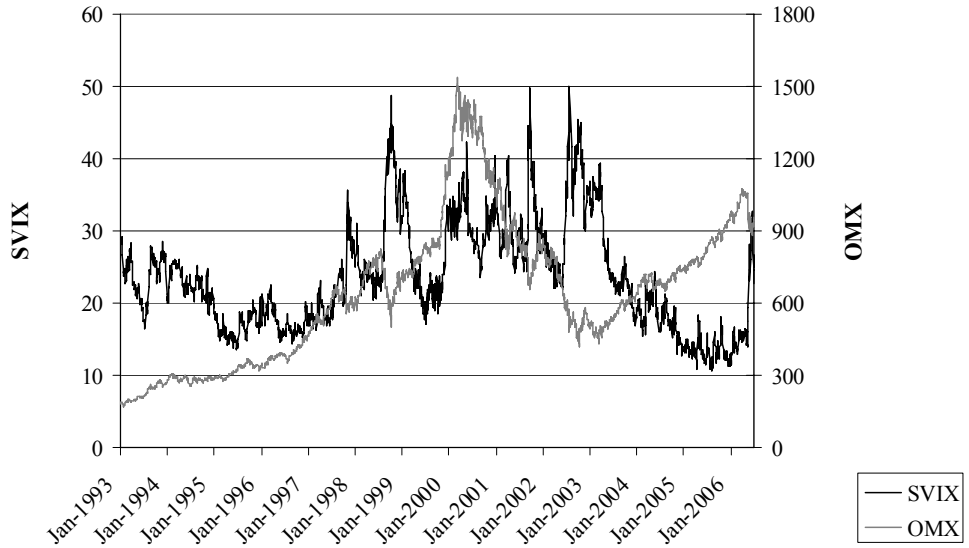
[34] Note that some of the testing procedures outlined below require fulfilment of certain statistical properties, such as stationarity and the ordinary least square (OLS) assumptions, and the reader is referred to appendix C for a review of those issues.

Due to space constraints the results presentation will be rather brief and, when necessary, the reader will be referred to appendix D for more elaborate discussions.

6.1 Description of SVIX

Figure 2 depicts the development of the SVIX index, next to the OMX index, from January 1993 to June 2006. The SVIX index starts off at a medium level, of about 25, in 1993 and then decreases to show a period of low expected volatility. Around 1997 SVIX starts to increase again and a period of higher volatility follows. The more pronounced spikes of the SVIX index relate to increased uncertainty caused by events with strong adverse effects on the financial markets. For example, the sharp upturn in the fall of 1998 corresponds to Russia defaulting on their government bonds and the LTCM crisis, and the spike in the fall of 2001 relates to the September 11 terror attacks, (see also enlarged graphs in *figure D.1*, appendix D1.1). Further, the large movements of SVIX during the late 1990's and early 2000's are attributable to the IT-bubble and its subsequent burst. In the middle of 2003 SVIX starts to decline again and from 2004 and onwards the volatility has been at a historically low level. *Figure 2* also indicates existence of a relationship between the SVIX and OMX indices; SVIX seems to increase as OMX decreases and vice versa, a pattern which is especially pronounced after June 2002 and during crises. The relation is not perfect however, and it will be more thoroughly examined in section 6.3.

Figure 2. Development of SVIX and OMX
The figure shows daily closing observations for SVIX (left axis) and OMX (right axis) for the time period January 1993 to June 2006. Note that the OMX series is adjusted for the split 4:1 April 27, 1998.



The SVIX index is further described by *figure 3*, which illustrates that the index exhibits a great dispersion both within individual years and over the entire period. This dispersion is also detailed in *table 1* and *2* which show a standard deviation of 7.5 percentage points and that SVIX varies from a minimum of 11 to a maximum of 50 around its median (mean) value of 22 (23). Furthermore, *table 1* and *2* give a first indication that SVIX is quite similar to its foreign counterparties VIX and VSTOXX. As for minimum, maximum and median / mean values SVIX is only somewhat higher than VIX and also has a slightly larger dispersion. Concerning VSTOXX, its descriptives relate to a shorter time period (starting 1999) and are not directly comparable to those for SVIX, however, the results indicate that SVIX in general is on a somewhat lower level and is slightly less dispersed than VSTOXX. A more thorough comparison of the three indices follows in section 6.5; see also *figure D.3* and *D.4*, appendix D5.1. Lastly, *table 2* also reports basic descriptives for daily changes of SVIX, ΔSVIX, defined as $\Delta SVIX_t = SVIX_t - SVIX_{t-1}$. Due to statistical considerations, this differenced series is in most cases used instead of the level series when properties of SVIX are tested.

Figure 3. Dispersion of SVIX
The figure shows the dispersion (max, median and min) of daily SVIX observations for each year for the period January 1993 to June 2006. Note that year 2006 only includes observations for January to June.

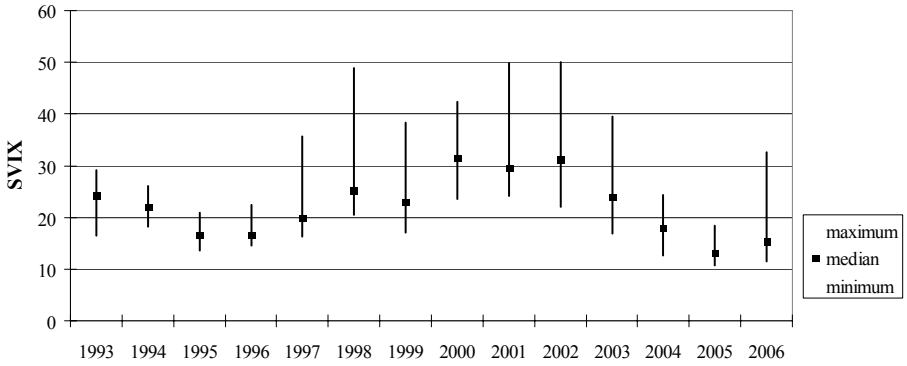


Table 1. Percentile Ranges for Daily SVIX Observations
The table shows percentile ranges, minimum, maximum and normal ranges for daily SVIX observations. The table also includes the same information for VIX, VSTOXX and SIXVX. See also *table D.2*, appendix D1.3 where the same information for SVIX is provided for subperiods.

		percentiles						normal range	
index	**min**	**5%**	**25%**	**50%**	**75%**	**95%**	**max**	**50%**	**90%**
SVIX	10.7	13.4	17.6	22.3	27.8	37.8	50.0	10.2	24.4
VIX	9.3	11.4	13.5	18.5	23.3	31.9	45.7	9.8	20.5
VSTOXX	11.6	13.2	18.5	24.1	28.7	47.1	62.7	10.2	33.9
SIXVX	9.6	10.7	12.4	14.0	16.5	23.1	32.5	4.1	12.4

Note: The time periods used are January 1993 to June 2006 (SVIX and VIX), January 1999 to June 2006 (VSTOXX) and May 2004 to June 2006 (SIXVX).

Table 2. Basic Descriptives for Daily SVIX and ΔSVIX Observations
The table shows the number of days with a valid SVIX / ΔSVIX observation (N), and the daily mean and standard deviation (std dev). The table also includes the same information for VIX, VSTOXX and SIXVX. See also *table D.3*, appendix D1.3 where the same information for SVIX is provided for subperiods.

	level series			differenced series		
index	**N**	**mean**	**std dev**	**N**	**mean**	**std dev**
SVIX	3023	23.42	7.48	2794	-0.037	0.98
VIX	3399	19.33	6.71	3398	0.000	1.20
VSTOXX	1906	25.50	10.05	1905	-0.007	1.52
SIXVX	536	14.99	3.82	531	0.009	1.10

Note: The time periods used are January 1993 to June 2006 (SVIX and VIX), January 1999 to June 2006 (VSTOXX) and May 2004 to June 2006 (SIXVX).

To consider the possibility that some characteristics of SVIX may become more or less pronounced depending on whether the general volatility level is high or low, we have divided our sample into four subperiods, the first comprising of 4 ½ years and the others 3 years each, see *table D.1*, appendix D1.2. The first and last subperiods are characterized by low volatility and an increasing trend of the OMX index while the second and third periods are characterized by high volatility and an increasing (subperiod 2) and decreasing (subperiod 3) OMX index trend. All results relating to subperiods will not, due to space limitations, be reported in the main text but can be found in appendix D. Naturally, when differing results are found for one or several subperiods these will be summarized in the main text. For an exposition of the basic descriptives of SVIX for the subperiods, see appendix D1.3.

The SVIX series accounted for this far (and the one used for subsequent tests) relates to our base specification.[35] For this specification we obtain a total of 3023 SVIX observations, corresponding to 89 percent of all trading days; a proportion that is slightly reduced to 83 percent of the total number of possible observations for the differenced series. Even if this can be seen as a rather large amount of missing values, comparing our numbers to those of Skiadopoulos (2004), who gets 55 percent valid GVIX observations when constructing an index for the Greek market, we believe the number of SVIX observations to be sufficient for our testing purposes. Moreover, a sensitivity analysis is performed in appendix D1.4, to assess whether the SVIX index (in its base specification) is stable and reliable. To briefly summarize, SVIX is found to be a good estimate of expected volatility in the sense that it is calculated using a rather large amount of OTM option prices (usually around 30 prices per day). Additionally, SVIX does not alter significantly if different restrictions are imposed on the dataset,[36]

[35] As a reminder, the base specification is calculated using a midquote of bid and ask prices with a maximum spread of 10 SEK and where the option series fulfil the non-arbitrage requirement. The cut-off point for including new options is at two trading days before expiration of the near term contract month, and additional requirements of at least two call-put differences and two OTM options on either side of K_0 are enforced.
[36] Although, the amount of missing observations is considerably higher for some other specifications.

and all alternative specifications accounted for in section 5.3 are well correlated with the base specification; correlations amount to 0.99 (p-value 0.000). Hence, the results obtained when testing properties of SVIX should be stable to different construction choices.

Finally, we compare SVIX with the existing SIXVX index. Even if the computational method is different they should yield almost the same results as both seek to measure the expected 30 (calendar) day volatility of the OMX index.[37] SIXVX descriptives are included in *table 1* and *2* above, but since SIXVX is only available for the last two years they can not be compared directly to the SVIX series results for the total period, but rather to the SVIX results for subperiod 4 in *table D.2* and *D.3*, appendix D1.3. The minimum, maximum and mean values as well as the standard deviation are roughly the same for the two indices and they move closely together over time, as seen in *figure D.2*, appendix D1.5. Additionally, the correlation between the indices is as high as 0.975 (p-value 0.000).

6.2 Basic Tests of SVIX: Normality, Stationarity, Autocorrelation, Weekday and Expiration Effects

In this section some simple tests on SVIX are performed to evaluate normality, stationarity and autocorrelation and its associated features, such as volatility persistence and clustering as well as mean reversion. Finally, the presence of weekday and / or expiration effects in the SVIX series is examined.

Using the Jarque-Bera test we reject normality for both levels and daily differences of the SVIX series, for the entire time period as well as for all subperiods, see *table 3* and *table D.8*, appendix D2.1. The level series is somewhat positively skewed whereas the differenced series shows a marginally negative skew. The kurtosis is around three for the level series, but substantially above three for the differenced series, indicating fat tails in the distribution of ΔSVIX. The stationarity of SVIX is examined using standard Dickey-Fuller (DF) or Augmented Dickey-Fuller (ADF) tests, and the null hypothesis of a unit root is rejected at one percent significance level for both level and differenced series for the total time period, see *table 3*. However, contradictory results are found for the level series for subperiod 2 and 4, which are found to be non-stationary, see *table D.8*, appendix D2.1. Then again, this is not surprising since a volatility series might exhibit a trend for a shorter period of time.

[37] SIXVX is computed using implied volatilities backed out from a BS model and the difference in construction method (compared to SVIX) matches the differences between the VIX and VXO, and comparisons of those indices have shown that they are roughly the same, see e.g. Carr and Wu (2006).

Table 3. Normality and Stationarity of SVIX and ΔSVIX
The first part of the table shows the skewness, kurtosis and Jarque-Bera test-statistic for normality for SVIX and ΔSVIX. Both Jarque-Bera statistics have a p-value of 0.0000. The second part of the table shows the results for Dickey-Fuller (DF) tests of SVIX and ΔSVIX. 'Model used' shows which DF model that is used; either DF without trend component (DF w/o t) or Augmented DF with lag length 1 (ADF m = 1), see further discussion in appendix C1. N is number of observations for the DF test, tau(obs) the observed tau-statistic and stat / non-stat the resulting outcome. *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively. For results relating to subperiods see *table D.8*, appendix D2.1.

	normality			**stationarity**			
	skewness	**kurtosis**	**Jarque-Bera**	**model used**	**N**	**tau(obs)**	**stat / non-stat**
SVIX	0.73	3.02	267.35	ADF (m = 1)	2600	-3.99***	stat
ΔSVIX	-0.05	7.82	2702.15	DF w/o t	2600	-59.47***	stat

The autocorrelation structure for lag one to three of the SVIX and ΔSVIX series is displayed in *table 4*. For the level series there is a strong positive autocorrelation for all three lags, a pattern confirmed by *figure 4*, which shows a very slowly decaying pattern with significant autocorrelation coefficients up to 500 lags, (the partial autocorrelation coefficients approach zero after 10 lags). This strong and slowly decaying autocorrelation function is an indication of volatility persistence and clustering in the SVIX series, a result which is further confirmed by the Ljung-Box (LB) statistics for 12, 30 and 60 lags.[38] The autocorrelation results for the level series are stable for all subperiods, see appendix D2.1.

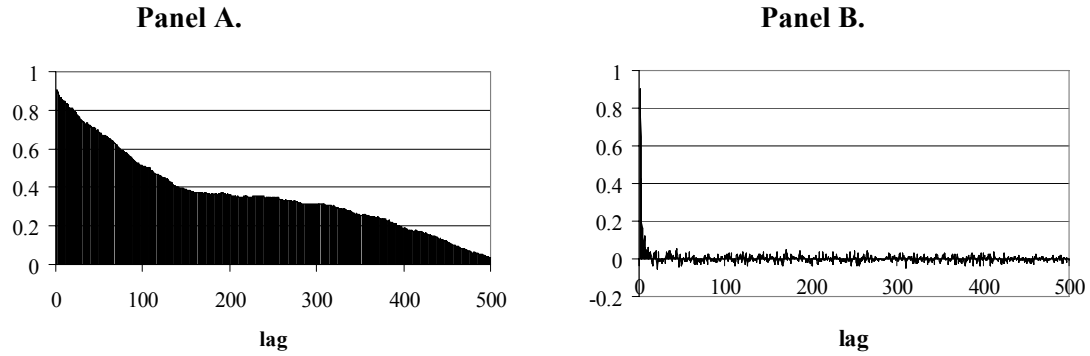
Concerning the differenced SVIX series, the first order autocorrelation coefficient is negative and additionally, the LB-statistics show that we can reject the null hypothesis of all autocorrelation coefficients up to 12, 30 or 60 lags simultaneously being zero. The negative first order autocorrelation of the differenced series can be a sign of mean reversion, as noted by e.g. Skiadopoulos (2004), and moreover, the first precondition for mean reversion, that the series does not contain a unit root, has been shown to apply previously. The reader may note that for the differenced series, some of the autocorrelation results are not significant across all subperiods, however, there is no indication of a reversed pattern for any subperiod, see *table D.9*, appendix D2.1.

[38] The LB statistic tests the joint hypothesis that all autocorrelation coefficients up to a certain lag are simultaneously zero, for more information about the LB test see e.g. Gujarati (2003).

Table 4. Autocorrelation of SVIX and ΔSVIX
The table shows the autocorrelation coefficients for the first three lags, $\rho(1)$, $\rho(2)$ and $\rho(3)$, and the Ljung-Box (LB) statistics for a joint autocorrelation test up to 12, 30 and 60 lags of the SVIX and ΔSVIX series. Numbers in parentheses denote t-statistics and *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively. For results relating to subperiods see *table D.9*, appendix D2.1.

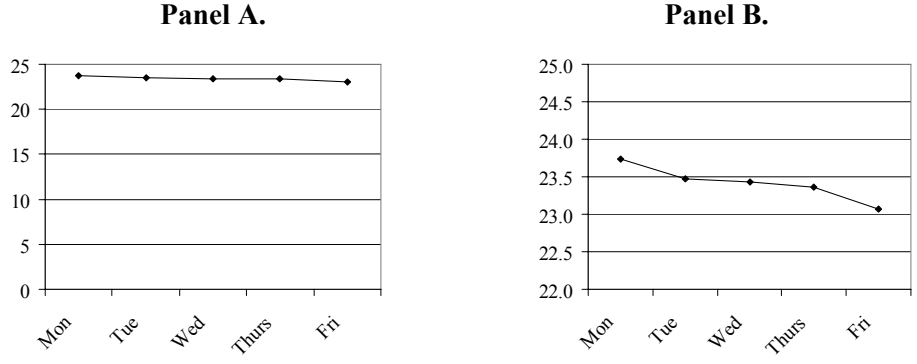
	$\rho(1)$	$\rho(2)$	$\rho(3)$	LB(12)	LB(30)	LB(60)
SVIX	0.905*** (53.24)	0.896*** (52.71)	0.885*** (52.06)	30211***	68211***	118276***
ΔSVIX	-0.114*** (-6.33)	0.003 (0.17)	-0.010 (-0.59)	68***	115***	181***

Figure 4. Autocorrelation Structure of SVIX
Panel A shows the autocorrelation coefficients and **Panel B** the partial autocorrelation coefficients of the first 500 lags of SVIX.



Next, we test the SVIX index for potential weekday and expiration day effects, beginning with a consideration of weekday effects in isolation. *Figure 5* plots the mean values of the level SVIX series throughout the week, and as seen in Panel A there does not seem to be any major differences in SVIX level between the weekdays. However, a magnified picture, Panel B, indicates a slight tendency of a declining SVIX throughout the week, an effect which seems to be largest on Mondays and Fridays. There is no specific economic explanation why the volatility on average should be higher on Mondays and lower on Fridays but the results are nevertheless, similar for all subperiods, see *table D.11*, appendix D2.2. Appendix D2.2 also comprises a more detailed analysis of the pattern seen in *figure 5*.

Figure 5. Average Intraweek SVIX
Panel A shows the average SVIX for each day of the week and **Panel B** shows the same information but with a modified scale on the y-axis.



To more formally evaluate the intraweek effects and to determine their statistical significance we employ a regression approach, similar to that of Fleming et al. (1995). The daily SVIX changes are regressed on day-of-the-week dummy variables, where e.g. $D_{Monday,t}$ is a dummy variable that equals 1 if day t is a Monday and 0 otherwise. The Wednesday dummy variable is excluded from the regression to avoid the dummy variable trap, and hence the following equation is estimated: [39]

$$\Delta SVIX_t = \beta_1 + \beta_2 D_{Monday,t} + \beta_3 D_{Tuesday,t} + \beta_4 D_{Thursday,t} + \beta_5 D_{Friday,t} + \varepsilon_t \quad (5)$$

The regression results, presented in *table 5*, confirm the existence of a significant positive Monday effect and a significant negative Friday effect. However, the adjusted R^2 for the regression is very low at 4.6 percent and one can also question the economical significance of the intraweek pattern as the change throughout the week is less than one percent, which is smaller than the daily standard deviation of the ΔSVIX series, cf. *table 2*, section 6.1. The weekday pattern is consistent for all subperiods, see *table D.12*, appendix D2.2.

Table 5. Regression Results Weekday and Expiration Effects
The table shows the results for the regression between the (daily) changes in SVIX and weekday and expiration dummy variables, i.e. regressions (5) and (6). Note that the coefficients (and t-statistics) relate to the differences between the respective dummy variable and the Wednesday values (i.e. the intercept). For each regression the adjusted R^2 (adj R^2) and number of observations (N) are reported. Numbers in parentheses denote t-statistics based on Newey-West standard errors and *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively. For results relating to subperiods see *table D.12*, appendix D2.2.

intercept	D_{Monday}	$D_{Tuesday}$	$D_{Thursday}$	D_{Friday}	D_{Exp-2}	D_{Exp-1}	D_{Exp}	adj R^2	N
-0.014	0.322***	-0.058	-0.075	-0.352***				0.046	2711
(-0.37)	(5.68)	(-1.06)	(-1.30)	(-6.30)					
0.023	0.278***	-0.086	-0.032	-0.306***	0.104	-0.319**	-0.449***	0.053	2563
(0.56)	(4.69)	(-1.54)	(-0.51)	(-5.20)	(0.84)	(-2.30)	(-3.49)		

[39] The reason for using Wednesday as the benchmark day, i.e. as the intercept in the regression, is that this is the day with least weekday effects judging from *figure 5*, and since the other days will be compared to the intercept we found it the easiest specification to illustrate and interpret.

One possible reason for an intraweek pattern could be existence of expiration effects. There is some evidence of increased volatility surrounding expiration days (Fleming et al., 1995) and since most expiration days are Fridays, there is a possibility that expiration day effects and intra-week effects influence each other. To evaluate whether this apply to the SVIX series we rerun the weekday regression adding dummy variables for the expiration day and the two preceding days, that is:[40]

$$\begin{aligned}\Delta SVIX_t = {} & \beta_1 + \beta_2 D_{Monday,t} + \beta_3 D_{Tuesday,t} + \beta_4 D_{Thursday,t} + \beta_5 D_{Friday,t} \\ & + \beta_6 D_{Exp-2,t} + \beta_7 D_{Exp-1,t} + \beta_8 D_{Exp,t} + \varepsilon_t\end{aligned} \quad (6)$$

If days close to the option expiration day are more volatile than average days the coefficients for the expiration dummy variables, $\beta_6 - \beta_8$, should be negative.[41] This is indeed the case for the expiration day and the closest preceding day in the SVIX series, see *table 5*. However, although statistically significant, the combined size of the expiration effects is rather small, less than one percent. The Monday and Friday effects decrease somewhat, but remain significant after the inclusion of expiration dummy variables, and therefore expiration effects can be ruled out as a complete explanation of the intraweek pattern. The expiration day results from regression (6) are not completely stable over time, and for a more detailed examination the reader is referred to appendix D2.2.

To summarize, the SVIX index exhibits a non-normal distribution, the stationarity of the level series in combination with negative autocorrelation for the differences series indicates a mean-reverting behavior and the strong positive autocorrelation for the level series and can be seen as a sign of both volatility persistence and clustering. Hence, the SVIX index seems to conform to previously established stylized facts about volatility. Moreover, SVIX shows weak signs of an intraweek pattern, with positive Monday and negative Friday effects, and also exhibits modest expiration effects.

6.3 The Relationship between SVIX and OMX Index Returns

As accounted for in the previous research section, there is a well documented negative relationship between volatility indices and their underlying stock indices. This section examines if the tendency of the SVIX and OMX indices to move in opposite direction of each other, as indicated in *figure 2*, section 6.1, can be more formally established. A first indication of the relationship is shown by a fairly strong negative correlation of -0.43 (p-value 0.0000) between daily changes in SVIX and the continuously compounded daily return of the OMX index, defined as $retOMX_t = 100 \times \left(\ln OMX_t - \ln OMX_{t-1}\right)$, where ln denotes natural logarithm. The correlation is

[40] Following Fleming et al. (1995) we also consider post-expiration day dummy variables, but just as Fleming et al. we find them insignificant and hence, do not include them in the final regression.

[41] To understand why they should be negative we refer back to the definition of SVIX as the expected volatility over the next 30 days. When a day with high expected volatility is dropped from the SVIX calculation and instead a day with average volatility at the other end of the period is included, SVIX should decline. Hence, if the expiration day, or the days just before or after, are more volatile than average days, SVIX should decrease when they are not longer covered in the 30 day period of expected volatility that SVIX measures.

roughly the same for all subperiods, however, there is a tendency of somewhat higher values in low volatility regimes, see *table D.13*, appendix D3.1. Moreover, the correlation between SVIX and its underlying index seems be lower than that of existing foreign volatility indices computed for large liquid markets; e.g. Carr and Wu (2006) find a correlation of -0.78 between VIX and S&P 500. However, compared to the correlation of -0.17 between the Greek volatility index, GVIX, and its underlying FTSE/ASE-20 index (Skiadopoulos, 2004), the SVIX and OMX indices exhibit a fairly strong relationship. The differences in correlations are potentially due to differences in size, efficiency and liquidity of the respective market.

To further examine the SVIX and OMX relationship and test whether it encompasses an asymmetric component, we follow the method in Whaley (2000). Daily returns of the OMX index are regressed on daily SVIX changes and on daily SVIX changes when the change is positive, $\Delta SVIX^+$, formally defined as $\Delta SVIX_t^+ = \Delta SVIX_t$ if $\Delta SVIX_t > 0$ and $\Delta SVIX_t^+ = 0$ otherwise. Hence, the regression we run is:

$$retOMX_t = \beta_1 + \beta_2 \Delta SVIX_t + \beta_3 \Delta SVIX_t^+ + \varepsilon_t \quad (7)$$

The coefficient for ΔSVIX captures the relation between changes in SVIX and return on the OMX index whereas the coefficient for $\Delta SVIX^+$ captures a possible asymmetric nature of the relationship. If the stock market's negative reaction to an increase in SVIX is greater (in absolute values) than a positive reaction to a (equally sized) decrease in SVIX, β_3 will be negative and significantly different from zero. The SVIX index can then be said to serve as an investor fear gauge for the Swedish market.

The regression results are displayed in *table 6*. Firstly, one may note that the positive and significant intercept implies that the OMX index on average increases by 0.083 percent if SVIX does not change from one day to the next, which seems reasonable since the OMX index increased over the total sample period. More interestingly, the significant coefficient for ΔSVIX shows that if SVIX falls by 1 percentage unit the OMX index experiences an average incremental increase of 0.564 percent whereas the combined effect of the ΔSVIX and $\Delta SVIX^+$ coefficients shows that a 1 percentage unit increase in SVIX causes an incremental decrease of 0.619 percent of the OMX index. This provides further evidence of the existence of a negative relationship between the SVIX and OMX indices, and also indicates an asymmetric aspect of this relationship, although the difference between the effects on the OMX index from a positive or negative SVIX change is not significant (seen by an insignificant $\Delta SVIX^+$ coefficient). Hence, despite the indication of an asymmetric relationship we cannot find clear evidence of this for the total sample period. However, the SVIX and OMX relationship differs somewhat depending on the time period examined, see appendix D3.2. The negative relationship is slightly stronger during low volatility periods, in line with the correlation results above, and moreover, in those periods we also find a significant asymmetric component. Thus, the market reacts more

strongly to negative SVIX changes than to positive ones during periods of low volatility, while the reaction is (almost) equally strong to positive and negative changes during high volatility periods.

Table 6. Regression Results Relationship the SVIX and OMX indices
The table shows the results for the regression between the (daily) return of the OMX index, (daily) changes in SVIX and (daily) change in the SVIX index when the change is positive,

$$retOMX_t = \beta_1 + \beta_2 \Delta SVIX_t + \beta_3 \Delta SVIX_t^+ + \varepsilon_t \quad (7)$$

For each regression the adjusted R^2 (adj R^2) and number of observations (N) are reported. Numbers in parentheses denote t-statistics based on Newey-West standard errors and *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively. For results relating to subperiods see *table D.14*, appendix D3.2.

intercept	ΔSVIX	$\Delta SVIX^+$	adj R^2	N
0.083**	-0.564***	-0.055	0.182	2794
(2.45)	(-10.59)	(-0.57)		

The negative relationship found between ΔSVIX and *retOMX* is similar to corresponding results for other volatility indices, but in contrast to previous studies it does not (or at least not consistently over time) exhibit an asymmetric pattern, cf. e.g. Whaley (2000) for VXO and S&P 100. Nevertheless, our results are in accordance with some previous studies, such as Giot (2005) who also finds an insignificant asymmetry effect when studying the VXN index (based on the Nasdaq100 index). As mentioned in the previous research section, the asymmetric effect can be caused by investors buying index put options as portfolio insurance in times of financial turmoil, which creates excess demand driving up option prices and hence the volatility index (Whaley, 2000). Applying this explanation to the results for SVIX implies that an OMX index decrease causes investors to buy excessively more put options as insurance in low volatility environments, but not when the volatility already is on a high level. This is in line with the rationale that traders in high volatility environments are unwilling to bid prices aggressively higher even if markets are falling (Giot, 2005). Another reason for a stronger relationship in low volatility environments (both concerning the relationship in general and the asymmetric component) could be that large changes in SVIX and OMX are rarer in a low volatility environment but when they do occur the reaction is stronger. If linked to the time varying risk premium explanation for the negative relationship, a large volatility shock might then generate a larger increase in the risk premium in low volatility environments, which lowers stock prices more than if the shock had taken place in a high volatility environment.

As a final note on the negative relationship between SVIX changes and OMX index returns we perform Granger causality tests in order to get an indication of whether the OMX index leads the SVIX index or vice versa. We proceed in the same fashion as Skiadopoulos (2004) (see testing procedure outlined in appendix D3.3), and the results show unidirectional causality from the OMX

index to SVIX, see *table D.15*, appendix D3.3. This lends some support to the leverage effect explanation for the negative relationship, however, given the complexity of the relationship and its sources, simple Granger tests are not enough to draw any definite conclusions.[42] Our results are nevertheless, in line with those of Skiadopoulos (2004), who finds unidirectional causality from the FTSE/ASE-20 index to GVIX, and Carr and Wu (2006) who find that the S&P 500 index returns can predict future changes in VIX, whereas the opposite is not true.

To sum up this section, we find, in line with previous literature, a negative relationship between changes of SVIX and return of the OMX index. We do not find convincing evidence of a consistent asymmetric effect of the relationship, but find indications of such an effect during low volatility regimes. Finally, Granger causality tests show that the return of the OMX index causes changes in the SVIX index while the reverse is not true.

6.4 Forecasting Ability of the SVIX Index

A good characterization of expected volatility should be able to forecast future realized volatility with adequate accuracy and hence, this section examines the predictive power of SVIX. We employ a regression approach and restrict the overall evaluation to comparing SVIX only to historical realized volatility. We let $RV_{t,t+30}$ ($RV_{t-30,t}$) denote the future (historical) realized volatility over a 30 calendar day window stretching from t to t+30 (t-30 to t) and calculate it according to the following equation:[43]

$$RV_{t,t+30} = 100 \times \sqrt{\frac{365}{30}\sum_{i=1}^{30}\left[\ln\left(S_{t+i} \big/ S_{t+i-1}\right)\right]^2} \quad (8)$$

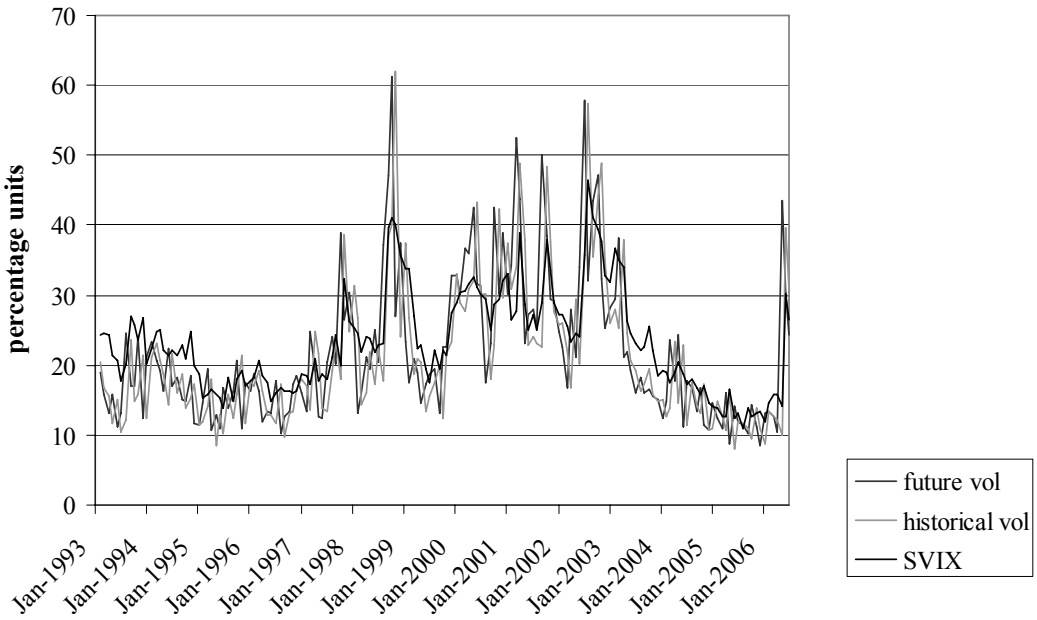
Where ln denotes natural log and S_{t+i} is the index level i calendar days after day t.

To mitigate problems arising from overlapping data we use a sampling procedure similar to that recommended by Christensen and Prabhala (1998). [44] For each month only the realized (future and historical) volatility and SVIX observations calculated seven trading days after the option expiration date are used.[45] Since the total time period is 13½ years, and due to some missing observations in the SVIX series, this yields 151 non-overlapping observations of each volatility series. All three series are shown in *figure 6*, where it can be seen that SVIX most often is higher than realized volatility (both historical and future). The most noticeable exceptions are during high spikes of realized volatility, e.g. the increased volatility caused by the terror attack September 11, 2001 could not be foreseen by SVIX.

[42] Several recent studies have tried to disentangle the leverage and time-varying risk premium effects and also tried to determine to which most of the asymmetry effect can be attributed, see e.g. Bekaert and Wu (2000).
[43] Since SVIX by construction represents the expected volatility over the future 30 calendar days, we use a 30 calendar day window when calculating realized volatility to avoid a maturity mismatch problem. Equation (8) follows the industry standard, as stated in Carr and Wu (2006), and calculates the realized volatility as the return squared, without demeaning the return, and annualizes it according to the actual/365 day-counting convention.
[44] If equation (8) is used to compute daily realized volatility the observations for two consecutive days will be almost identical since they share all return observations but one.
[45] This day will most often fall on a Tuesday or Wednesday and therefore the use of these observations limit the influence of potential expiration day effects and weekday bias in the SVIX series.

The descriptives in *table D.16*, appendix D4.1, further show that the mean value of SVIX is slightly above that of realized volatility whereas the maximum (minimum) value is larger (smaller) for realized volatility. The greater dispersion of realized volatility is also seen by a greater standard deviation.

Figure 6. Development of SVIX, Realized Future Volatility and Historical Volatility
The figure shows monthly observations of SVIX, future realized volatility, $RV_{t,t+30}$, and historical volatility, $RV_{t-30,t}$. For each month the observations seven days after the expiration of that month's options are used. The pattern is the same using daily observations.



To obtain a first indication of the relationship between SVIX / historical volatility and future realized volatility simple correlations are run. These correlations show that both SVIX and historical volatility contain information about future realized volatility and that the linkage with future realized volatility is somewhat stronger for SVIX, 0.7, than for historical volatility, 0.6 (p-values 0.000). Next, to more formally assess the ability of the SVIX index to forecast future realized volatility, we follow the method of Christensen and Prabhala (1998) and estimate the following three regressions: [46]

$$\ln RV_{t,t+30} = \alpha_0 + \alpha_1 \ln SVIX_t + \varepsilon_t \quad (9)$$

$$\ln RV_{t,t+30} = \alpha_0 + \beta_1 \ln RV_{t-30,t} + \varepsilon_t \quad (10)$$

$$\ln RV_{t,t+30} = \alpha_0 + \alpha_1 \ln SVIX_t + \beta_1 \ln RV_{t-30,t} + \varepsilon_t \quad (11)$$

[46] Logged volatility series are used for the regression approach since they conform better to normality than ordinary series in levels, see *table D.16*, appendix D4.1, which shows summary statistics for both logged and level series. Note also that Christensen and Prabhala (1998), in addition to the method described here, propose use of instrumental variable (IV) technique to reduce potential impact of error-in-variables (EIV) problems. However, since the method used for the SVIX calculation does not depend on the accuracy of a specific option pricing model, potential EIV problems should be substantially less severe in our study. Moreover, Corrado and Miller (2005) argue that the EIV problem has disappeared from the CBOE volatility index data since 1995, and additionally, that IV regressions do not consistently improve ordinary OLS regressions.

Three hypotheses concerning SVIX are tested using equation (9). Firstly, if SVIX contains information about future realized volatility the coefficient for lnSVIX should be significantly different from zero. Secondly, if SVIX is an unbiased forecast the intercept should be zero and the coefficient for lnSVIX should equal one. Thirdly, if SVIX is an efficient predictor the regression residuals, ε_t, should be white noise, uncorrelated with any variable in the market's information set, and the variance of the residuals should be constant over time. For comparison purposes, the predictive ability of historical volatility is examined applying the same hypotheses on regression (10). Lastly, to more precisely determine how the information content of SVIX compares to that of historical volatility three hypotheses, similar to those above, are tested using regression (11). Firstly, if SVIX subsumes all information of historical volatility the coefficient for the historical volatility should be zero. Secondly, if SVIX is an unbiased predictor the joint hypothesis of a zero intercept, zero coefficient for historical volatility and unity coefficient for lnSVIX, should hold true. Thirdly, if SVIX is an efficient predictor, the same requirements on the error term as outlined for regression (9) above should apply.

Results for all regressions are displayed in *table 7*. Concerning regression (9) and (10) and the first hypothesis, the lnSVIX coefficient of 1.018 as well as the $\ln RV_{t-30,t}$ coefficient of 0.641 are significantly different from zero, indicating that both volatility measures contain information about future realized volatility. Even so, in both cases F-tests reject the joint hypothesis of a zero intercept and an lnSVIX / $\ln RV_{t-30,t}$ coefficient equal to one, showing that both forecasts are biased. Further, the Durbin-Watson statistics and White's general heteroscedasticity tests show no autocorrelation and constant variance of the error terms, i.e. both volatility measures are efficient estimators of future realized volatility. However, even if the results for the individual regressions for SVIX and historical volatility show that these measures are very similar in that they both provide biased (but efficient) forecasts, there are some indications that SVIX is a slightly better predictor. Firstly, in regression (9) the lnSVIX coefficient is not statistically different from one and the intercept is not significantly different from zero using individual t-tests, whereas for the historical volatility regression (10) both corresponding t-tests are rejected. Secondly, regression (9) has somewhat higher explanatory power in terms of adjusted R^2, 0.530 compared to 0.403.

Table 7. Regression Results Volatility Forecasting

The table shows the results for the regressions between the monthly (seven days after option expiration) series of logged future realized volatility, ln$RV_{t,t+30}$, logged SVIX, lnSVIX, and / or logged historical volatility, ln$RV_{t-30,t}$, i.e. the following regressions:

$$\ln RV_{t,t+30} = \alpha_0 + \alpha_1 \ln SVIX_t + \varepsilon_t \quad (9)$$

$$\ln RV_{t,t+30} = \alpha_0 + \beta_1 \ln RV_{t-30,t} + \varepsilon_t \quad (10)$$

$$\ln RV_{t,t+30} = \alpha_0 + \alpha_1 \ln SVIX_t + \beta_1 \ln RV_{t-30,t} + \varepsilon_t \quad (11)$$

For each regression the adjusted R^2 (adj R^2), number of observations (N), Durbin-Watson statistic (DW), statistic for White's general heteroscedasticity test (White's) and F-statistic corresponding to biasedness tests (F(obs)) are reported. The F-statistic is defined in a similar way as the F-statistic used for the Granger causality tests, see appendix D3.3. Numbers in parentheses denote t-statistics (except for White's and F(obs) where they denote p-values) and *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively. The results are robust to estimation using Newey-West standard errors.

regression	intercept	lnSVIX	ln$RV_{t-30,t}$	adj R^2	N	DW	White's (p-value)	F(obs) (p-value)
eq. (9)	-0.169 (-0.70)	1.018*** (13.06)		0.530	151	1.888	0.16 (0.9231)	11.49 (0.0000)
eq. (10)	1.087*** (5.77)		0.641*** (10.11)	0.403	151	2.238	0.22 (0.8958)	16.67 (0.0000)
eq. (11)	-0.194 (-0.74)	1.055*** (6.35)	-0.030 (-0.25)	0.527	151	1.853	0.93 (0.9681)	7.63 (0.0001)

The encompassing regression (11) enables additional comparison between the two measures. The lnSVIX coefficient is 1.055 and still significantly different from zero, indicating that SVIX contains information about future volatility, but the coefficient for historical volatility is in this regression insignificant. This suggests that adding historical volatility to regression (9) does not bring any incremental information; the information in historical volatility seems to be subsumed by SVIX. Moreover, the adjusted R^2 for specification (11) is slightly less than the one obtained for regression (9), reinforcing the conclusion that historical volatility does not improve the forecast provided by SVIX. Finally, one can note that the encompassing model still provides a biased, although efficient, forecast, as indicated by the F-test, and the Durbin-Watson statistic and White's general heteroscedasticity test.

The main conclusion from the regression approach is that SVIX is a biased (yet efficient) predictor of future realized volatility and that no incremental information can be gained by adding historical volatility to the forecast.[47] That SVIX, as a measure of expected volatility, produces a superior forecast of future realized volatility compared to that of a model based on historical data is in line with the consensus of the most recent literature, see e.g. Poon and Granger (2003). Concerning the question of biasness the view in previous literature is more divided, some authors find that implied volatility and

[47] As a further robustness check of our results we conduct out-of-sample forecast tests. These tests support the main results accounted for here and give no indication that the predictive power of SVIX should be reversed in the later part of the sample. The results are also stable to various specifications of realized volatility, see further discussion in appendix D4.2.

volatility indices provide an unbiased forecast, see e.g. Christensen and Strunk Hansen (2002), while others, similar to us, find that the forecast is biased, see e.g. Fleming (1998).

Even if it can be concluded that SVIX provides a biased forecast, the direction of the bias has not yet been discussed. *Figure 6* shows that SVIX most often is on a somewhat higher level than future realized volatility, which is in line with previous research that notes an upwards bias of implied volatility. An upwards bias would however, imply a coefficient slightly less than one for the lnSVIX parameter and / or a negative intercept in regression (9), see also Fleming (1998). Somewhat in contrast to that we find the lnSVIX coefficient to be slightly larger than one, then again combining this coefficient with the negative intercept may produce results consistent with an upwards bias. Furthermore, that the lnSVIX coefficient is greater than one could be due to influences from the peak observations with extremely high realized volatility not foreseen by SVIX, for instance September 11, 2001. Removing such observations and re-estimating the regressions renders the lnSVIX coefficient slightly less than one while the main conclusions concerning biasness and efficiency remain the same, see appendix D4.2 for an elaboration of this matter. Altogether, indications are found of an upwards direction of the SVIX forecasting bias.

Worth noting is also the important distinction between unbiasedness and predictive power; even if the forecast is biased its predictive power may still be good if correction of the bias is possible, i.e. if the bias is stable over time. In order to establish if this is the case, the source of the bias needs to be determined, something that may prove to be difficult. Two explanations put forward in previous studies might be able to account for the bias of SVIX, namely inefficient markets (see e.g. Poon and Granger (2003)) and variance risk premium (see e.g. Fleming (1998)). It is possible that the bias of SVIX originates from a not fully efficient market, since especially for the early years of the sample the liquidity of the OMX index options might have been insufficient. However, this explanation does not imply a certain direction of the bias, whereas the variance risk premium explanation is able to explain an upwards bias, since empirical evidence suggests that the risk premium for variance is negative (Carr and Wu, 2006). Independent of which explanation might be true in this case, both explanations have been found to imply a change in size of the bias over time, either since the efficiency of the market changes or since the variance risk premium varies over time. Thus, correction of the bias inherent in SVIX might be difficult.

To sum up, we find SVIX to be a slightly upwards biased, yet efficient, predictor of future realized volatility. SVIX is also found to be superior to historical volatility when it comes to predictive ability and even subsumes the information contained in historical volatility.

6.5 Volatility Transmission between the Swedish, US and Eurozone Markets

The substantial integration of financial markets worldwide makes it probable that the expected volatility on the Swedish market is sensitive to volatility changes in other markets. This section therefore examines to what extent the expected volatility on the Swedish market (as measured by SVIX) is affected by the expected volatility in the US and Eurozone markets (as measured by the VIX and VSTOXX indices). [48] There is no clear-cut theoretical case whether VIX or VSTOXX should affect SVIX the most.[49] One could argue that VSTOXX should be able to explain a larger part of the variation in SVIX since the Swedish and Eurozone markets are more integrated (cf. Baele, 2003), but considering the importance of the US market it is possible that its influence is greater (cf. Aboura, 2003). Furthermore, the effects from VSTOXX and VIX may be difficult to completely disentangle since they also interact with each other.

Existence of volatility co-movements across the three markets are indicated by a graphical inspection of the indices. *Figure D.3* and *D.4*, appendix D5.1, illustrate that SVIX, VIX and VSTOXX share the same general trends, except before 1996 for the SVIX and VIX indices. Moreover, SVIX is for the most part of the sample on a slightly higher (lower) level than VIX (VSTOXX), cf. *table 1* and *2*, section 6.1. In the subsequent analysis it is important to note the time-zone differences between Europe and the US; events during US trading hours might not affect SVIX and VSTOXX until the next day, while events during European trading hours affect VIX the same day. [50] To account for this we will also consider lagged values of VIX, VIX_{t-1}.

Concerning cross-correlations between the level series of SVIX, VIX and VSTOXX, all correlations are high, around 0.9, reinforcing that expected volatility have evolved similarly over time, see *table 8*. Moreover, *table D.17*, appendix D5.2, shows that the correlations increase over time (although not consistently for VIX and SVIX in the last subperiod) indicating that the general volatility level in the different countries have converged, which is in line with a hypothesis of increased financial interaction. Concerning the correlations for series of daily differences these are consistently lower than those for the levels series, which is to be expected since it should be easier to match the general level of volatility across markets than the exact day to day changes. Moreover, the lower correlations between ΔVIX and ΔSVIX / ΔVSTOXX when using lagged VIX values, show that the relationship between the US and European markets seems to be more a contemporaneous one, despite the trading

[48] Note that since data for VSTOXX is only available from January 1999, the analysis in this section focuses on the period January 1999 to June 2006.
[49] Since Sweden is a rather small market compared to the US and Eurozone, we believe it to be unlikely that Sweden to any greater extent influences the other two markets, however, to verify that this is the case we later in this section explicitly consider causality.
[50] Trading hours for S&P 500 index options are 8:30 a.m. - 3:15 p.m. Chicago time (CBOE, 2007) which corresponds to 3:30 p.m. - 10:15 p.m. Swedish time. Compared to the trading hours for the Swedish derivatives market, 9:00 a.m. - 5:20 p.m. (OMX, 2007b) this gives an overlap of only about two hours.

hour discrepancy. Further, the higher correlation between ΔSVIX and ΔVSTOXX compared to ΔSVIX and ΔVIX suggests a somewhat stronger relationship between the Swedish and Eurozone market. Considering the temporal development of the correlations for the differenced series, they stay roughly the same over time, however, VIX seems to have a slightly greater impact during times of high volatility and falling markets, see *table D.17*, appendix D5.2.

Table 8. Correlations SVIX, VIX and VSTOXX
The table shows the correlations between daily levels and daily differences (diffs) of SVIX, VIX (also lagged one day, VIX_{t-1}) and VSTOXX for the time period January 1999 to June 2006. All correlations have a p-value of 0.0000. For results relating to subperiods see *table D.17*, appendix D5.2.

	SVIX and VIX	SVIX and VIX_{t-1}	SVIX and VSTOXX	VSTOXX and VIX	VSTOXX and VIX_{t-1}
levels	0.91	0.91	0.88	0.90	0.90
diffs	0.30	0.24	0.50	0.49	0.24

The graphical inspection and correlations of SVIX, VIX and VSTOXX indicate existence of volatility co-movements, and to more thoroughly investigate the magnitude and speed of this volatility transmission we follow the procedure outlined in Aboura (2003). Specifically, we regress daily changes of SVIX on daily changes of VIX and / or VSTOXX using the following three equations:[51]

$$\Delta SVIX_t = \alpha_0 + \beta_1 \Delta VIX_t + \beta_2 \Delta VIX_{t-1} + \varepsilon_t \quad (12)$$

$$\Delta SVIX_t = \alpha_0 + \gamma_1 \Delta VSTOXX_t + \gamma_2 \Delta VSTOXX_{t-1} + \varepsilon_t \quad (13)$$

$$\Delta SVIX_t = \alpha_0 + \beta_1 \Delta VIX_t + \beta_2 \Delta VIX_{t-1} + \gamma_1 \Delta VSTOXX_t + \gamma_2 \Delta VSTOXX_{t-1} + \varepsilon_t \quad (14)$$

All regression results are reported in *table 9*. The results for regressions (12) and (13), which examine the impact on SVIX from the foreign indices separately, show that there is both a contemporaneous and a lagged positive and significant effect from VIX and VSTOXX to SVIX. Hence, evidence is provided of a transmission of expected volatility from both the US and Eurozone markets to the Swedish market. The contemporaneous effect is larger than the lagged one for both indices, however, concerning VIX the contemporaneous effect is only slightly larger than the lagged one (0.280 vs. 0.218) whereas the contemporaneous effect for VSTOXX is about four times the size of the lagged one (0.380 vs. 0.095). Hence, some time is needed for the Swedish market to incorporate US information, while the transmission process from the Eurozone is somewhat faster, even if all information is not fully incorporated instantaneously. The delay of the information flow from the US is however, reasonable due to the time zone differences between the countries. Lastly, from regressions (12) and (13) one can also note that VSTOXX has higher explanatory power in terms of

[51] Up to four lags of ΔVIX and ΔVSTOXX are tested for significance (due to time-zone differences and since the volatility transmission might not be instant) however, since lag two to four were found to be insignificant, they are not included in the final models.

adjusted R^2, 0.27 compared to 0.15. This suggests that VSTOXX is better at explaining movements in SVIX, and that the Swedish market is more aligned with the Eurozone market than the US market.

Table 9. Regression Results Volatility Transmission
The table shows the results for the regressions between daily changes in SVIX, VIX and / or VSTOXX for the time period January 1999 to June 2006. The following regressions are estimated:

$$\Delta SVIX_t = \alpha_0 + \beta_1 \Delta VIX_t + \beta_2 \Delta VIX_{t-1} + \varepsilon_t \quad (12)$$
$$\Delta SVIX_t = \alpha_0 + \gamma_1 \Delta VSTOXX_t + \gamma_2 \Delta VSTOXX_{t-1} + \varepsilon_t \quad (13)$$
$$\Delta SVIX_t = \alpha_0 + \beta_1 \Delta VIX_t + \beta_2 \Delta VIX_{t-1} + \gamma_1 \Delta VSTOXX_t + \gamma_2 \Delta VSTOXX_{t-1} + \varepsilon_t \quad (14)$$

For each regression the adjusted R^2 (adj R^2) and number of observations (N) are reported. Numbers in parentheses denote t-statistics based on Newey-West standard errors and *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively. For results relating to subperiods see *table D.18*, appendix D5.3.

regression	intercept	ΔVIX_t	ΔVIX_{t-1}	$\Delta VSTOXX_t$	$\Delta VSTOXX_{t-1}$	adj R^2	N
eq. (12)	-0.050**	0.280***	0.218***			0.151	1403
	(-2.45)	(9.19)	(7.60)				
eq. (13)	-0.034**			0.380***	0.095***	0.267	1505
	(-1.99)			(15.53)	(4.65)		
eq. (14)	-0.045**	0.097***	0.101***	0.318***	0.055**	0.265	1379
	(-2.49)	(2.88)	(2.81)	(11.09)	(1.97)		

To further compare the transmission effects from VIX and VSTOXX, we consider the combined regression (14). In this regression both the contemporaneous and lagged effects of VIX and VSTOXX remain significant, but the magnitude of each effect decreases somewhat compared to the individual regressions. The variable with the greatest impact on the SVIX index is the contemporaneous VSTOXX, with a coefficient of 0.318, followed by lagged and contemporaneous VIX, with coefficients of 0.101 and 0.097, respectively. The effect from the lagged VSTOXX variable is the smallest, only 0.055. These results indicate that the VSTOXX index is able to explain more of the variation in SVIX compared to VIX, which is further supported by the fact that the adjusted R^2 for regression (14) is of the same size as the one obtained for regression (13), indicating that adding VIX to the individual VSTOXX regression (13) does not increase the explanatory power.

Hence, the overall results imply that the Swedish market is primarily affected by contemporaneous movements in the Eurozone market, but that also US influences, both contemporaneous and lagged, are of importance. That the Swedish market seems to be more integrated with the Eurozone than the US market is in line with the reasoning that intra-regional patterns and increased financial integration within the EU make these markets more correlated, since they tend to react simultaneously to new information. However, our results are somewhat in contrast to the pattern found by Aboura (2003), who concluded that the French and German markets are more correlated with the US market than with each other.

One reason that we find a stronger relationship between the Swedish and Eurozone markets could be that the VSTOXX captures Europe specific events that affects Sweden, and thereby SVIX, but has no particular effect on the US market, and that the events originating in the US generally affect the Swedish and Eurozone markets in the same way, hence, also that information is captured by VSTOXX and possibly transmitted to SVIX through that channel. To more formally determine the structure of the international lead-lag relationship between the three markets we employ Granger causality tests in line with Aboura (2003). These tests show that the flow of volatility transmission seems to go from the US market to the Swedish and Eurozone markets and from the Eurozone market to Sweden, but not in the opposite directions, see appendix D5.4. On a related matter one can note that although the Swedish market is too small to influence the Eurozone and US markets, it is nevertheless, integrated enough with the world markets to be affected by them, in contrast to the smaller Greek market which was found not to be affected by the US market (Skiadopoulos, 2004).

Re-estimating regression (12) – (14) for different subperiods, we find three primary differences in the transmission pattern depending on the prevailing volatility regime and over time. Firstly, we find signs of greater volatility transmission in high volatility environments, which is in line with King and Wadhwani (1990) and Baele (2003) who conclude that the links between markets become stronger in times of high volatility. Secondly, we find the largest effect from the US market during high volatility and falling markets, i.e. even if the general volatility transmission increases during times of high volatility, the influence from the US market becomes even more pronounced in falling markets. This is in line with Cifarelli and Paladino (2001) who conclude that larger markets become more influential in times of financial turbulence. Thirdly, the diffusion of information from the US and Eurozone market takes longer time in high volatility environments and falling markets. One possible reason for this might be that in times of financial turmoil it is more difficult to correctly interpret the signs originating from other markets and under- as well as overreactions to information might be more common. See appendix D5.3 for further discussion and regression results.

To summarize the conclusions from this section, SVIX, as a measure of the expected volatility on the Swedish market, seems to be more affected by the expected volatility on the Eurozone market (VSTOXX) than the one on the US market (VIX). The influence from both markets is largely contemporaneous, but the lagged effect from the US market is also quite influential. We find that the general volatility levels have converged over time and moreover, that the pattern of volatility transmission depends on the prevailing market conditions. We observe a higher degree of transmission in high volatility environments, a larger influence of the US market in times of falling stock markets and a longer information diffusion process (both for European and US information) when volatility is high and the markets are falling.

7 CONCLUSION

The main purpose of this paper has been to construct and examine an index aimed at measuring the expected 30 calendar day volatility on the Swedish market. This index, SVIX, was constructed from OMX index option prices by applying the same method as used in the VIX calculation, and the subsequent examination was conducted in two dimensions. Firstly, we assessed whether it was achievable at all to construct a volatility index based on Swedish options data, and secondly, we examined whether SVIX could be deemed to provide a good characterization of the expected volatility on the Swedish market, and in connection to that considered related features such as the relationship with its underlying stock index, the OMX index, and with two existing volatility indices, VIX and VSTOXX.

The first objective was approached directly through the actual construction of the index. The lower liquidity on the Swedish option market compared to its US equivalent made it impossible to obtain a SVIX observation for each trading day. However, for January 1993 to June 2006, we were able to construct SVIX for 89 percent of all trading days and hence, the liquidity problem was not large enough to render the construction exercise futile. Furthermore, for the days where SVIX construction was possible, the index was calculated using a rather large amount of OTM options, which should ensure that the resulting SVIX series comprises a fairly good estimate of true expected future volatility.

To address the second objective and to further assess whether the SVIX index is a good indicator of expected volatility, we evaluated the index in regards to certain well known features of volatility. The overall implication from these examinations was that the properties of the SVIX index conformed well to those of foreign volatility indices and volatility in general. Firstly, we found that SVIX was non-normally distributed and that it exhibited signs of both volatility clustering and mean reversion, and hence conformed to previously established properties. However, we also found weak signs of an intraweek pattern, as well as modest expiration effects. Secondly, SVIX was shown to have a negative relationship with the returns of the underlying OMX index, but in contrast to most previous literature we could not detect a consistent asymmetric component in the relationship. It might be the case that the relationship between expected volatility and return of a market index is of a somewhat different nature for the Swedish market compared to other countries. Thirdly, and most interestingly, we found that SVIX provided an efficient and only slightly biased forecast of future realized volatility, and that no additional information could be gained by adding historical volatility to the forecasting model. This is indeed a strong indication that the SVIX index is a good indicator of expected future volatility. Fourthly, a comparison between SVIX, VIX and VSTOXX illustrated that the overall development of expected volatility on the Swedish market was rather similar to that of the US and Eurozone markets, and that SVIX was somewhat more affected by the Eurozone (VSTOXX) than the US market (VIX).

The influence from both markets was found to be largely contemporaneous, but the lagged effect from the US market was also rather influential. Moreover, the pattern of volatility transmission was found to depend on prevailing market conditions.

To conclude, our findings are that it is possible to construct a volatility index, SVIX, based on OMX index options and that this index provides a good estimate of the true expected volatility. Moreover, we find that SVIX exhibits desirable and frequently found characteristics of expected volatility. Hence, we believe that the evidence put forward in this paper is in favor of SVIX being a good indicator of expected future volatility on the Swedish market. The index could therefore be used as an indicator of the sentiments of the Swedish market and could additionally be used for trading strategies, risk management purposes and in derivatives pricing.

8 SUGGESTIONS FOR FURTHER RESEARCH

Our discussion concerning the expected volatility index for the Swedish market, SVIX, has been of a broad character rather than an in-depth analysis of a specific area and hence, many interesting angles remain to be examined. Each subsection in the result part is appropriate for more detailed studies and numerous things can be evaluated: the interaction between the SVIX and OMX indices can be studied more thoroughly as well as the underlying reason for this relationship; the assessment concerning forecasting ability can be extended to include several other forecasting measures such as GARCH models and other more complex techniques, and it can also be conducted using more sophisticated evaluation methods than the ones used in this paper; the comparison with volatility indices for other markets and the study concerning international transmission can be expanded to evaluate additional indices such as VXN, VDAXnew, VSMI etc. as well as broadened to examine the underlying reasons for these co-movements. Another interesting area for further research is applications for which the SVIX index could be used. For example the success of SVIX as an indicator in various trading strategies, and pricing and demand of futures and options on SVIX, as well as the performance of those instruments when used for speculation or hedging purposes are topics well suited for further studies.

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DATA SOURCES

CBOE [www.cboe.com]: VIX Index Data

OMX Group: OMX Index and OMX Index Option Price Data

SIX: SIXVX Index Data

STOXX [http://www.stoxx.com]: VSTOXX Index Data

Sveriges Riksbank [www.riksbank.se]: STIBOR 1M Interest Rate Data

APPENDIX A: LIST OF VOLATILITY INDICES

Table A.1 accounts for the most well known volatility indices, as well as some other indices mentioned in this paper. Most of the volatility indices attempt to measure the expected 30 day volatility on the respective market; the exception is VX6 which uses a time horizon of six months. The volatility indices can be divided into two groups concerning their calculation method. The model dependent indices are calculated using the BS model to derive implied volatilities, whereas the non-model dependent indices are calculated directly from option prices using a method similar to the one described in section 5.1 – 5.2 (concerning VIX).

Table A.1. Volatility Indices
The table shows the abbreviation as well as the name in its long form for each volatility index, the market which the index seeks to measure the expected volatility on, the underlying stock index, whether the index calculation is model dependent or not, and where additional information about the index can be obtained.

Volatility Index	Long Name	Market	Underlying Stock Index	Model Dependence	For More Information
VIX	CBOE Volatility Index	US	S&P 500	No	http://www.cboe.com/micro/vix/introduction.aspx
VXO	Until 2003: CBOE Volatility Index	US	S&P 100	Yes	http://www.cboe.com/micro/vix/introduction.aspx
VXN	CBOE Nasdaq Volatility Index	US	Nasdaq-100	No	http://www.cboe.com/micro/vxn
VXD	CBOE DJIA Volatility Index	US	Dow Jones Industrial Average	No	http://www.cboe.com/micro/vxd
VSTOXX	DJ EURO STOXX 50 Volatility Index	Eurozone	Dow Jones EURO STOXX 50	No	http://www.stoxx.com/indices/download.html?symbol=V2TX
VSMI	Volatility Index on the SMI	Switzerland	SMI	No	http://www.swx.com/trading/products/indices/stock_indices/vsmi_indices_en.html
VDAX-NEW	Volatility Index on the DAX	Germany	DAX	No	http://deutsche-boerse.com/dbag/dispatch/en/kir/gdb_navigation/trading_members/45_Indices/36_volatility_indices
VDAX	(Old Volatility Index on the DAX)	Germany	DAX	Yes	http://deutsche-boerse.com/dbag/dispatch/en/kir/gdb_navigation/trading_members/45_Indices/36_volatility_indices
VX1	(French Implied Volatility Index)	France	CAC 40	Yes	http://www.euronext.com/editorial/wide/0,5371,1732_201302333,00.html
VX6	(French Implied Volatility Index)	France	CAC 40	Yes	http://www.euronext.com/editorial/wide/0,5371,1732_201302333,00.html
GVIX	(Greek Implied Volatility Index)	Greece	FTSE/ASE-20	Yes	Only theoretical index, not publicly available, see Skiadopoulos (2004)
SIXVX	SIX Volatility Index	Sweden	OMX	Yes	http://www.six.se

APPENDIX B: DATA RELATED TABLES AND GRAPHS

Table B.1. Summary Statistics for the OMX Index, STIBOR 1M, VIX, VSTOXX and SIXVX
The table shows the total number of observations (N), average number of observations per year (ave year N), mean, median, maximum, minimum and standard deviation (std dev) for daily close observations of the (split-adjusted) OMX index, STIBOR 1M interest rate, VIX, VSTOXX and SIXVX.

	N	ave year N	mean	median	max	min	std dev
OMX	3387	251	643	646	1539	171	295
STIBOR 1M	3387	251	4.7%	4.1%	11.3%	1.6%	2.3%
VIX	3399	252	19.33	18.47	45.74	9.31	6.71
VSTOXX	1906	254	25.50	24.08	62.73	11.60	10.05
SIXVX	536	-	14.99	13.97	32.54	9.64	3.82

Table B.2. Summary Statistics for OMX Index Options
The table shows the mean, median, maximum, minimum and standard deviation (std dev) for the daily amount of options measured as number of midquote (i.e. bid and ask) (**Panel A**) and close prices (**Panel B**). Note that these figures are based on a database including observations on all options starting 75 days prior to their respective expiration. Due to computational difficulties and since we in some occasions use different options in different specifications, this database will slightly overestimate the number of options actually used. Moreover, note that a substantial amount of the observations will not be used specifically in the SVIX calculation since they e.g. are in-the-money.

Panel A.

period	mean	median	max	min	std dev
1993 – 2006	78	70	197	8	37
1993	38	37	60	24	8
1994	54	50	91	32	13
1995	61	60	93	37	14
1996	66	66	110	42	15
1997	111	106	186	69	29
1998	101	100	188	50	35
1999	100	99	197	62	30
2000	104	96	183	53	33
2001	122	119	186	41	28
2002	114	115	175	80	23
2003	69	66	130	16	26
2004	42	40	73	8	10
2005	46	45	83	20	11
2006	48	48	69	18	11

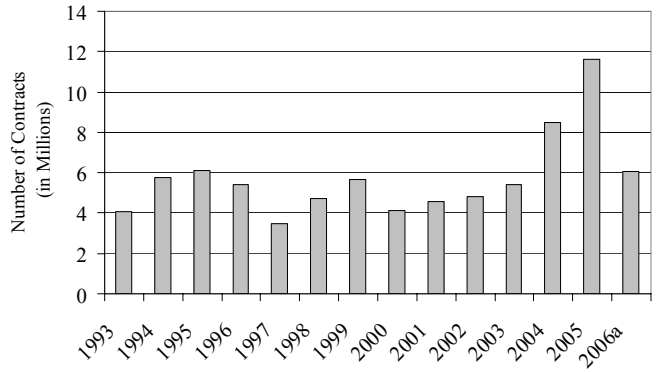
Note: For year 2006 only observations for January to June are included.

Panel B.

period	mean	median	max	min	std dev
1993 – 2006	42	41	104	14	12
1993	24	23	35	14	3
1994	33	33	49	20	5
1995	39	38	62	19	7
1996	44	43	64	27	7
1997	55	54	97	33	11
1998	50	50	83	27	11
1999	51	49	104	28	11
2000	44	43	81	23	10
2001	53	51	87	25	12
2002	49	48	86	30	12
2003	38	37	58	20	7
2004	36	35	57	20	7
2005	37	35	59	23	7
2006	40	39	67	26	9

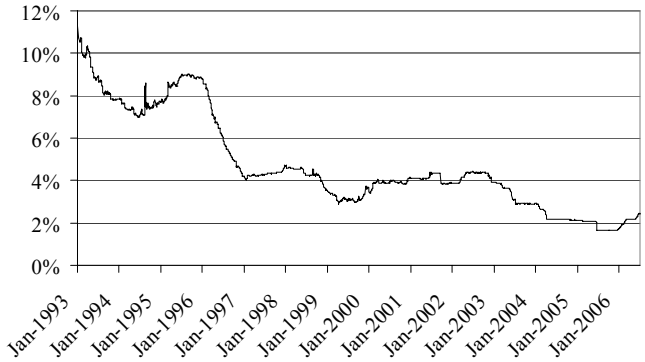
Note: For year 2006 only observations for January to June are included.

Figure B.1. OMX Index Option Trading Volume
The figure shows the total OMX index option trading volume (in million contracts) for each year from 1993 to 2006. Note that this figure relates to the total amount of contracts, i.e. also the contracts not included in the actual SVIX calculation.



Note: For year 2006a only observations for January to June are included.

Figure B.2. Development of STIBOR 1M
The figure shows daily observations of the STIBOR 1M interest rate for the period January 1993 to June 2006.



APPENDIX C: STATISTICAL CONSIDERATIONS AND ASSUMPTIONS

This appendix reviews the considerations and assumptions underlying the statistical methods used to assess the properties of SVIX. First, the stationarity property is evaluated, next follows a discussion of the Ordinary Least Square (OLS) assumptions and the appendix end with a discussion concerning normality of the error term.

C1 Stationarity of Variables

To avoid spurious regression all variables included must be stationary. When testing the stationarity property, we first employ the most general version of the standard Dickey-Fuller (DF) test (i.e. random walk with a drift around a stochastic trend) and if the trend is found to be insignificant we subsequently exclude that parameter. Moreover, if the residuals from the DF test are correlated we use an Augmented Dickey-Fuller (ADF) test instead (where the lag length is determined as the smallest number of lags that render the error terms uncorrelated). The null hypothesis of a unit root is in all cases rejected at 5 percent significance level and hence, all variables used in the regressions for this study fulfill the stationary criteria. Although, one could note that some of the variables, e.g. VSTOXX and OMX, are non-stationary in their original level form, nevertheless, the differenced form (which is the one used for the regressions) is always stationary.

C2 OLS Assumptions

For the results from OLS regressions to be valid a number of assumptions must be fulfilled. If a particular assumption is found not to be fulfilled we describe the procedures taken to reduce potential problems resulting from this violation. For a more extensive discussion of the OLS assumptions we refer the reader to e.g. Brooks (2002).

1. Zero mean value of error term. All our regressions include an intercept and hence, by design fulfill this assumption.

2. Homoscedasticity. In order to detect occurrence of heteroscedasticity we use White's general heteroscedasticity test. For most regressions (except forecasting of future realized volatility) the null hypothesis of homoscedasticity is rejected. Consequently, we use Newey-West autocorrelation and heteroscedasticity consistent standard errors when estimating these regressions.

3. No autocorrelation between the error terms. To test for autocorrelation we use the Durbin-Watson d-test. The Durbin-Watson d-test rests on several assumptions, and the SVIX series violates the assumption of no missing values in the data, however, for our purposes we nevertheless believe that this test will suffice. For the regressions relating to weekday and expiration effects and volatility transmission the null hypothesis of no autocorrelation is rejected, which we take into account by use of Newey-West standard errors when estimating these regressions.

4. The regressors are non-stochastic. Since many financial time series are stochastic this assumption may seem to be unsatisfied. However, the OLS estimator is consistent and unbiased even if the regressors are stochastic under the condition that the regressors are uncorrelated with the error term of the estimation equation. We find no reason that this should not be fulfilled in our case.

C3 Normality of the Error Term

To be able to draw inferences about the statistical significance of regression coefficients it is required that the error term is normally distributed. The Jarque-Bera test is used to test this requirement and normality can be rejected for most regressions used in this study. However, since we have a large number of observations, generally around 2 000, normality is assumed according to the central limit theorem.

APPENDIX D: COMPLEMENTARY INFORMATION CONCERNING THE RESULTS PART

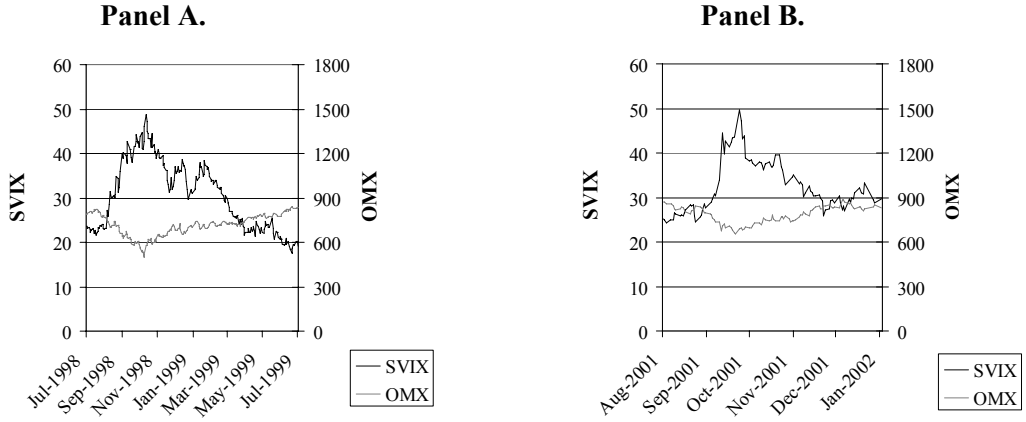
This appendix goes through some of the results presented in part 6 in greater detail, and also adds some additional material concerning the SVIX construction choices (sensitivity analysis) and the properties and features of the SVIX index. The appendix is preferably read side by side with the main text in part 6.

D1 Description of SVIX

D1.1 Development of the SVIX and OMX Indices

As mentioned in the main text, events with negative effects on the financial markets tend to cause increased uncertainty and a higher SVIX level. *Figure D.1* shows in greater detail how the events during the fall of 1998 and 2001 led to an increased SVIX level (and also decreased the OMX index level).

Figure D.1. Development of the SVIX and OMX indices during Financial Instability
The figure shows daily closing observations for SVIX (left axis) and the OMX index (right axis) for the time period surrounding the fall of LTCM in 1998 (**Panel A**) and for the time period surrounding the terror attacks September 11, 2001 (**Panel B**).



D1.2 Definition of Subperiods

We have, when applicable, divided our sample into four subperiods, to be able to consider whether the features of SVIX differ over time and for different volatility regimes. The subperiods and their characterization can be seen in *table D.1* below.

Table D.1. Subperiods
The table shows the division of the entire sample period, i.e. January 1993 to June 2006, into subperiods, and the characterization of each subperiod.

subperiod	scope	volatility level	OMX index trend
1	January 1993 to June 1997	low	increasing
2	July 1997 to June 2000	medium to high	steep increasing
3	July 2000 to June 2003	medium to high	sharp declining
4	July 2003 to June 2006	low	increasing

D1.3 Subperiod Results: SVIX Descriptives

Table D.2 and *D.3* display the same kind of descriptive information about SVIX as *table 1* and *2* in the main text, but here the results are given for the different subperiods outlined above. The first subperiod is characterized by rather low volatility, which does not fluctuate too much around its median value. The minimum (14), maximum (29) and mean (20) are well below those of the following two subperiods, and 90 percent of all SVIX values are within a range of 11 percentage points centered on a median of 19. Entering subperiod 2 the dispersion, as well as the overall volatility level, increases abruptly. This higher volatility level can be seen by the high minimum (17), maximum (49) and mean (28) and the large fluctuations are shown by the standard deviation, which is the highest of all periods. The pattern of high volatility persists in subperiod 3, where the minimum (22), maximum (50) and mean (31) are the highest out of all periods. Also the dispersion continues to be high in subperiod 3 and the standard deviation is just somewhat lower than for subperiod 2. In the final period, subperiod 4, the SVIX index reverts back to lower levels; the mean (17) and median (16) are the lowest of all subperiods and this subperiod also includes the lowest value of all periods (11).

Table D.2. Percentile Ranges for Daily SVIX Observations for Subperiods
The table shows percentile ranges, minimum, maximum and normal ranges for daily SVIX observations.

		percentiles						normal range	
period	**min**	**5%**	**25%**	**50%**	**75%**	**95%**	**max**	**50%**	**90%**
subperiod 1	13.6	15.1	16.7	18.8	22.1	26.0	29.2	5.4	10.9
subperiod 2	17.0	19.5	22.3	25.0	32.4	39.8	48.8	10.1	20.3
subperiod 3	22.1	23.5	26.5	29.9	35.1	42.4	50.0	8.6	18.9
subperiod 4	10.7	11.9	13.5	16.0	19.8	23.9	32.6	6.3	12.0

Note: Subperiod 1: January 1993 to June 1997, subperiod 2: July 1997 to June 2000, subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

Table D.3. Basic Descriptives for Daily SVIX and ΔSVIX Observations for Subperiods
The table shows the number of days with a valid SVIX / ΔSVIX observation (N), and the daily mean and standard deviation (std dev).

	SVIX			ΔSVIX		
period	**N**	**mean**	**std dev**	**N**	**mean**	**std dev**
subperiod 1	1007	19.67	3.52	940	-0.030	0.64
subperiod 2	667	27.51	6.49	610	-0.025	1.27
subperiod 3	687	31.18	5.75	637	-0.062	1.20
subperiod 4	662	16.94	4.12	607	-0.032	0.84

Note: Subperiod 1: January 1993 to June 1997, subperiod 2: July 1997 to June 2000, subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

D1.4 Sensitivity Analysis of Input Option Prices and Construction Choices

This section of the appendix gives a more detailed account of the sensitivity analysis that has been conducted in order to ensure the stability of SVIX. The sensitivity analysis is comprised of two parts. The first part considers whether the SVIX index (in its base specification) can be considered a good estimate of true expected volatility of the Swedish market. This relates to the amount and quality of the options data underlying the SVIX calculation. The second part considers the possibility that the SVIX series may have been unduly affected by choices we have made when deciding upon our base specification. The constructional choices we faced when computing SVIX were more specifically: (1) whether to use close or midquote prices, (2) whether to include new far term option strips eight *calendar* days or two *trading* days before the expiration of the near term contracts, (3) which type of

screening procedures to use to certify the reliability and reduce noise in the underlying option data, and (4) whether to impose any additional demands on the data, such as minimum restrictions on number of call-put differences and number of OTM option prices, to assure stability of the resulting SVIX index. To test the reliability of the base specification, we have computed SVIX for several alternative specifications, which will be considered later in this section.

For reasons explained in section 5.2 and 5.3 we chose to create our base SVIX specification from midquote prices, to include new option strips two *trading* days before expiration of the near term options, to screen the data using three different price screenings (removing bid / ask prices equal to zero, removing options with bid-ask spreads exceeding 10 SEK and removing observations not fulfilling the non-arbitrage requirement) and to impose minimum requirements of two call-put differences and two OTM puts and calls. As previously mentioned, to ensure that this SVIX index provides a good approximation of true expected volatility, the calculation should for each day include a large number of OTM options. The underlying reason is explained in section 5.1; for the variance replicating portfolio to give a good approximation of true expected variance a wide range of option prices is necessary. Additionally, it is important that the underlying option data is as error and noise free as possible. To be able to consider the option data underlying the SVIX calculation in greater detail, we include some statistics on the option database in *table D.4* and *D.5*.

Table D.4 shows the total amount of options in the dataset and how many options that are removed by each of the different price screenings performed for the base specification. For the full time period about three percent of all options are removed in the first screening since either the bid and / or ask price is zero and about one percent are removed in the second price screening, which aims to remove options with unreasonable large spreads. The third price screening, the non-arbitrage requirement, reduces the original sample with slightly more than ten percent, but the variation between individual years for this screening is large. A larger proportion is removed for the years in the middle of the total period, years where the amount of options is initially very large, so this should therefore not pose a major problem. Moreover, even after the price screenings have been performed there are on average a fairly high number of option prices available for each day (69), although it shifts substantially over the years ranging from 35 (in 1993) to 105 (in 2001). Even though all of these options are not included explicitly in the SVIX calculation (since some are ITM options), this nevertheless indicates that the minimum call-put difference is chosen from a rather large amount of available option prices.

Table D.4. Price Screenings of OMX Index Options
The table shows the total amount of option prices (N tot), the amount removed in Screening 1 (i.e. zero ask and / or bid price), Screening 2 (i.e. spread larger than 10 SEK) and Screening 3 (i.e. non-arbitrage restriction not fulfilled), the amount remaining after Screening 3 and the daily average of the options remaining after Screening 3 (i.e. available for use in the SVIX calculation). Note that these figures relate to midquotes of ask and bid prices and are based on a database including observations on all options starting 75 days prior to their respective expiration. Due to computational difficulties and since we in some occasions use different options in different specifications, this database will slightly overestimate the number of options actually used. Moreover, note that a substantial amount of the observations will not be used directly in the SVIX calculation since they are in the money.

period	N tot	removed screening 1	removed screening 2	removed screening 3	remaining after screening 3	remaining daily average
1993 - 2006	273 059	8 963	3 446	29 189	231 461	69
1993	9 728	79	113	728	8 808	35
1994	13 836	102	7	1 071	12 656	51
1995	15 518	140	64	1 187	14 127	57
1996	16 803	249	125	1 179	15 250	61
1997	27 717	160	1 576	3 329	22 652	91
1998	25 714	288	782	3 235	21 409	86
1999	25 499	205	99	3 326	21 869	87
2000	26 325	258	357	3 825	21 885	88
2001	30 913	324	125	4 221	26 243	105
2002	28 743	230	94	4 263	24 156	97
2003	18 169	995	5	1 836	15 333	61
2004	13 258	2 589	24	292	10 353	41
2005	13 784	2 052	60	427	11 245	45
2006	7 052	1 292	15	270	5 475	44

Note: For year 2006 only observations for January to June are included.

In contrast to *table D.4*, *table D.5* displays a summary of the options used directly in the SVIX calculation (for the base specification). Of the on average 69 options remaining after the third price screening above, slightly less than half are OTM options which are used explicitly in the calculation of SVIX for a typical day. For an average day the minimum call-put difference is chosen among 12 (near term) and 11 (next term) call-put differences and the average amount of OTM call and put options used is 7 or 8. The number of call-put differences is higher than 5 for both near and next term options and for all years, it is even above 10 for most years. Moreover, the number of puts and calls on each side of K_0 is also quite high for all years, except perhaps 1993. Hence, SVIX is calculated using a rather large amount of options, which should be enough to ensure that a reasonable minimum call-put difference is chosen for the calculation and that the strike range is wide enough to enable a good estimate of true volatility, even if perfect replication is not viable. Additionally, that the number of puts and calls on each side of K_0 are almost equal indicates that K_0 is in the middle of the range of strike prices and hence, problems of underestimating the variance that can arise if K_0 is close to one of the edges should be somewhat mitigated. We conclude that the SVIX index in this respect fulfills the criteria of a stable index.

Somewhat contrary to these results, which show an on average rather large amount of call-put differences and OTM options, *table D.5* also shows that the proportion of SVIX is reduced by the K_0 restriction. As a reminder the 'K_0-restriction not fulfilled' means that the call and put series are non-overlapping and no call-put differences can be calculated, or that no corresponding call and put price exist for strike price K_0. The problems with non-overlapping series are especially severe for the next term options, e.g. in 2004 17 percent of the potential SVIX observations are removed due to this restriction. Additionally, since we do not only require that the K_0 restriction is fulfilled for both near and next term, but also that there exists at least two call-put differences and two OTM option prices on either side of K_0, the proportion SVIX is even lower than what is reduced by the K_0 restriction. As

mentioned in the main text, we are able to calculate SVIX for 89 percent of all trading days for the entire period, however, the difference between individual years is rather large and e.g. for year 2004 we are only able to obtain SVIX for 77 percent of all possible days. This is nevertheless, more than e.g. Skiadopoulos (2004), who gets 55 percent valid GVIX observations when constructing an index for the Greek market. To conclude, even though 11 percent missing observations (for the entire period) can be seen as a rather large percentage of missing observations, we still believe that the number of SVIX observations is sufficient for our testing purposes in this paper.

Table D.5. Summary of Underlying Options Data Used in Calculation for Base Specification of SVIX

The table shows the average number of differences used to evaluate the minimum difference between call and put prices each day (N diffs), the proportion of days when the K_0 restriction is not fulfilled (K_0 not fulfilled), i.e. there is no call - put options pair for K_0, and the average number of puts (N puts) and call options (N calls) used in the resulting SVIX calculation each day when calculation of SVIX is possible (i.e. K_0 restriction fulfilled for both near and next term). The table shows the information for both near and next term options included in the SVIX calculation and relates to the base specification of SVIX. The table also shows the proportion of days with a valid SVIX / ΔSVIX observation (prop SVIX / ΔSVIX), calculated as number of days with a valid SVIX / ΔSVIX observation divided with the total number of trading days for that period.

	near term				next term					
period	**N diffs**	**K_0 not fulfilled**	**N puts**	**N calls**	**N diffs**	**K_0 not fulfilled**	**N puts**	**N calls**	**prop SVIX**	**prop ΔSVIX**
1993 - 2006	12	3%	7	7	11	7%	8	7	89%	83%
1993	8	0%	5	4	5	15%	5	4	81%	73%
1994	10	1%	6	5	8	11%	7	6	87%	80%
1995	11	0%	6	5	10	2%	6	5	94%	90%
1996	12	2%	8	6	10	2%	7	6	96%	93%
1997	16	12%	11	9	14	12%	11	10	79%	66%
1998	14	5%	8	7	14	5%	9	8	91%	84%
1999	15	1%	8	6	15	1%	10	7	98%	97%
2000	15	8%	9	8	13	8%	9	9	84%	71%
2001	17	3%	8	10	18	8%	9	12	90%	82%
2002	15	2%	7	8	17	3%	7	11	94%	90%
2003	9	1%	6	7	8	4%	8	8	96%	92%
2004	6	2%	6	5	5	17%	5	5	77%	67%
2005	7	1%	6	5	6	5%	7	5	93%	89%
2006	6	5%	7	6	6	11%	7	6	89%	80%

Note: For year 2006 only observations for January to June are included.

After having established that SVIX, in its base specification, should be able to reliably capture the expected volatility of the Swedish market, we consider whether the construction choices made have caused SVIX to be biased. We have constructed several alternative SVIX series based on different combinations of construction choices and restrictions and will consecutively go through the choices of when to include new far term option strips, different screening procedures to reduce noise in the underlying option data, additional requirements on number of call-put differences and number of OTM option prices, and the use of either close or midquote option prices. For each alternative specification, the resulting amount and proportion of SVIX observations and the alternative specification's correlation with the SVIX base specification are reported in *table D.6*.

Panel A shows alternative specifications based on midquote prices. Firstly, if a cut-off point of eight *calendar* days instead of two *trading* days before expiration is used this produces a series very similar to the base SVIX. This series correlation with the base specification is 1.000 for the whole series and 0.994 for the observations that differ between the two specifications and hence, one can deem the SVIX series to be stable to this construction choice. Secondly, applying a different price screening procedure (using interval screening, see *table D.7*) diminishes the proportion of obtained SVIX observations to 74 percent, but the series is still highly correlated with the base specification (0.995), indicating stability also in this respect. Moreover, the correlation remains high even if no screening procedure at all is implemented and hence, we do not think that our SVIX series have been affected by an improper screening procedure. Thirdly, imposing harsher demands on the number of minimum call-put differences and OTM options can be seen to severely diminish the amount of SVIX observations obtained. E.g. if demands of three OTM puts and calls are enforced the proportion of SVIX reduces to 84 percent and if demanding four puts and calls to 67 percent. The proportion of SVIX observations also decreases as the number of call-put differences demanded for the calculation increases, but not to the same extent as for the number of puts and calls restriction. Concerning these two restrictions (minimum requirements on the number of call-put differences and number of (OTM) options on either side of K_0) we cannot use a simple correlation to the base specification to draw any conclusions about the differences between the series. This since these restrictions do not alter the calculated SVIX observations, they only impact whether an observation for a specific day is part of the final series or not. Therefore, as an alternative robustness check we perform regression (7) (which examines the SVIX and OMX index relationship), section 6.3, for each alternative specification. Overall, very similar results are obtained for all specifications, which lead us to conclude that the base specification is not very different from the alternative series with harsher demands and hence is stable also in that respect.

Finally, Panel B reports the alternative specifications based on close prices instead of midquote prices. The proportion of SVIX observations is dramatically decreased and ranges from 17 percent to 54 percent depending on the construction choices made and the restrictions imposed. However, all correlations with the base specification are high and close to 1, indicating that using midquote or close prices does not alter the resulting SVIX observations in any significant way, and that the SVIX series is stable also to this choice.

Table D.6. Number of SVIX Observations for Alternative Specifications and Their Correlation with the SVIX Base Specification

The table shows the number of SVIX observations for the alternative specifications accounted for in section 5.2 and 5.3, and the proportion of days with a valid SVIX observation (prop SVIX) calculated as number of days with a valid SVIX observation divided with the total number of trading days for the total period. The table also shows the alternative specifications correlations with the base specification (corr with BASE SPEC) and additionally, the number of valid SVIX observations that are different from the base specification (i.e. missing values will not have an impact) (N of obs that differ from BASE SPEC), and the correlation between those values and the corresponding values for the base specification (corr with BASE SPEC (adj)). All correlations have a p-value of 0.0000.

Panel A shows specifications based on midquote option prices and **Panel B** shows specifications based on close prices of the included options (type of price). The tables are constructed based on when the calculation is shifted to include a new far term month, either two trading days or eight calendar days (shift to new far term options), the requirement on minimum number of differences used to evaluate the minimum difference between call and put prices each day (N differences), the requirement of number of OTM call and put options on the respective side of K_0 (N puts and calls), the type of price screening used (price screening), one of the following: observations with bid-ask spread greater than 10 SEK excluded from SVIX calculation (max spread 10), observations with bid-ask spread greater than the intervals accounted for in *table D.7* excluded from SVIX calculation (interval), close observations which violate the BS theoretical price with more than 10 SEK excluded from SVIX calculation (max BSdiff 10) or no price screening at all (no), and whether option prices not fulfilling the non-arbitrage restriction are excluded or not from the SVIX calculation (non-arbitrage screening).

Panel A.

	BASE SPEC	**MidQ - Alternative specifications**						
type of price:	**MidQ**	MidQ	MidQ	MidQ	MidQ	MidQ	MidQ	MidQ
shift to new far term options (days):	**2**	2	2	2	2	***8***	2	2
N differences:	**2**	2	2	***3***	***3***	2	2	2
N puts and calls:	**2**	***3***	***4***	2	***3***	2	2	2
price screening:	**max spread 10**	max spread 10	max spread 10	max spread 10	max spread 10	max spread 10	***intervals***	***no***
non-arbitrage screening:	**yes**	yes	yes	yes	yes	yes	yes	***no***
number of SVIX observations	3023	2838	2279	3002	2817	2979	2503	3152
prop SVIX	89%	84%	67%	89%	83%	88%	74%	93%
corr with BASE SPEC		1.000	1.000	1.000	1.000	1.000	0.995	0.998
corr with BASE SPEC (adj)						0.994	0.988	0.998
N of obs that differ from BASE SPEC						180	819	2580

Panel B.

	Close - Alternative specifications						
type of price:	**Close**	Close	Close	Close	Close	Close	Close
shift to new far term options (days):	**2**	2	2	2	2	***8***	2
N differences:	**2**	2	2	***3***	***3***	2	2
N puts and calls:	**2**	***3***	***4***	2	***3***	2	2
price screening:	**max BSdiff 10**	max BSdiff 10	max BSdiff 10	max BSdiff 10	max BSdiff 10	max BSdiff 10	***no***
non-arbitrage screening:	**yes**	yes	yes	yes	yes	yes	***no***
number of SVIX observations	1292	1155	572	1096	993	1110	1825
prop SVIX	38%	34%	17%	32%	29%	33%	54%
corr with BASE SPEC	0.996	0.996	0.996	0.996	0.996	0.996	0.995
corr with BASE SPEC (adj)	0.996	0.996	0.996	0.996	0.996	0.996	0.995
N of obs that differ from BASE SPEC	1239	1112	555	1047	952	1081	1718

Table D.7. Maximum Spreads for OMX Index Options
The table shows, for each option (bid) price, the maximum bid-ask spread allowed for market makers in OMX index options. The spreads quoted in the column 'artificial max spread 2000-2006' are the spreads prevailing as of August, 2006 (OMX, 2006a). In the stricter price screening we use today's max spread levels for year 2000 until 2006 (artificial max spread 2000 – 2006) since the spreads have been fairly stable during this period (OMX, 2006a), and then arbitrarily add 2 SEK to each max spread interval for the earlier years to account for the fact that the spreads have narrowed over the years (artificial max spread 1993 – 1999).

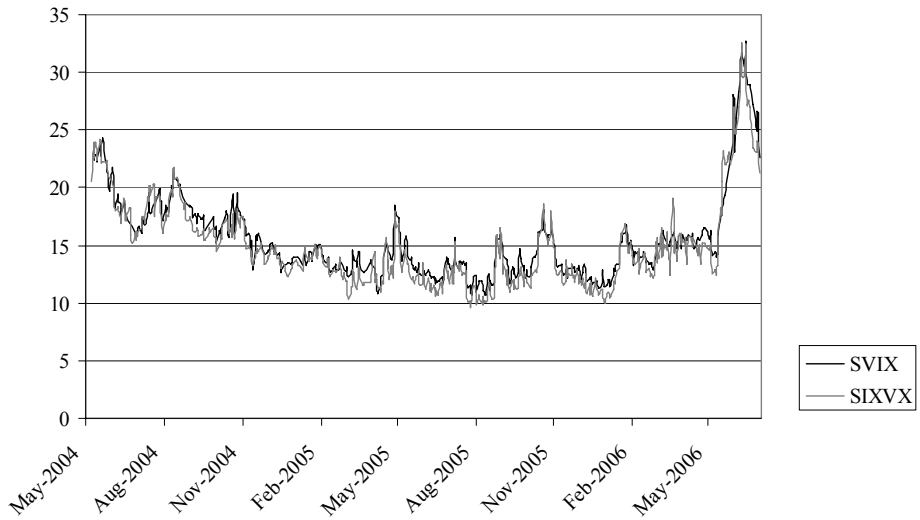
option price (SEK)	artificial max spread 1993-1999 (SEK)	artificial max spread 2000-2006 (SEK)
0 – 1.99	3.00	1.00
2 – 9.99	3.50	1.50
10 – 19.99	5.00	3.00
20 – 29.99	6.00	4.00
30 –	7.00	5.00

To sum up, the sensitivity analysis shows that the SVIX series resulting from the base specification represents a fairly good estimate of true expected volatility of the Swedish market, since it has been calculated using quite a large amount of options. One drawback is however, the rather large amount of missing observations. Moreover, the SVIX base specification series is robust to altering the construction choices and the restrictions placed on it. Hence, the results obtained when examining different properties of SVIX should be stable to the use of either midquote or close prices, to our noise removal and stabilization procedures and to the choice of including a new far term contract month either eight *calendar* days or two *trading* days before expiration of the near term options.

D1.5 Comparison of SVIX and SIXVX

Both the SVIX and SIXVX indices aim to extract information about the expected 30 day volatility of the OMX index from OMX index option prices. Hence, even though their computational method differs, they should evolve fairly similarly over time, if they both give a fair representation of expected volatility.

Figure D.2. Comparison of the Development of SVIX and SIXVX
The figure shows daily closing observations for SVIX and SIXVX for the time period May 2004 to June 2006. Note the bias in SIXVX due to calculation using BS option pricing model; see also e.g. Carr and Wu (2006) for a related discussion about the bias of VXO compared to VIX.



D2 Basic Tests of SVIX: Normality, Stationarity, Autocorrelation, Weekday and Expiration Effects

D2.1 Subperiod Results: Normality, Stationarity and Autocorrelation

Table D.8 and *D.9* display the results of the normality and stationarity tests as well as the autocorrelation structure and Ljung-Box (LB) statistics for SVIX and ΔSVIX for each subperiod. Concerning normality, the results for the different subperiods are, as mentioned in the main text, in line with those for the entire time period; both the SVIX and ΔSVIX series are consistently found to be non-normal. As for stationarity, two of the subperiods (subperiod 1 and 3) entail a stationary SVIX level series, whereas the other two (subperiod 2 and 4) are found not to be stationary. However, it is not uncommon for a volatility series to exhibit a trend for a shorter period of time.

Concerning the autocorrelation structure, the strong positive autocorrelation for the SVIX series is present in all subperiods. Moreover, the LB-statistics reject, for all subperiods, the joint hypothesis that all autocorrelation coefficients up to 12, 30 and 60 lags are simultaneously zero. For the differenced SVIX series, the individual first order autocorrelation coefficient is negative for all periods, although not statistically significant for subperiods 1 and 3. Additionally, the LB-statistics show that we (in most occasions) can reject the null hypothesis that all autocorrelation coefficients up to 12, 30 or 60 lags are simultaneously zero.

Table D.8. Normality and Stationarity of SVIX and ΔSVIX for Subperiods
The first part of the table shows the skewness, kurtosis and Jarque-Bera test-statistic for normality for SVIX and ΔSVIX. All Jarque-Bera statistics have a p-value of 0.0000. The second part of the table shows the results for Dickey-Fuller (DF) tests of SVIX and ΔSVIX. 'Model used' shows which DF model that is used; either DF without trend component (DF w/o t) or Augmented DF with lag length 1 (ADF m = 1), see further discussion in appendix C1. N is number of observations for the DF test, tau(obs) the observed tau-statistic and the stat / non-stat the resulting outcome. *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively.

		normality			stationarity			
	period	**skewness**	**kurtosis**	**Jarque-Bera**	**model used**	**N**	**tau(obs)**	**stat / non-stat**
SVIX	**subperiod 1**	0.52	2.28	67.25	DF w/o t	940	-3.23**	stat
	subperiod 2	0.71	2.64	59.80	ADF (m = 1)	563	-2.29	non-stat
	subperiod 3	0.64	2.75	48.50	DF w/o t	637	-4.40***	stat
	subperiod 4	0.79	3.15	68.79	ADF (m = 1)	559	-2.41	non-stat
ΔSVIX	**subperiod 1**	0.50	12.55	3608.40	DF w/o t	886	-30.91***	stat
	subperiod 2	0.16	5.84	206.85	DF w/o t	563	-30.02***	stat
	subperiod 3	-0.46	5.59	200.35	DF w/o t	592	-26.49***	stat
	subperiod 4	0.19	6.59	329.25	DF w/o t	559	-29.65***	stat

Note: Subperiod 1: January 1993 to June 1997, subperiod 2: July 1997 to June 2000, subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

Table D.9. Autocorrelation of SVIX and ΔSVIX for Subperiods
The table shows the autocorrelation coefficients for the first three lags, $\rho(1)$, $\rho(2)$ and $\rho(3)$, and the Ljung-Box (LB) statistics for a joint autocorrelation test up to 12, 30 and 60 lags of the SVIX and ΔSVIX series. Numbers in parentheses denote t-statistics and *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively.

	period	$\rho(1)$	$\rho(2)$	$\rho(3)$	LB(12)	LB(30)	LB(60)
SVIX	**subperiod 1**	0.897***	0.848***	0.804***	8000***	16652***	26924***
		(29.90)	(28.27)	(26.80)			
	subperiod 2	0.890***	0.881***	0.872***	6170***	12471***	16675***
		(24.05)	(23.81)	(23.57)			
	subperiod 3	0.893***	0.874***	0.845***	5523***	8643***	9379***
		(24.14)	(23.62)	(22.84)			
	subperiod 4	0.872***	0.844***	0.828***	5456***	10172***	15787***
		(23.57)	(22.81)	(23.00)			
ΔSVIX	**subperiod 1**	-0.035	-0.061**	-0.013	17	33	60
		(-1.09)	(-1.97)	(-0.43)			
	subperiod 2	-0.170***	0.036	-0.017	35***	49**	97***
		(-4.36)	(0.97)	(-0.46)			
	subperiod 3	-0.051	0.020	-0.019	18	53***	82**
		(-1.34)	(0.54)	(-0.51)			
	subperiod 4	-0.190***	-0.050	0.023	44***	80***	118***
		(-4.87)	(-1.35)	(0.62)			

Note: Subperiod 1: January 1993 to June 1997, subperiod 2: July 1997 to June 2000, subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

D2.2 Subperiod Results and Additional Information: Weekday and Expiration Effects

There are two noteworthy things about the evaluation of weekday effects. Firstly, for this assessment we use a slightly transformed ΔSVIX series in order to only get differences that relate to differences between two adjacent weekdays (i.e. removed from this series are differences between e.g. a Thursday and a Monday which arise when the intermediate Friday is a holiday). Therefore the differenced series used in this section contains somewhat fewer observations than the original ΔSVIX series. Secondly, due to the rather large amount of missing observations in the level SVIX series, the mean of the level series (SVIX mean) and the mean of the differenced series (ΔSVIX mean) are calculated using slightly different observations and as a consequence the average differences do not directly correspond to changes between average level of SVIX (i.e. you cannot directly add the Monday difference to the Monday SVIX value to get the Tuesday SVIX value), see *table D.10*.[52] As can be seen in the same table there are about 10 percent fewer ΔSVIX compared to SVIX observations. If the missing observations were equally spread out over time as well as over the weekdays, and moreover, do not represent days with any common feature we would not expect to see any deviations between the two series. However, since some weekdays have a larger proportion missing observations than others (see *table D.10*) this could potentially cause the dissimilarity between the SVIX and ΔSVIX series, and moreover, we cannot completely rule out another pattern in the missing data, even though it appears to be completely random. However, although the SVIX and ΔSVIX series do not match perfectly they share the same overall trend and the dissimilarities should not pose a problem.

[52] To understand why the ΔSVIX series are calculated using less observations, consider the most extreme case in which a level observation is surrounded by two missing observations. This level SVIX observation will be included in the level mean, but since it does not result in any difference it will not impact the difference series mean. I.e. all level observations that are adjacent to a missing observation will not have full impact on the differenced series.

As mentioned in the main text, we find a weekday pattern with a positive Monday effect and negative Friday effect, see also *table D.10*. This general pattern is the same for all subperiods even though the overall volatility level changes over time, see *table D.11*.

Table D.10. Intraweek SVIX and ΔSVIX and Structure of Missing SVIX and ΔSVIX
The table shows the average SVIX and ΔSVIX for each day of the week, the total number of trading days for each weekday (N trading days), the number of SVIX / ΔSVIX observations for each weekday (N SVIX / ΔSVIX) and the proportion of missing SVIX / ΔSVIX observations as percentage of the total number of trading days for that weekday (prop missing SVIX / ΔSVIX).

day	SVIX	ΔSVIX	N trading days	N SVIX	N ΔSVIX	prop missing SVIX	prop missing ΔSVIX
Monday	23.73	0.31	664	605	523	9%	21%
Tuesday	23.47	-0.07	692	616	554	11%	20%
Wednesday	23.43	-0.01	691	614	567	11%	18%
Thursday	23.36	-0.09	677	596	549	12%	19%
Friday	23.07	-0.37	663	592	518	11%	22%

Table D.11. Intraweek SVIX and ΔSVIX for Subperiods
The table shows, for each subperiod, the average SVIX and ΔSVIX for each day of the week.

	subperiod 1		subperiod 2		subperiod 3		subperiod 4	
day	SVIX	ΔSVIX	SVIX	ΔSVIX	SVIX	ΔSVIX	SVIX	ΔSVIX
Monday	19.92	0.17	27.83	0.36	31.38	0.45	17.06	0.32
Tuesday	19.68	-0.02	27.50	-0.21	31.12	-0.09	16.85	0.02
Wednesday	19.53	-0.02	27.40	-0.02	31.35	0.02	17.09	-0.03
Thursday	19.58	-0.10	27.64	0.12	31.39	-0.18	16.79	-0.18
Friday	19.63	-0.24	27.17	-0.40	30.65	-0.54	16.89	-0.36

Note: Subperiod 1: January 1993 to June 1997, subperiod 2: July 1997 to June 2000, subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

Table D.12 displays the results for the weekday effects regression (eq. 5) as well as the combined weekday- and expiration day effects regression (eq. 6) for the different subperiods. In accordance with the results for the total sample period there is a positive Monday effect and a negative Friday effect for all subperiods in both regressions (although the Monday effect is insignificant for regression (6) in subperiod 2). The negative expiration effects are most visible in the first three subperiods, however, the statistical significance differs largely between the periods. For the last subperiod we find, contrary to our expectations, a significant positive effect for the day two days prior to the expiration date. There is no underlying economic reason why this day should have a positive effect, and the following two days have the expected negative sign (although the effects are insignificant). Important to note is that the combined weekday- and expiration day effects regression (eq. 6) could potentially be affected by high multicollinearity between the day of the week and expiration dummy variables, as most expiration days are Fridays. However, multicollinearity does not seem to be a large problem as the variance inflation factor is below two for all coefficients and the condition index is lower than five for all dimensions. Moreover, the correlations between the included variables never exceed 0.30.

To sum up, even though all results are not completely stable over time, the SVIX index nevertheless, seem to exhibit positive Monday and negative Friday effects as well as negative expiration effects.

Table D.12. Regression Results Weekday and Expiration Effects for Subperiods
The table shows, for each subperiod, the results for the regression between the (daily) changes in SVIX and weekday and expiration dummy variables, i.e. the following regressions:

$$\Delta SVIX_t = \beta_1 + \beta_2 D_{Monday,t} + \beta_3 D_{Tuesday,t} + \beta_4 D_{Thursday,t} + \beta_5 D_{Friday,t} + \varepsilon_t \quad (5)$$

$$\Delta SVIX_t = \beta_1 + \beta_2 D_{Monday,t} + \beta_3 D_{Tuesday,t} + \beta_4 D_{Thursday,t} + \beta_5 D_{Friday,t} + \beta_6 D_{Exp-2,t} + \beta_7 D_{Exp-1,t} + \beta_8 D_{Exp,t} + \varepsilon_t \quad (6)$$

For each regression the adjusted R^2 (adj R^2) and number of observations (N) are reported. Numbers in parentheses denote t-statistics based on Newey-West standard errors and *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively.

period	intercept	D_{Monday}	$D_{Tuesday}$	$D_{Thursday}$	D_{Friday}	D_{Exp-2}	D_{Exp-1}	D_{Exp}	adj R^2	N
subperiod 1	-0.024	0.196***	0.002	-0.078	-0.214***				0.043	913
	(-0.57)	(3.19)	(0.04)	(-1.40)	(-3.55)					
subperiod 2	-0.020	0.377**	-0.188	0.136	-0.377**				0.032	590
	(-0.19)	(2.38)	(-1.11)	(0.79)	(-2.41)					
subperiod 3	0.023	0.428***	-0.114	-0.199	-0.558***				0.065	617
	(0.24)	(3.15)	(-0.96)	(-1.51)	(-3.81)					
subperiod 4	-0.028	0.349***	0.049	-0.150	-0.330***				0.069	591
	(-0.46)	(3.63)	(0.55)	(-1.44)	(-3.37)					
subperiod 1	0.034	0.142**	-0.051	-0.065	-0.215***	-0.018	-0.178	-0.517***	0.060	863
	(0.78)	(2.35)	(-0.86)	(-1.09)	(-3.36)	(-0.14)	(-1.61)	(-4.03)		
subperiod 2	0.099	0.252	-0.293	0.038	-0.443**	-0.109	-0.153	-0.206	0.028	553
	(0.73)	(1.39)	(-1.59)	(0.18)	(-2.32)	(-0.40)	(-0.49)	(-0.66)		
subperiod 3	0.015	0.438***	-0.104	0.021	-0.393***	0.204	-0.854**	-0.570*	0.080	582
	(0.16)	(3.13)	(-0.81)	(0.15)	(-2.60)	(0.61)	(-2.25)	(-1.78)		
subperiod 4	-0.101	0.393***	0.150	-0.023	-0.220**	0.604***	-0.162	-0.331	0.080	565
	(-1.47)	(3.83)	(1.46)	(-0.19)	(-2.26)	(3.24)	(-0.72)	(-1.26)		

Note: Subperiod 1: January 1993 to June 1997, subperiod 2: July 1997 to June 2000, subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

D3 The Relationship between SVIX and OMX Index Returns

D3.1 Subperiod Results: Correlations between the SVIX and OMX Indices

Table D.13 reports the correlations between daily changes in SVIX and the daily return of the OMX index for the different subperiods. The correlations are negative for all periods and roughly the same size, but one can note a slight tendency of higher correlations in the first and fourth period, i.e. in low volatility environments.

Table D.13. Correlations ΔSVIX and *retOMX* for Subperiods
The table shows the correlation between (daily) changes in SVIX, ΔSVIX, and (daily) return of the OMX index, *retOMX* for subperiods. All correlations have a p-value of 0.0000.

period	correlation
subperiod 1	-0.53
subperiod 2	-0.41
subperiod 3	-0.40
subperiod 4	-0.50

Note: Subperiod 1: January 1993 to June 1997, subperiod 2: July 1997 to June 2000, subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

D3.2 Subperiod Results: Regression Approach Relationship between the SVIX and OMX Indices

Table D.14 displays the results for the regression of daily changes in SVIX and daily positive changes in SVIX on the daily return of the OMX index (eq. 7) for all four subperiods. The relationship between the SVIX and OMX index differs somewhat depending on the time period and volatility regime, where the positive effect on the OMX index from a 1 percentage unit fall of SVIX varies from about 0.7 percent in subperiod 1 to 0.4 percent in subperiod 4, and also the asymmetry component varies over time. Contrasting to the results for the total period we find a significant asymmetry effect for the low volatility regimes, significant on the 10 percent level in subperiod 1 and on the 5 percent level in subperiod 4. The largest asymmetry effect is found for the last subperiod, where the positive effect from a fall of SVIX is lowest, and can be seen as partly compensate for the smaller ΔSVIX coefficient in this period.

The pattern with a stronger relationship in the subperiods with low volatility is consistent with the results from the simple correlations and enforces that the relationship between the SVIX and OMX indices is stronger during low volatility regimes. One can also note that the regressions for the two low volatility periods have higher adjusted R^2, i.e. variations in SVIX are able to explain a larger extent of the variations in the index returns for those periods.

As a last note, we adopt a slight difference from Whaley's (2000) method in that we (in line with Skiadopoulos, 2004) first and foremost use daily changes of SVIX and the OMX index in regression (7), as compared to weekly changes. Therefore, as a robustness check we also conduct the test using weekly data, i.e. Wednesday to Wednesday changes, but the results do not change significantly and are therefore not reported here.

Table D.14. Regression Results Relationship between the SVIX and OMX Indices for Subperiods

The table shows the results for the regression between the (daily) return of the OMX index, (daily) changes in SVIX and (daily) change in the SVIX index when the change is positive,

$$retOMX_t = \beta_1 + \beta_2 \Delta SVIX_t + \beta_3 \Delta SVIX_t^+ + \varepsilon_t \quad (7)$$

For each regression the adjusted R^2 (adj R^2) and number of observations (N) are reported. Numbers in parentheses denote t-statistics based on Newey-West standard errors and *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively.

period	intercept	ΔSVIX	ΔSVIX$^+$	adj R^2	N
subperiod 1	0.132***	-0.698***	-0.176*	0.278	940
	(3.53)	(-10.11)	(-1.73)		
subperiod 2	0.153*	-0.555***	0.059	0.163	610
	(1.74)	(-6.86)	(0.32)		
subperiod 3	-0.135	-0.623***	0.033	0.153	637
	(-1.38)	(-5.36)	(0.17)		
subperiod 4	0.184***	-0.383***	-0.303**	0.261	607
	(4.43)	(-4.04)	(-2.15)		

Note: Subperiod 1: January 1993 to June 1997, subperiod 2: July 1997 to June 2000, subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

D3.3 Granger Causality Tests for SVIX and the OMX Index

To examine whether changes in the OMX index tend to lead changes in SVIX or vice versa we follow Skiadopoulos (2004) and conduct Granger causality tests. The following pair of regressions is formulated:

$$retOMX_t = \phi_0 + \sum_{i=1}^{m} \alpha_i retOMX_{t-i} + \sum_{i=1}^{m} \beta_i \Delta SVIX_{t-i} + \varepsilon_t \quad \text{(D1)}$$

$$\Delta SVIX_t = \theta_0 + \sum_{i=1}^{m} \gamma_i retOMX_{t-i} + \sum_{i=1}^{m} \delta_i \Delta SVIX_{t-i} + u_t \quad \text{(D2)}$$

To test if ΔSVIX (Granger) causes *retOMX*, we estimate equation (D1) and obtain the residual sum of squares for this unrestricted model (RSS_{UR}). Subsequently, we estimate a restricted version of the same equation (D1), where all the ΔSVIX variables are dropped, and obtain the residual sum of squares for this restricted model (RSS_R). We then test the null hypothesis of no (Granger) causality from ΔSVIX to *retOMX*, i.e. $H_0 = \beta_1 = \ldots = \beta_m = 0$, by use of an ordinary F-test. Test statistic for the F test is $F = \dfrac{(RSS_R - RSS_{UR})/m}{RSS_{UR}/(n-k)} \sim F_{m,(n-k)}$ where (RSS_{UR}) RSS_R is the residual sum of squares for the (un-)restricted model, m is the number of lags used, n the total number of observations and k the number of parameters estimated in the regression. The test statistic follows an F-distribution with m and (n - k) degrees of freedom. The lag length, m, used for the test is determined using the Akaike Information Criteria, AIC. [53]

Likewise, to test if *retOMX* (Granger) causes ΔSVIX, we estimate RSS_{UR} for equation (D2) and subsequently RSS_R by dropping all *retOMX* variables, and then test the null hypothesis of no (Granger) causality from *retOMX* to ΔSVIX, i.e. $H_0 = \gamma_1 = \ldots = \gamma_m = 0$ by use of an F-test. Four potential cases are possible; (1) unidirectional causality from ΔSVIX to *retOMX*, (2) unidirectional causality from *retOMX* to ΔSVIX, (3) feedback or bilateral causality and (4) independence.

The results from the Granger causality tests are reported in *table D.15*. We find unidirectional causality from *retOMX* to ΔSVIX, i.e. the return of the OMX index causes changes in the SVIX index while SVIX does not cause the return of the OMX index. Hence, the changes in the volatility level do not seem to be leading the changes of the OMX index, whereas OMX index changes seem to precede the volatility index changes.

Table D.15. Granger Causality Tests for the SVIX and OMX Indices

The table shows the results for Granger causality test between the (daily) return of the OMX index and the (daily) changes in SVIX, i.e. the following pair of regressions:

$$retOMX_t = \phi_0 + \sum_{i=1}^{m} \alpha_i retOMX_{t-i} + \sum_{i=1}^{m} \beta_i \Delta SVIX_{t-i} + \varepsilon_t \quad \text{(D1)}$$

$$\Delta SVIX_t = \theta_0 + \sum_{i=1}^{m} \gamma_i retOMX_{t-i} + \sum_{i=1}^{m} \delta_i \Delta SVIX_{t-i} + u_t \quad \text{(D2)}$$

Where the first equation tests if ΔSVIX causes *retOMX*, and the second tests if *retOMX* causes ΔSVIX. The null hypotheses of no causality are: $H_0 = \beta_1 = \ldots = \beta_m = 0$ and $H_0 = \gamma_1 = \ldots = \gamma_m = 0$, for the first and second equation respectively, and they are tested using a standard F-test. The F-statistics are provided for lag length m, which is determined by the Akaike Information Criteria. Results are stable up to 10 lags.

null hypothesis	lag length *(m)*	F-statistic	p-value	outcome
ΔSVIX does *not* Granger cause *retOMX*	10	0.82	(0.6050)	no causality
***retOMX* does *not* Granger cause ΔSVIX**	5	5.60	(0.0000)	causality

[53] For additional information about Granger causality tests see e.g. Gujarati (2003).

D4 Forecasting Ability of the SVIX Index

D4.1 Descriptive Statistics of SVIX, Future Realized Volatility and Historical Volatility

Table D.16 shows descriptives for the monthly-sampled SVIX, future realized volatility and historical volatility series used for the assessment in this section. The table also shows the same type of information for the logged equivalents of the series, since those series are the ones used in the regression approach. As can be seen, the logged series follow the same general pattern as the original series in levels. Note, however, that the logged series conform somewhat better to normality.

Table D.16. Summary Statistics for SVIX, Future Realized Volatility and Historical Volatility
The table shows the number of observations (N), minimum, maximum, mean, standard deviation (std dev), skewness (S), kurtosis (K) and Jarque-Bera statistic (JB) with corresponding p-value for SVIX, future realized volatility, $RV_{t,t+30}$, and historical volatility, $RV_{t-30,t}$, and for their logged equivalents. The series are based on monthly observations, where for each month the observations seven days after the expiration of that month's options are used. If the SVIX observation is missing also the realized volatility observations are removed to enhance comparison between the series (the same approach is used for all tests in this section).

	N	min	max	mean	std dev	S	K	JB	(p-value)
SVIX	151	10.88	46.41	22.96	7.22	0.78	3.20	15.50	(0.0004)
$\boldsymbol{RV_{t,t+30}}$	151	8.47	61.18	21.52	10.31	1.45	5.09	80.40	(0.0000)
$\boldsymbol{RV_{t-30,t}}$	151	8.00	61.86	20.89	10.05	1.54	5.54	100.10	(0.0000)
lnSVIX	151	2.39	3.84	3.09	0.31	0.12	2.45	2.29	(0.3182)
$\boldsymbol{\ln RV_{t,t+30}}$	151	2.14	4.11	2.97	0.43	0.49	2.63	6.89	(0.0319)
$\boldsymbol{\ln RV_{t-30,t}}$	151	2.08	4.12	2.94	0.43	0.50	2.78	6.53	(0.0382)

D4.2 Robustness Tests

The results from the forecasting section are subjected to three types of robustness checks. Firstly, we consider whether the results are dependent on the definition of realized (historical and future) volatility, i.e. equation (8). Specifically, we consider alternative cases where the realized volatility is (1) calculated using a demeaning specification of realized volatility in eq. (8), (2) calculated using 22 trading days (instead of, and as an approximation of, 30 calendar days) and (3) sampled in another fashion, i.e. by varying the day after expiration when the observations are sampled. We find that the results and qualitative conclusions reached in section 6.4 are stable to all these alternative specifications of realized volatility.

Secondly, as e.g. Poon and Granger (2003) point out, much of the success of a model to forecast future realized volatility lies in its out-of-sample predicting power, and therefore we perform one-step-ahead, out-of-sample forecasts in the same fashion as Christensen and Prabhala (1998). This gives an indication whether the relationship is stable over time, whereas the original regressions focus only on how the relation has been in the past (over the whole sample period taken together). Particularly, we use data for the first 10 years (113 observations) to estimate equations (9) – (11) and then use these estimated parameter values for one-period-ahead forecasts over the remaining 3½ years (38 observations). As evaluation measure we use the mean-squared-errors (*MSE*) of the forecasted and actual realized volatility, computed as:

$$MSE = bias^2 + std\ dev^2 \quad \text{(D3)}$$

If SVIX provides a better forecast than historical volatility the *MSE* for equation (9) and (11) should be smaller than that for equation (10). As it turns out, the *MSE* for regression (9) and (11) are almost identical, at 0.1028 and 0.1029, and they are clearly smaller than the one for the regression with only historical volatility, 0.1325. This is a further sign that SVIX is a better predictor than historical volatility. Furthermore, that the *MSE* for the encompassing regression (11) is not lower than that for the regression with only lnSVIX (9) indicates that adding historical volatility to the model does not improve the out-of-sample forecasting ability. Hence, the out-of-sample forecasts support the results from the tests performed for the entire time period and there is no indication that the predictive power of SVIX should be reversed in the later part of the sample. Furthermore, re-estimation of the original regressions using rolling regression (with a window of 30 trading days) also shows that the results are fairly stable over time.

Thirdly, we test if the lnSVIX coefficient found to be larger than one in regression (9) and (11) (implying a downwards bias and hence contradicting other indications of upwards bias) could be due to influence from the 'crashes', i.e. the peaks with extremely high realized volatility impossible to anticipate with the SVIX index (e.g. the terror attack September 11, 2001). SVIX were substantially lower than the realized volatility during those periods and that would imply a coefficient larger than one. In order to investigate whether the biasedness of SVIX as a predictor is caused by these (unpredictable) extreme observations of future realized volatility we re-estimate regressions (9) – (11) excluding all peak observations. We define a peak observation as an observation where the realized volatility is above 45, and we have in total five such observations.

Removing the peak observations does not change the main conclusions, however the individual coefficients changes somewhat. The coefficient for lnSVIX in regression (9) as well as in regression (11) becomes slightly lower than one (0.928 and 0.989, respectively) although they remain not significantly different from one by use of ordinary t-tests. Moreover, the intercepts becomes marginally positive although not significantly different from zero (0.088 and 0.046, respectively). However, F-tests still show that the forecasts are biased. Nevertheless, the result with lnSVIX coefficients slightly less than one is more in line with the indications from *figure 6* and from the combined effect of the negative intercept and larger coefficient in the original regression (9). The overall conclusion remains that SVIX is an upwards biased, yet efficient, predictor of future realized volatility.

D5 Volatility Transmission between the Swedish, US and Eurozone Markets

D5.1 Graphical Comparison of SVIX, VIX and VSTOXX

The SVIX, VIX and VSTOXX indices seek to measure the expected 30 calendar day volatility on the Swedish, US and Eurozone markets, respectively. *Figure D.3* and *D.4* show that, overall, the general trends seem to be aligned for all series, except for the first few years of the SVIX and VIX series. Note that the analysis performed in section 6.5 and appendix D5 primarily relates to the time period January 1999, to June 2006, since VSTOXX data is only available from January 1999. Note also that subperiod $2^{\dagger}$ (January 1999 to June 2000) in this section is somewhat shorter than the original subperiod 2 (July 1997 to June 2000).

Figure D.3. Comparison of SVIX and VIX
The figure shows the development of SVIX and VIX (based on daily closing observations) for the period January 1993 to June 2006. Note that observations for September 11, 2001, and the subsequent week, are absent in the VIX series.

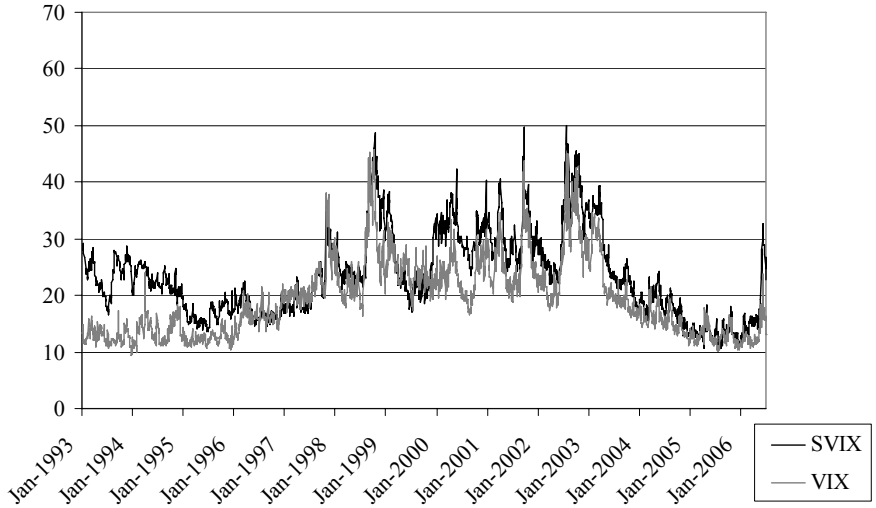
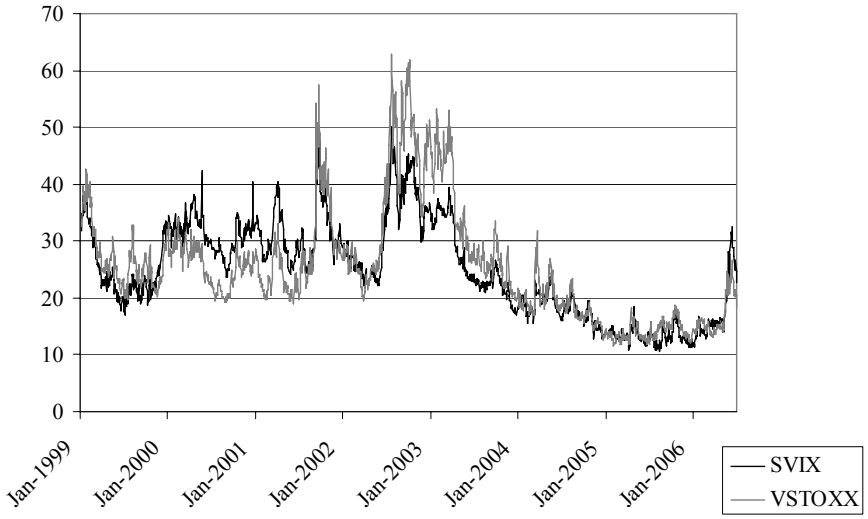


Figure D.4. Comparison of SVIX and VSTOXX
The figure shows the development of SVIX and VSTOXX (based on daily closing observations) for the period January 1999 to June 2006.



D5.2 Subperiod Results: Correlations between SVIX, VIX and VSTOXX

Table D.17 shows the correlations between SVIX, VIX and VSTOXX for the different subperiods. For the level series the correlations are overall high (except for the SVIX and VIX correlations for subperiod 2) and they show an increasing trend over time (the only exception is a slightly lower correlation between SVIX and VIX for the very last subperiod). The correlation between SVIX and VIX increases from close to zero at the early and mid 1990s to almost 0.9 at the end of our sample, and the correlation between SVIX and VSTOXX increases from 0.7 in early 2000 to 0.9 at the end. That the levels of volatility become more similar over time could be due to the increased economic, monetary and financial integration, and in the case of VSTOXX it could also be linked to increased cooperation within the EU (cf. Baele, 2003).

However, even though the general level of volatility is more aligned over time, the pattern of increased co-movements is not confirmed by the correlations for the differenced series. In this case correlations remain roughly the same over time, and the most notable difference between the subperiods is an increased linkage between VIX and SVIX / VSTOXX during subperiod 3, i.e. high volatility and falling markets. The fact that larger markets have greater impact in falling markets has been found in previous research, see e.g. Koutmos and Booth (1995), and we return to this matter when discussing the regression results below.

Lastly, a note on the speed of the volatility transmission. Both for the total sample period and individual subperiods, the correlations between SVIX / VSTOXX and lagged VIX for the level series, are (almost) identical to the contemporaneous correlations, which seems plausible since the level series all exhibit very high positive autocorrelation. However, if there is any autocorrelation present in the differenced series it is most likely negative and hence, that we find a positive correlation between lagged VIX differences and SVIX / VSTOXX is a sign that the transfer of volatility is not instant. In line with the results for the total period, the contemporaneous correlations between ΔVIX and ΔSVIX / ΔVSTOXX are consistently higher than the lagged over the subperiods, indicating a primarily contemporaneous relationship.

Table D.17. Correlations SVIX, VIX and VSTOXX for Subperiods
Panel A shows the correlations between daily levels of SVIX, VIX (also lagged one day, VIX_{t-1}) and VSTOXX. The correlation between SVIX and VIX (VIX_{t-1}) is 0.83 (0.84) for the full time period, i.e. 1993 to June 2006, and slightly negative for subperiod 1. All correlations have a p-value of 0.0000.
Panel B shows the correlations between daily differences of SVIX, VIX (also lagged one day, VIX_{t-1}) and VSTOXX. The correlation between ΔSVIX and ΔVIX (ΔVIX_{t-1}) is 0.30 (0.21) for the full time period, i.e. 1993 to June 2006, and approximately the same as subperiod 2 for subperiod 1. All correlations have a p-value of 0.0000.

Panel A.

period	SVIX and VIX	SVIX and VIX_{t-1}	SVIX and VSTOXX	VSTOXX and VIX	VSTOXX and VIX_{t-1}
subperiod 2†	0.37	0.37	0.70	0.70	0.68
subperiod 3	0.90	0.91	0.83	0.85	0.85
subperiod 4	0.85	0.86	0.90	0.93	0.92

Panel B.

period	ΔSVIX and ΔVIX	ΔSVIX and ΔVIX_{t-1}	ΔSVIX and ΔVSTOXX	ΔVSTOXX and ΔVIX	ΔVSTOXX and ΔVIX_{t-1}
subperiod 2†	0.23	0.19	0.55	0.42	0.27
subperiod 3	0.35	0.30	0.50	0.54	0.25
subperiod 4	0.28	0.15	0.50	0.46	0.21

Note: Subperiod 2† is in this case based on the time period January 1999 to June 2000, due to unavailability of VSTOXX data for the first part of the original subperiod 2. Subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

D5.3 Subperiod Results: Regression Approach Volatility Transmission

Table D.18 reports the results for the volatility transmission regressions for the different subperiods. As for regression (12), where ΔVIX and lagged ΔVIX parameters are regressed on ΔSVIX, all subperiods exhibit the same general pattern as the total sample. Although the individual coefficients change to some degree, there is both a contemporaneous and a lagged effect, where the contemporaneous is slightly larger than the lagged one. The largest contemporaneous as well as lagged effect is observed for subperiod 3, i.e. in a period of high volatility and falling stock markets. Furthermore, the adjusted R^2 values suggest that the explanatory power is higher for this subperiod

than for the other two, adjusted R^2 of 0.219 compared to 0.081 and 0.100, for subperiod $2^{\dagger}$ and 4 respectively.

As for regression (13), where ΔVSTOXX and lagged ΔVSTOXX parameters are regressed on ΔSVIX, the pattern is not as consistent over the different subperiods. Only the contemporaneous effect is significant for all subperiods, whereas the lagged effect is significant only in subperiod 3, i.e. when volatility is high and the market is falling. Comparing the magnitude of the contemporaneous effect over time it is found to be somewhat higher in subperiod $2^{\dagger}$ and 4 than in subperiod 3, then again during subperiod 3 there is a rather large and significant lagged effect, and the combined size of the contemporaneous and lagged effects are roughly of the same size for all periods. Hence, the magnitude of total volatility transmission seems to be more or less equal over time, but it takes a longer time for the information to diffuse between the markets in periods with high volatility and a declining stock market trend. This is reinforced by the adjusted R^2 that stays about the same over all periods, only slightly higher during high volatility regimes.

As for regression (14), where contemporaneous and lagged ΔVIX as well as ΔVSTOXX parameters are included, the results show that the contemporaneous VSTOXX effect is the largest effect for all subperiods and in fact the only significant effect on 5 percent level in subperiod $2^{\dagger}$ (high volatility and rising markets) and subperiod 4 (low volatility and rising markets). The only subperiod when the effects of VIX (contemporaneous and lagged) and lagged VSTOXX are significant is subperiod 3 (high volatility and falling markets). Subperiod 3 is also the period where the contemporaneous VSTOXX effect is at its smallest. It seems that in times of high volatility and falling markets, the volatility transmission has a different pattern than in other environments. The contemporaneous VSTOXX effect, otherwise so dominant, gives way for both a lagged VSTOXX effect as well as contemporaneous and lagged effects of VIX. Furthermore, the explanatory power (in terms of adjusted R^2) is somewhat higher for subperiod $2^{\dagger}$ and 3, indicating that the explanatory power of VSTOXX and VIX is larger during high volatility regimes.

Table D.18. Regression Results Volatility Transmission

The table shows the results for the regressions between daily changes in SVIX, VIX and / or VSTOXX, i.e. the following regressions:

$$\Delta SVIX_t = \alpha_0 + \beta_1 \Delta VIX_t + \beta_2 \Delta VIX_{t-1} + \varepsilon_t \quad (12)$$

$$\Delta SVIX_t = \alpha_0 + \gamma_1 \Delta VSTOXX_t + \gamma_2 \Delta VSTOXX_{t-1} + \varepsilon_t \quad (13)$$

$$\Delta SVIX_t = \alpha_0 + \beta_1 \Delta VIX_t + \beta_2 \Delta VIX_{t-1} + \gamma_1 \Delta VSTOXX_t + \gamma_2 \Delta VSTOXX_{t-1} + \varepsilon_t \quad (14)$$

For each regression the adjusted R^2 (adj R^2) and number of observations (N) are reported. Numbers in parentheses denote t-statistics based on Newey-West standard errors and *, **, and *** denote significance at 10 percent, 5 percent and 1 percent level, respectively.

Estimation of the VIX regression (12) for the full time period, i.e. 1993 to 2006, does not alter the results given for the time period 1999 to 2006, and a regression for subperiod 1 gives results approximately as those provided for subperiod 2†.

period	intercept	ΔVIX_t	ΔVIX_{t-1}	$\Delta VSTOXX_t$	$\Delta VSTOXX_{t-1}$	adj R^2	N
subperiod 2†	-0.018	0.218***	0.162***			0.081	294
	(-0.36)	(4.30)	(3.00)				
subperiod 3	-0.075*	0.308***	0.260***			0.219	565
	(-1.93)	(6.89)	(6.50)				
subperiod 4	-0.041*	0.297***	0.162***			0.100	544
	(-1.77)	(4.94)	(3.41)				
subperiod 2†	-0.001			0.539***	-0.065	0.293	312
	(-0.02)			(8.83)	(-1.27)		
subperiod 3	-0.044			0.327***	0.143***	0.297	608
	(-1.40)			(11.93)	(6.19)		
subperiod 4	-0.033			0.435***	0.048	0.254	585
	(-1.55)			(8.60)	(1.60)		
subperiod 2†	-0.009	0.004	0.063	0.533***	-0.108*	0.312	287
	(-0.20)	(0.07)	(1.18)	(7.40)	(-1.79)		
subperiod 3	-0.062*	0.154***	0.119**	0.231***	0.108***	0.300	555
	(-1.82)	(3.16)	(2.18)	(7.24)	(3.00)		
subperiod 4	-0.041*	0.089	0.063	0.374***	0.021	0.240	537
	(-1.88)	(1.36)	(1.02)	(7.13)	(0.52)		

Note: Subperiod 2† is in this case based on the time period January 1999 to June 2000, due to unavailability of VSTOXX data for the first part of the original subperiod 2. Subperiod 3: July 2000 to June 2003, and subperiod 4: July 2003 to June 2006.

The results from the subperiod regressions indicate that the pattern of volatility transmission has changed over time and is dependent on the prevailing volatility regime. As summarized in the main text, we find three primary differences in the transmission pattern. Firstly, we find indications of greater volatility transmission during high volatility periods, i.e. subperiod 2† and 3. The regressions with only VSTOXX (13) and with both VSTOXX and VIX (14) have a higher adjusted R^2 for these periods. The regression with only VIX (12) has a high R^2 for subperiod 3, but a comparably low R^2 for subperiod 2†. This low R^2 in the early subperiod can however be due to generally low correlations between VIX and SVIX during the first part of the sample period (compare also the correlations above). Nevertheless, despite the somewhat inconclusive evidence from the VIX regressions, the volatility transmission seems to be more pronounced during high volatility periods.

Secondly, the effect from the US market is largest during high volatility and falling markets, i.e. subperiod 3. Concerning regression (12) containing only VIX, the adjusted R^2 value is doubled in subperiod 3, and moreover, in the encompassing regression (14) subperiod 3 is the only period in which VIX is found to have a significant effect. One can also relate back to the correlations where the

correlation between SVIX and VIX is larger than the correlation between SVIX and VSTOXX only in subperiod 3, reinforcing the importance of the US market over the Eurozone market in high volatility environments and falling markets. All this indicates that the influence from the US market increases during falling stock markets.

Thirdly, we find that the diffusion of information from the US and Eurozone markets takes longer time in high volatility and falling markets since the lagged effects are especially pronounced in subperiod 3 for all three regressions (12) – (14).

D5.4 Granger Causality Tests for SVIX, VIX and VSTOXX

In order to establish the direction of the transmission of expected volatility between the Swedish, US and Eurozone markets, and to be able to see which market tends to lead the others, we conduct Granger causality tests. This approach is line with e.g. Skiadopoulos (2004) and Aboura (2003). The method for the Granger causality tests is essentially the same as when investigating the causality between the SVIX and OMX indices, see appendix D3.3. Specifically, the following pair of regressions is used to test the relationship between SVIX and VIX:[54]

$$\Delta SVIX_t = \phi_0 + \sum_{i=1}^{m} \alpha_i \Delta SVIX_{t-i} + \sum_{i=1}^{m} \beta_i \Delta VIX_{t-i} + \varepsilon_t \quad \text{(D4)}$$

$$\Delta VIX_t = \theta_0 + \sum_{i=1}^{m} \gamma_i \Delta SVIX_{t-i} + \sum_{i=1}^{m} \delta_i \Delta VIX_{t-i} + u_t \quad \text{(D5)}$$

To test the relationship between VSTOXX and SVIX, we simply substitute ΔVSTOXX for ΔVIX in equation (D4) and (D5) above, and when testing VIX and VSTOXX, we substitute ΔVSTOXX for ΔSVIX.

Table D.19 reports the results from all Granger causality tests, and we conclude that there is unidirectional causality from VIX to SVIX, from VSTOXX to SVIX and from VIX to VSTOXX. Hence, the flow of volatility transmission seems to go from the US market to the Swedish and Eurozone market and from the Eurozone market to Sweden. These results are not surprising, since the US market is one of the leading financial markets in the world and consequently affects both the Swedish market as well as the European one. The Eurozone area is in turn not large enough to lead the US market, but due to the EU integration and its relatively larger size compared to Sweden it does influence the Swedish market. The Swedish market is in turn too small to have any significant international influence.

[54] As suggested by Skiadopoulos (2004) we also perform the Granger tests using the lead-lag approach described by Malliaris and Urrutia (1992) to account for the potential effect from the time zone differences between the US and Europe. Equation (D4) then is modified into (D4*):

$$\Delta SVIX_{t+1} = \phi_0 + \sum_{i=1}^{m} \alpha_i \Delta VIX_{t-i} + \sum_{j=0}^{m} \beta_j \Delta SVIX_{t-j} + \varepsilon_t \quad \text{(D4*)}$$

The results from these regressions are somewhat mixed. The tests of causality from SVIX and VSTOXX to VIX are unaffected by this approach. However, this testing procedure shows that VIX in some cases does not cause VSTOXX or SVIX. Then again, if one only considers the 'optimal' lag-length as suggested from the AIC criteria, one cannot reject causality from VIX to SVIX and VSTOXX. The overall results of no causality can be seen as a further indication that the relationship from the VIX to the VSTOXX and SVIX index is to a large degree contemporaneous.

Table D.19. Granger Causality Tests for SVIX, VIX and VSTOXX

The table shows the results for Granger causality tests between the (daily) changes in SVIX, VIX and VSTOXX for the time period January 1999 to June 2006. To test the causality between SVIX and VIX the following pairs of regressions are used:

$$\Delta SVIX_t = \phi_0 + \sum_{i=1}^{m} \alpha_i \Delta SVIX_{t-i} + \sum_{i=1}^{m} \beta_i \Delta VIX_{t-i} + \varepsilon_t \quad \text{(D4)}$$

$$\Delta VIX_t = \theta_0 + \sum_{i=1}^{m} \gamma_i \Delta SVIX_{t-i} + \sum_{i=1}^{m} \delta_i \Delta VIX_{t-i} + u_t \quad \text{(D5)}$$

Where the first equation tests if ΔVIX causes ΔSVIX, and the second tests if ΔSVIX causes ΔVIX. The null hypotheses of no causality are: $H_0 = \beta_1 = \ldots = \beta_m = 0$ and $H_0 = \gamma_1 = \ldots = \gamma_m = 0$, for the first and second equation respectively, and they are tested using a standard F-test,

$$F = \frac{\left(RSS_R - RSS_{UR}\right)/m}{RSS_{UR}/\left(n-k\right)} \sim F_{m,(n-k)}$$

Where *(RSS_{UR}) RSS_R* is the residual sum of squares for the (un-)restricted model, *m* is the number of lags used, *n* the total number of observations and *k* the number of parameters estimated in the regression. The test statistic follows an F-distribution with *m* and (*n* - *k*) degrees of freedom.

For causality tests between VSTOXX and SVIX, ΔVSTOXX is substituted for ΔVIX and for causality test between VIX and VSTOXX, ΔVSTOXX is substituted for ΔSVIX in the equations above.
The F-statistic is provided for lag length *m*, which is determined using the Akaike Information Criteria, AIC. Results are stable up to 10 lags, stable to controlling for VSTOXX in the VIX and SVIX regressions, and controlling for VIX in the VSTOXX and SVIX regressions, additionally the VIX and SVIX results are stable to use of the full period, January 1993 to June 2006.

null hypothesis	lag length *(m)*	F-statistic	p-value	outcome
ΔSVIX does *not* Granger cause ΔVIX	6	1.23	(0.2871)	no causality
ΔVIX does *not* Granger cause ΔSVIX	4	23.93	(0.0000)	causality
ΔSVIX does *not* Granger cause ΔVSTOXX	2	0.29	(0.7463)	no causality
ΔVSTOXX does *not* Granger cause ΔSVIX	4	21.33	(0.0000)	causality
ΔVSTOXX does *not* Granger cause ΔVIX	5	0.96	(0.4392)	no causality
ΔVIX does *not* Granger cause ΔVSTOXX	6	23.39	(0.0000)	causality