Credit-Implied Equity Volatility –
Long-Term Forecasts and Alternative Fear Gauges

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Abstract

This study discusses how to compute long-term stock return volatilities using credit derivatives prices and how such volatilities can be used in different areas ranging from the valuation of employee stock options and other long-term derivatives to the construction of market-based fear gauges. Our credit-implied volatilities are long-term forecasts of future stock return volatilities, typically with a 5-year horizon or longer, which make them particularly suitable for the long expected terms of executive compensation plans. Credit-based "fear gauges", comparable to the equity-based CBOE VIX indexes but emanating from the credit market, can be backed out from credit-implied volatilities in selected countries or market segments. Such fear gauges differ from traditional fear gauges by having longer horizons, by covering different market segments and by reflecting the view of the credit investor rather than the equity investor. In the empirical part of the paper we focus on the European financial sector and on forecasting of long-term stock return volatilities in this market. We also construct country-specific fear gauges with a focus on the financial sector for a set of European countries. We find the major movements of the credit-implied volatilities and fear gauges to be similar to those of historical volatilities and equity-implied fear gauges. We also find the credit-implied volatilities and fear gauges to behave in ways consistent with economic and financial developments both on a Europe-wide level and on country- and firm-specific levels. Finally, the forecasting accuracy of the credit-implied volatilities is found to be better than that of horizon-matched historical volatilities.

Keywords: credit default swaps; implied volatility; CreditGrades; VIX; fear gauge; long-term forecast
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1. Introduction

Volatility plays a very important role in finance. It is not only used on a day-to-day basis by banks and other investors in risk management and derivatives pricing, but it is also frequently used by central banks and financial regulators in measures of financial stability. Typically, out-of-sample forecasts of future volatility are more useful than in-sample estimates of past volatility, and volatility forecasting has therefore kept both academics and practitioners busy for the last twenty years. Up until 2002, Poon and Granger (2003) counts at least 93 published articles and working papers that study the forecasting performance of different volatility models, and over the last ten years the list of articles has become even longer. This huge body of research is testament to the importance of financial volatility, and in this paper we build on this literature by estimating and forecasting so-called credit-implied stock return volatilities. Byström (2013) describes how one can back out implied stock return volatilities (or implied stock prices) from credit default swaps (CDS) using a model linking stock prices to credit derivatives prices in the same way as ordinary implied stock return volatilities are backed out from call- or put-options prices using the Black Scholes model (Black and Scholes (1973)). The credit-implied volatilities differ from traditional equity-implied volatilities by reflecting the sentiment of the credit derivatives market rather than the equity options market. In addition, the credit-implied volatilities described in Byström (2013) look several years into the future while equity-implied volatilities typically look just some months ahead. While there are many methods of modelling and predicting volatility, models specifically focused on long-term volatility forecasts are much less prevalent. The innate long-term focus of our credit-implied stock volatilities therefore has the potential to make them particularly useful in forecasting volatility over the long horizon.

In this paper we follow Byström (2013) and back out credit-implied stock volatilities from credit default swap spreads using the industry benchmark model, i.e. the CreditGrades model. This model builds on the Merton (1974) credit risk model and was developed by Deutsche Bank, Goldman Sachs and JP Morgan together with RiskMetrics Group (CreditGrades (2002)). CreditGrades uses a firm’s stock price dynamics and debt levels to compute theoretical credit default swap spreads. Instead of backing out CDS spreads from stock prices, however, as is typically the procedure, we follow Byström (2013) and work the CreditGrades model backwards by backing out credit-market implied stock return volatilities from the CDS spreads. Although the method of computing the volatilities is the same, our study differs from Byström (2013) in several ways (in addition to focusing entirely on volatilities). First, while Byström (2013) never studies the forecasting ability of the credit-implied volatilities, we focus primarily on that, i.e. on volatility forecasts. Second, we focus on long-term forecasts and highlight the particular usefulness of the Byström (2013) approach in long-term forecasting, rather than in the more common short-term forecasting of volatility. Specifically, we suggest that credit-implied volatilities are used in the pricing of employee stock options, convertibles, warrants and other derivatives with a long expected term before being exercised or called. We also believe that the credit-implied volatilities can be used as inputs to credit risk models, i.e. models where the focus normally lies many years into the future. Third, while Byström (2013) looks at non-financial firms we have instead chosen to focus on financial firms, i.e. banks and insurance companies. Furthermore, instead of the US market we have chosen to study the European market, an interesting market for bank studies considering the recent turmoil in the European financial system. Fourth, instead of merely looking at market-wide VIX-like fear gauges, we compute country-specific fear gauges. In addition, our fear indicators have a narrow focus on financial firms rather than on a broad universe of firms in different industries. Fifth, finally, the time-series dynamics of our financial fear gauges are compared to several other fear gauges as well as systematic risk indicators.

We find the time-varying properties of the individual credit-implied volatilities quite similar to those of historical (sample) volatilities. The same holds for the aggregated (CIVX) index of credit-implied volatilities when it is compared to well-known equity-implied volatility indexes such as VIX, VSTOXX and VSTOXX 24M. Compared to historical volatilities, the credit-implied volatilities lack ghost effects, and compared to equity-implied volatilities, the credit-implied volatilities demonstrate much less short-term fluctuations (noise). Moreover, the forecasting accuracy of the credit-implied volatilities is generally better than that of horizon-matched historical volatilities; the forecasting errors are not only on average smaller but they are also more stable over time. The credit-implied volatilities are inherently forward-looking and the *Europe-wide* CIVX financial fear gauge correlates with the Composite Indicator of Systemic Stress (CISS) developed by the European Central Bank (Hollo et al. (2012)). Furthermore, the *country-specific* fear gauges demonstrate a behavior consistent with the country-specific economic and financial development, not least during the recent turbulent crisis-period. On the *individual firm* level, finally, the ranking of our European banks' level of credit-implied volatility at the height of the euro-crisis is similar to the ranking of Moody's long-term credit ratings for the same set of banks. In other words, whether we look at the pan-European level, the country-specific level or the firm level, the behavior of the credit-implied volatility is consistent with that of other well-known measures.

The paper is organized as follows. Chapter two describes our method of backing out stock return volatilities from the credit market. Chapter three describes various ways in which these volatilities can be used, and chapter four presents the empirical study of credit-implied volatilities and volatility indexes in the European financial sector. Chapter five, finally, concludes the paper.

2. Credit-Implied Stock Return Volatilities

While ordinary (equity-) implied volatilities typically are backed out from traded call- and put-options using the industry benchmark Black-Scholes options pricing model (Black & Scholes (1973)) our credit-implied volatilities are instead backed out from credit default swaps (CDS) using the industry benchmark CreditGrades CDS pricing model (CreditGrades (2002)). The CreditGrades model links a firm's default swap price (spread) with the firm's stock price, stock return volatility and debt level using a set of model assumptions similar to those behind the Black-Scholes model. While the CreditGrades model typically is used to calculate credit default swap spreads we instead follow Byström (2013) by solving the CreditGrades model backwards; i.e. we back out stock return volatilities that are consistent with empirically observed CDS spreads and stock prices. The process is directly comparable to the traditional method of backing out implied volatilities, but with the equity option market replaced by the credit derivatives market.

The CreditGrades (2002) model is similar in spirit to the Merton (1974) model and, just like Merton (1974) it models the risk that a firm defaults on its debt. Both models assume that default occurs whenever a firm's asset value, V_t, falls below its debt level, D. While the Merton model assumes a constant recovery rate, L_t, however, CreditGrades introduces randomness to the recovery rate. L_t represents the global recovery rate on all liabilities of the firm while R is the recovery on the specific liability underlying the credit default swap that is to be priced. CreditGrades further models the asset value as a standard geometric Brownian motion and defines default as the point when the asset value falls below the (stochastic) default threshold L_tD. The CreditGrades CDS spread for a certain maturity, T, is then equal to

$$CDS_{CreditGrades} = r(1-R)\frac{1-P(0)+e^{r\xi}(G(T+\xi)-G(\xi))}{P(0)-P(T)e^{-rT}-e^{r\xi}(G(T+\xi)-G(\xi))} \qquad (1)$$

where $P(t)$ is the survival probability

$$P(t) = N(-\frac{A_t}{2}+\frac{\ln(d)}{A_t}) - dN(-\frac{A_t}{2}-\frac{\ln(d)}{A_t})$$

and where

$$d = \frac{V_0}{L_{mean}D}e^{\lambda^2},$$

$$A_t{}^2 = \sigma^2 t + \lambda^2,$$

$$G(t) = d^{z+\frac{1}{2}}N(-\frac{\ln(d)}{\sigma\sqrt{t}} - z\sigma\sqrt{t}) + d^{-z+\frac{1}{2}}N(-\frac{\ln(d)}{\sigma\sqrt{t}} + z\sigma\sqrt{t}),$$

$$\xi = \frac{\lambda^2}{\sigma^2},$$

$$z = \sqrt{\frac{1}{4}+\frac{2r}{\sigma^2}}.$$

σ is the asset return volatility, r is the risk-free interest rate and L_{mean} and λ is the mean and standard deviation, respectively, of the log-normally distributed global recovery rate, L_t. The asset return volatility, σ, is calculated from the stock return volatility, σ_E, since the asset value process is not observable. To calculate the asset return volatility CreditGrades uses the linear approximation $V_t = E_t + L_{\text{mean}}D$, where E_t is the equity value, which implies that $\sigma = (\sigma_E E_t) / (E_t + L_{\text{mean}}D)$. For details regarding the derivation of the CreditGrades model we refer to the original CreditGrades Technical Document (CreditGrades (2002)).

Instead of computing theoretical credit default swap spreads we invert the CreditGrades model (numerically) in order to back out stock return volatilities, σ_E, that are consistent with observed credit default swap spreads and stock prices. Of course, just like the Black-Scholes model, the CreditGrades model suffers from fairly strong model assumptions. Also, while the Black-Scholes model wrestles with the well-known volatility smile across different strike prices, the CreditGrades model instead has to deal with the estimation of the stochastic recovery rate (the recovery rate in CreditGrades is comparable to the strike price in Black-Scholes).

3. When Are Credit-Implied Stock Return Volatilities Useful?

There are numerous ways of estimating and forecasting stock return volatilities. The most natural way is perhaps to extract the volatility directly from the stock returns themselves using more or less advanced time-series methods. Another way is to focus on options traded on the stock and extract the implied stock return volatility using an options pricing model such as Black-Scholes. In this paper we have chosen the implied volatility alternative but instead of following the ordinary path of backing out the volatility from an equity option, such as an ordinary stock call-option, we back out the volatility from a credit derivative, more exactly from the price of a credit default swap. These credit-implied stock return volatilities can be interpreted as the credit market's opinion on the likely future variability in the equity market and as such they represent an alternative estimate/forecast of stock volatility with unique properties. Below, we discuss some potential applications of this volatility measure.

3.1. Pricing of Long Maturity Employee Stock Options and Other Derivatives

Employee stock options, convertible securities, and warrants are examples of equity derivatives that require long-term volatility forecasts, sometimes as far out as five to seven years, to be accurately priced (Alford & Boatsman (1995)). The reason is the long expected term of such contracts before they are exercised or called. When it comes to employee stock options there is an additional reason for why accurate pricing of such options is important, i.e. the requirement of firms to report the cost of their employee stock options to the authorities. The Financial Accounting Standard Board (FASB), for example, requires US firms to properly recognize the full cost of stock options granted to their employees (Jiang & Tian (2010)). In a financial reporting, and accounting, context the typical method of forecasting volatility is to extrapolate historical volatility estimates into the future. Often, the estimation period is chosen to match the forecasting horizon, so-called horizon-matching. The somewhat ad-hoc character of this approach, however, has led to the common practice of using option-implied volatilities instead (Reitter (2012)). Implied options have the advantage of being forward-looking but are only available to firms with traded equity options. Furthermore, equity options tend to have much shorter maturities than the five to seven years needed to accurately price employee stock options and other similar derivatives.

As an alternative to both historical volatilities and option-implied volatilities we therefore suggest that credit-implied volatilities are used when pricing employee stock options and other long-term equity derivatives. These volatilities have several advantages. First, they are, per construction, long-term volatilities since credit default swaps have maturities ranging from one to ten years. Second, they are strictly forward-looking which is appealing since it is the expected future volatility that is needed when pricing for instance employee stock options. Third, no stock price history is needed when constructing the forecast. The latter is an advantage for instance if a firm recently went public, if a firm has no traded stocks (perhaps it is fully owned by the government) or if a stock is very illiquid. In these situations neither historical volatilities nor option-implied volatilities are available. Fourth, by being backed out from the credit market rather than from the equity market, credit-implied volatilities are likely to represent a different risk-return view-point than the equity-based volatilities. Even though it is impossible to tell which view-point is the better, it is possible that a careful selection, or even a combination of forecasts from both the equity- and the credit-side of the capital structure, paints a more accurate picture of the long-term future volatility of a stock. To sum up, there are several reasons to use credit-implied volatilities when pricing employee stock options and other long-term equity derivatives such as convertible securities and warrants.

3.2. Construction of Credit Based Fear Indexes

Byström (2013) suggests a credit-based “fear gauge” based on portfolios of credit-implied volatilities as an alternative to the well-known CBOE VIX index, the widely used equity-based fear gauge. While the VIX index is backed out from the equity option market the Byström (2013) credit-implied volatility index (CIVX) is backed out from the credit derivatives market. Consequently, while the VIX index quantifies the equity market´s beliefs of future market-wide stock market volatility, the CIVX index instead quantifies the credit market´s beliefs of the same volatility.

The individual credit-implied volatilities used to compute the CIVX index are backed out from the credit default swap market, which nowadays is a very liquid market. Byström (2013) bases his volatility indexes on portfolios of *single-name* credit default swaps, but established and widely used *indexes* of credit default swaps such as the iTraxx- and CDX indexes could possibly also be used for the development of regional and country-specific fear gauges. Such region- or branch-specific volatility indexes, whether they are backed using single-name CDS contracts or CDS indexes, are likely to appeal to market participants; in fact, Goltz and Tang (2011) reports of a recent investor survey made by Edhec-Risk Institute where lack of choice when it comes to volatility indexes is ranked as the most important limitation of the volatility market. Compared to traditional implied volatilities, as well as fear gauges such as the VIX index, that are backed out from equity options, the credit-implied volatilities are backed out from a much younger market. However, the growth of the credit derivatives market over the last decade has led to credit derivatives increasingly covering more and more regions, countries, industries as well as firms. In fact, the Bank for International Settlements (BIS) in their "*OTC derivatives market activity in the first half of 2013"* report from November 2013 reports much larger notional amounts outstanding at the end of June 2013 for credit default swaps (24500 billion US dollars) than for for equity options (4600 billion US dollars). In other words, the future potential of the credit default swap market, as for extracting stock return volatilities, is at least as strong as that of the equity option market.

Moreover, a nice feature of the CIVX index is that it can be designed to focus on as long-term forecasts as five to ten years. This is not normally possible when equity options are used to back out implied volatilities; the VIX index is for instance based on options maturing in one month's time. And VIX is not the only fear indicator that is based on (short-term) equity options. The Credit Suisse Fear Barometer (CSFB), for example, is based on the relative pricing of 3-month OTM put and call-options; the more expensive the put-option is relative to the call-option, the higher the level of fear (Xu (2012)). Compared to these rather myopic fear gauges the CIVX index looks further into the future and, depending on the maturity of the credit default swaps, is available in different versions with horizons ranging from one to ten years.

An index such as CIVX is not necessarily interpreted as a fear gauge; it can also, possibly, be interpreted as an indicator of systemic risk. There are many different systemic risk indicators available; some, but not all, driven by stock return volatilities. The European Central Bank (ECB), for instance, has developed their Composite Indicator of Systemic Stress (CISS) that measures the degree of instability in the financial system as a whole using a battery of stress indicators (Hollo et al. (2012)). Compared to complicated indicators such as CISS, however, simple indicators such as CIVX have the advantage of being both easy to compute and of having a clear-cut interpretation. Whether the CIVX index has the other properties needed of an indicator of systemic stress is an open issue that will be studied further in the empirical part of this paper.

3.3. Risk Management

An asset's (market) risk is often measured, directly or indirectly, as the volatility of the asset's returns. For a stock this typically means that the stock return volatility has to be estimated or, even better, forecasted. And depending on the horizon of the risk manager, both short-term and long-term volatility forecasts are needed. Moreover, in addition to the wide-spread use of volatility as a measure of risk, other risk measures like Value at Risk (VaR) are also typically indirectly linked to the volatility. If the stock returns are normally distributed, for example, VaR is simply a multiple (1.96•, 2.33•….) of the volatility. Furthermore, not only market risk is regularly represented by the volatility, but so is credit risk. In commonly used models such as Merton (1974), one of the most important inputs when estimating default probabilities and credit losses is the asset's long-term volatility. While there are many methods of modelling and predicting volatility, models specifically focused on long-term forecasts are much less prevalent. Credit risk is, however, one area of risk management where long-term volatility forecasts are required. It is not the only area, though, and any novel way of forecasting future (long-term) volatility is therefore welcome. The credit-implied volatility described in this paper is one such example.

3.3. Trading and Arbitrage

For options traders to beat the market it is necessary for them to make more accurate volatility forecasts than other market participants. Since volatility changes in a seemingly stochastic fashion, volatility forecasting typically involves complex modelling of the volatility dynamics. Or, alternatively, the options trader backs out volatilities from various other derivatives contracts, often from call- or put options with a different underlying stock or a different strike price or maturity. Here, we suggest that these traders look further afield and back out equity volatilities from the credit market instead. If the credit market happens to be better informed than the equity market, credit-implied stock return volatilities could be better at predicting the future than those hailing directly from the equity market, and consequently generate profits to the options trader. This approach could be particularly profitable when pricing illiquid long-term options such as warrants. And of course, nothing stops credit derivatives traders from doing the same; i.e. the credit derivatives trader can mimic the strategies used by equity options traders and use credit-implied volatilities of one set of firms to price credit derivatives on another set of firms.

Arbitrageurs could also profit from taking positions based on the credit-implied volatility and on its relationship to equity-based volatilities, whether historical or implied. Credit derivatives such as credit defaults swaps are often priced off the equity market and the stock return volatility is then the single most important input parameter (Cao et al. (2011)). A discrepancy between equity-based and credit-based stock return volatilities could therefore indicate arbitrage possibilities for traders trading across the capital structure, i.e. for capital structure arbitrageurs (Yu (2006), Duarte et al. (2007)).

4 Credit-Implied Stock Return Volatilities in the European Financial Sector – An Empirical Analysis

In this section, we empirically examine the properties of our credit-implied stock return volatilities. We have chosen to focus on financial firms, i.e. banks and insurance companies, since the backing out of volatilities is likely to be more difficult for financial firms than for non-financial firms due to the former's often rather opaque capital structure. Moreover, our choice of European firms is motivated by the long-lasting turbulence in the European financial sector. Both the US-initiated 2007-2008 financial crisis and the subsequent Europe-centered sovereign debt crisis starting in 2010 have had a great effect on more or less all European financial firms. This is likely to make the exercise of estimating and forecasting volatility particularly challenging in the European market.

The scope of the study is limited by the general lack of traded credit default swaps, in Europe and elsewhere, before 2004. This limits the possibilities of extending the start of the sample period further back in time, and in order to avoid serious data quality issues we have chosen to limit our time-period to June 8, 2004 to November 5, 2013. The starting point could have been extended some months further back in time but at the cost of a smaller sample of firms and of a less liquid credit default swap market. Just like any other study of credit default swaps our study is limited not only in the time-dimension but also cross-sectionally. To get a large enough sample of European financial firms for our empirical tests, we select the 50 largest banks in Europe (by total assets) that also have credit default swap data with a daily frequency in Thomson Reuters

Datastream for the entire time-period above. This limits the sample to 23 large European banks. In addition to these 23 banks we add the remaining 7 financial firms (all of them insurance firms) included in the iTraxx Europe CDS index (Series 20). The resulting sample thus consists of 30 of the most important financial firms in Europe, which is a large enough data set for our purposes, most notably for the construction of half a dozen country-specific fear indexes.

Compared to the CDS spread series, the stock price series in this study cover five additional years, June 8, 1999 to June 7, 2004, since historical stock price data is needed when estimating historical stock return volatilities (using up to 5-year long estimation windows) from June 8, 2004 onwards. Daily stock prices, CDS spreads and risk-free interest rates (proxied by the 3-month Euribor rate) are all downloaded from Datastream. The CDS spread data is represented by senior 5-year euro-denominated credit default swaps. Finally, yearly debt-to-equity ratios for the 30 firms were downloaded from the home page of Professor Aswath Damodaran at Stern School of Business. The yearly debt-to-equity ratios are transformed to daily data using a linear interpolation between year-end observations.

While our study of credit-implied stock volatilities is limited by the fairly young stage of the credit default swap market it should be stressed that although the equity market, of course, covers many more firms than the CDS market this is not necessary the case for the stock options markets typically used to extract implied volatilities. In other words, the limits of our study when it comes to the number of firms and the length of the time-period should be seen in the light of similar studies of equity option-implied stock volatilities.

4.1. *Credit-Implied Stock Return Volatilities*

This section focuses on individual firm volatilities and the next section (section 4.2.) focuses on volatility (fear) indexes. Our credit-implied volatilities are computed using the industry benchmark CreditGrades model; i.e. a particular firm's implied stock return volatility is backed out from the firm's CDS spread, stock price and debt level (analogue to call option price, stock price and exercise price in ordinary calculations of implied volatilities). All the implied volatilities are computed on a daily basis and are, essentially, the credit derivatives market's long-term forecasts of the firm's stock return volatility over the coming 5-year period (since we use 5-year credit default swaps).

The CreditGrades model requires estimates of the mean global recovery rate, L_{mean}, the standard deviation of the global recovery rate, λ, as well as the bond-specific recovery rate, R. In this study we follow the CreditGrades Technical Document (CreditGrades (2002)) in our choice of the global recovery rate; i.e. L_{mean} =0.5. We further choose the bond-specific recovery rate R to be equal to the global recovery rate. When it comes to, λ, however, the CreditGrades Technical Document explicitly mentions that the standard deviation of the global recovery rate is expected to be lower for financial firms than for the sample of US non-financial firms in the benchmark implementation in CreditGrades (2002). Unfortunately, neither the CreditGrades Technical Document nor any other source we are aware of gives any information on how much lower λ should be. We therefore choose λ=0.03, which is a tenth of the value used in the benchmark implementation of CreditGrades, and our choice is based on the difference in leverage ratio between the US non-financial firms used by CreditGrades and the European financial firms in our study. According to Kalmeli-Ozcan et al. (2012) the average leverage ratio (total assets over equity) for listed US non-financial firms over the time-period 2000-2009 varies from 2.2 to 2.5 while the average leverage ratio for large European banks over the same time-period is roughly ten times that, varying from 22 to 26. As a result, we believe that λ=0.03 gives a reasonable estimate of the level of uncertainty attached to the default barrier for a typical financial firm in Europe over the last ten years. Of course, in real-life practical situations one would probably want to estimate λ using large data bases of financial firms' empirical recovery rates (CreditGrades (2002)). Or alternatively, if ease of implementation is more important than accuracy, the standard assumption of a constant recovery rate is consistent with λ=0.

As mentioned, financial firms differ from non-financial firms by being much more leveraged. This would, ceteris paribus, result in financial firms having much higher credit default swap spreads than similar non-financial firms. The government often supports financial firms in times of crisis, however, and, as mentioned by the CreditGrades Technical Document, this makes financial firms' "effective leverage ratio lower than that implied by standard debt-per-share calculations". Again, the CreditGrades Technical Document does not give any information on how much lower this "effective leverage ratio" should be for financial firms. As a result, we calculate effective debt levels for our financial firms by multiplying the actual debt levels by a half (0.5). This choice shares similarities with the way Moody's|KMV chooses the default point in its KMV model as the sum of the short-term debt and half the value of the long-term debt.[1] In practical situation we reckon that a more careful analysis of the firms' capital structure would be useful when calculating effective leverage ratios.

4.1.1 Volatility Comparisons

In this sub-section, our credit-implied stock return volatilities are compared to ordinary historical volatilities estimated using either 1 year, 3 years or 5 years of historical stock returns. The forecast accuracy of the various volatilities is presented in the next sub-section (sub-section 4.2.2.), and all through the paper we follow Jiang & Tian (2010) and standard practice in the option pricing literature by using the standard deviation as our volatility metric. Each day across the time-period June 8, 2004 to November 5, 2013 *past* stock price quotes are used to compute daily historical volatilities (HI 1-year , HI 3-year and HI 5-year) while *current* stock, CDS and debt quotes are used to compute daily credit-implied volatilities (CI). The 30 firms in the study are listed in the Appendix and some descriptive volatility statistics is presented on an averaged level in Table 1. Meanwhile, in Figure 1 the volatility dynamics is presented on a firm by firm basis.

From the average values in Table 1 it is evident that the standard deviation of the implied volatility is much lower than the standard deviations of the three historical volatility measures. Meanwhile, the standard deviation of the historical volatility estimate is, not surprisingly, lower the longer the window used. The variability of the implied volatility is consequently most similar to the 5-year historical volatility despite being instantaneously backed out. The mean volatility is also lowest for the implied volatility estimator (35.7%) but a comparison with the historical volatilities is not straightforward since the credit-implied volatility is forward-looking (covering 2004-2018) and the historical volatility is backward-looking (covering 1999-2013).

The volatilities of the individual financial firms are plotted in Figure 1 and a visual inspection of the volatility graphs reveals that both the credit-implied volatility and the (1-year and 5-year) historical volatilities demonstrate a clear upward trend across the 10-year time-period, at least for most firms. In other words, the volatility is typically higher towards the end than towards the start of the sample, regardless of how the volatility is estimated. Due to its instantaneous character the

[1] We do not have information on how much of the debt of our financial firms that is short-term and how much that is long-term.

credit-implied volatility, of course, varies much more from day to day than the two smoothed out historical volatilities but it also lacks the typical ghost effects of long-window historical estimates. Interestingly, the financial crisis has a much less profound effect on the implied volatility than on the two historical volatilities where, particularly, the 1-year volatility increases drastically in mid-2008. This difference could possibly be explained by the long-term forward-looking property of the credit-implied volatility coupled with the credit market expecting the stock market turbulence in 2008 of being temporary. Overall, though, the credit-implied volatility behaves as expected and the major movements are quite similar to those of the historical volatilities. The relative volatility levels of the various individual firms are also largely ranked as expected and even if it is difficult to evaluate the accuracy of the relative volatilities, both the problem laden Italian bank *Banca Monte Dei Paschi* and its (relatively) very high implied volatility levels as well as the stable Swedish bank *Svenska Handelsbanken* with its (relatively) very low volatility levels are examples that are in line with stylized facts. A further illustration of this can be found in Table 2 where we have ranked the 23 European banks' credit-implied volatilities at the height of the European sovereign debt crisis (June 2012) from lowest to highest and compared it with the ranking of the banks' credit ratings at the same point in time (June 2012).[2] From basic financial theory (Merton (1974)) one would expect a negative link between a firm's stock volatility and its credit rating and Table 2 confirms this by demonstrating a fairly strong negative link between our credit-implied volatilities and Moody's long-term credit ratings for banks in Europe during the recent financial crisis; for example, all the (three) top-rated banks occupy the three lowest volatility slots and the (single) worst rated bank has the highest implied volatility etc.

4.1.2. Forecast Accuracy

In section 3, we showed some examples of areas where credit-implied stock volatilities can be useful, and in many of these applications the most important feature of the volatility measure is

[2] The insurance firms are excluded since bank ratings are different from non-bank credit ratings. The ratings were collected online from Wall Street Journal at the web-link http://online.wsj.com/news/articles/SB10001424052702303734204577464824288867112 and represent Moody's long-term debt ratings as of June 27, 2012. This date is clearly representative for the debt crisis in Europe with a request for financial assistance by both the Spanish government http://www.consilium.europa.eu/uedocs/cms_data/docs/pressdata/en/ecofin/131309.pdf and the Cypriot government http://www.consilium.europa.eu/uedocs/cms_data/docs/pressdata/en/ecofin/131308.pdf filed on the very same day (June 27, 2012).

the extent to which it is able to predict *future* stock return volatility. Whether one wants to price complex long-term employee stock options or simply wants to price and manage the risk of one's equity portfolio, perhaps using Value at Risk or some other widely used risk measure, the future volatility is the most crucial input. In this sub-section we will therefore investigate the forecasting ability of the credit-implied volatilities computed in the previous sub-section. Since the focus in this paper, first and foremost, is on long-term (1-year to 5-year) forecasts, we compare the implied volatilities to simple (model-free) historical volatilities. That is, no GARCH models, stochastic volatility models, regime switching models or any other advanced model focusing mainly on shorter horizons is included in the study. This choice is also motivated by the finding that more complex volatility models often perform worse when the forecast horizon is long. Instead, historical volatilities, estimated over a period that is at least as long as the forecast horizon, often work best when making long-term forecasts (Reitter (2012)). Moreover, our interest in long historical estimation windows also stems from the current Financial Accounting Standards Board (FASB) and its accounting treatment of employee stock options, where an acceptable way of forecasting volatility is to use horizon-matched historical volatility (Jiang & Tian (2010)). Importantly, our long forecasting horizons exclude any possibility of comparing directly with equity option-implied volatilities since few equity options have maturities extending beyond a year.

To evaluate the forecasting performance of the credit-implied volatility we compare the volatility forecast with the realized (sample) volatility over the forecasting horizon using daily data. Moreover, since our focus is on long-term forecasts with horizons of several years we have chosen to compare the forecast accuracy of implied volatilities to that of historical volatilities estimated using several years of historical data, i.e. we build on the FASB idea of horizon-matching. Each day over the sample period starting in June 8, 2004 we forecast the stock volatility over the next 6 months, 1 year, 3 years and 5 years, respectively.[3] The forecasting exercise ends either 6 months, 1 year, 3 years or 5 years before the end date November 5, 2013, depending on the horizon. The % error is defined as $\frac{volatility_{realized} - volatility_{forecasted}}{volatility_{realized}}$. For each firm in the sample the median % error, the median absolute % error and 90th-percentile absolute

% error over the sample period is calculated. The *Median ERROR* is then calculated by taking the median across the 30 firms' median % errors, the *Median |ERROR|* is calculated by taking the median across the 30 firms median absolute % errors and the *90% |ERROR|* is calculated by taking the median across the 30 firms' 90th-percentile absolute % errors. *Fraction Positive* is the fraction (%) of the errors that are positive. *Median ERROR* and *Fraction Positive* measure bias and *Median |ERROR|* and *90% |ERROR|* measure forecast accuracy (median and dispersion of the absolute error distribution). The results are summarized in Table 3 and show that regardless of how the forecasting accuracy is measured the credit-implied volatility is better at forecasting future realized stock return volatility than historical volatility is. It is only at the longest 5-year horizon that the (5-year) historical volatility produces smaller errors and even at that horizon the credit-implied forecasts are better than both the 1-year and 3-year historical forecasts. Our main focus is on multi-year forecast but even at the shorter 6-month horizon the credit-implied volatility does a relatively good job.[4] One reason behind the superior forecasting performance of the credit-implied volatility could be its inherent forward-looking properties; the credit-implied volatility can be interpreted as the collective opinion of the credit derivatives market about the *future* variability in the stock market. Despite historical volatilities' relative long-term forecasting superiority in the literature (Alford & Boatsman (1995)) historical volatilities are still just estimates of stocks' past variability without any obvious intrinsic forward-looking ability.

From Table 3 it is clear that at longer horizons, all forecasts regardless of method, are negatively biased, i.e. the realized volatility is higher than the forecasted volatility, while at the shortest horizon (6 months) we find the opposite result. For the 5-year horizon more than 90% of the errors are positive. Meanwhile, for the 6-month horizon just around 40% are positive and only for the 1-year horizon we find the expected 50% positive errors. To demonstrate the time-variation of the size and sign of the forecasting errors, Figure 2 plots the time-series behavior of both the error and the absolute error averaged across the 30 firms for the four different forecast horizons. Regardless of forecasting horizon the credit-implied forecasts are relatively more stable than the three historical volatilities in the sense that the forecasting error is never largest; not at any single date over the sample period is either the error or absolute error in the credit-implied

[3] The shorter 6-month forecasting horizon is included despite our focus on long-term forecasts. The reason is that in most situations even a 6-month forecast is considered a long-term forecast. We also include this shorter horizon in order to shed some light on the more short-term forecasting performance of the credit-implied volatility.
[4] Preliminary results suggest that at even shorter horizons the credit-implied volatility performs better still.

forecasts the largest of the four. Meanwhile, the errors in all of the three historical volatility forecasts are the largest at one point or another. Furthermore, the size of the credit-implied forecasting error is much more stable over time and it never explodes to the extent that the historical volatility forecasts errors all, occasionally, tend to do.

There are few studies dealing with long-term forecasting of stock return volatility (Jiang & Tian (2010)) but compared to both Jiang & Tian (2010) and Alford & Boatsman (1995), the errors in our study, when historical volatility is used, are quite large. While the horizon-matched median absolute 5-year forecasting error in our study (of large financial firms in Europe) is 32.4%, Jiang & Tian (2010) reports errors of 22.8% for large US firms. Similarly, Alford & Boatsman (1995) reports corresponding errors of 19% in their study on US firms. Since the time-period in Alford & Boatsman (1995) ends already in 1987 and since the time-period in Jiang & Tian (2010) ends in 2004 neither study includes the very turbulent recent crisis environment. As a result, it is not surprising that our forecasting errors are significantly larger than those in previous studies. Interestingly, though, as for the documented forecasting superiority of horizon-matching volatility, we do indeed find confirming evidence of horizon-matching volatility being superior for all forecasting horizons (except 3-year absolute errors) whether we look at *ERROR*, *|ERROR|* or *90% |ERROR|*; i.e. the 5-year historical volatility is best in predicting 5-year volatility, the 1-year historical volatility is best in predicting 1-year volatility and so on.

4.2. European Financial Sector Fear Indexes

As an alternative to the well-known equity-based VIX fear gauge, Byström (2013) suggests a credit-based “fear gauge” based on credit-implied volatilities. Here, we calculate such credit-implied volatility indexes (CIVX) for the European financial sector. We calculate both a Europe-wide financial fear index, called $CIVX^{Fin,EU}$, and individual country indexes, called $CIVX^{Fin,Country}$. The time-series of the credit-based fear index is then compared to that of various other fear gauges and systemic risk indicators across the turbulent time-period June 8, 2004 to November 5, 2013.

4.2.1. Fear Index Comparisons

Our European financial fear index is calculated by averaging over the credit-implied volatilities of the 30 banks and insurance firms in our sample (see Appendix). The firms are major financial firms in the eleven European countries Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland and the UK, and the Europe-wide credit-implied volatility index $CIVX^{Fin,EU}$ is presented together with the CBOE VIX index in Figure 3. The bold line represents the credit-implied fear index and it is clear how a tranquil pre-crisis regime gives way to a crisis regime around mid-2007. From 2007 the "fear", i.e. the average market-wide credit-implied stock volatility in the European financial sector, increases steadily for five years until the volatility starts to taper in mid-2012. In addition, two fear peaks are clearly visible; there is one distinct peak in early 2009 and there is one (double) peak that lasts from late 2011 until the middle of 2012. These two peaks represent the two phases of the financial crisis, i.e. the global 2008 Lehman Brothers induced financial crisis and the subsequent Europe-centered sovereign debt crisis. Not surprisingly, considering the $CIVX^{Fin,EU}$ fear index' narrow focus on financial firms in Europe, the second peak (or peaks) is even higher than the first peak at around 50% annual volatility. This is about twice the volatility observed before the crisis. Towards the end of the sample, from about July 2012 to November 2013, the fear recedes but despite this drop the fear (volatility) remains much higher than before the crisis.

The dynamics of the $CIVX^{Fin,EU}$ fear index can be compared to that of the VIX fear index. The VIX index is backed out from options on the firms in the S&P500 US stock index and, just like the $CIVX^{Fin,EU}$ index, the fear, as measured by the VIX index, starts increasing in 2007. Unlike the $CIVX^{Fin,EU}$ index, however, the VIX index has just one distinct extreme peak (in October 2008) that is much higher than any of the other peaks. The extreme 2008-peak is followed by two much lower peaks in mid-2010 and late 2011. Overall, though, the two fear indexes, $CIVX^{Fin,EU}$ and VIX, tend to peak and bottom at roughly the same points in time (the sample correlation is 0.40) while their general daily- and weekly movements tend to be more idiosyncratic. One of the most notable differences between the two fear indexes is the VIX index' steady decrease from September 2012 onwards that eventually levels out at levels that are as low as those before the crisis. This is in sharp contrast to the $CIVX^{Fin,EU}$ index where the volatility in late 2013 is about one and a half times as high as before the crisis. This discrepancy is possibly a signal that the credit market is having a more pessimistic stock market outlook than the equity market itself.

It should be remembered that a direct comparison of the two indexes is not possible due to their very different forecasting horizons, five years versus one month. The number of firms included in the index is also very different (30 versus 500) as is the industry and geographical coverage (financials versus non-financials, Europe versus US). In Figure 4, we therefore compare the $CIVX^{Fin,EU}$ index with two European VSTOXX indexes. There are various VSTOXX indexes with different horizon, each measuring the equity option-implied volatility of the euro-zone EURO 50 STOXX stock index. The VSTOXX index, the mother index, is based on one-month implied option-volatilities and the VSTOXX 24M index is based on two-year implied volatilities. As revealed by Figures 3 and 4, the two VSTOXX indexes, particularly the short-term VSTOXX index, have a dynamics that is very similar to that of the VIX index. A comparison of the two figures shows that the European volatility is slightly higher than the US volatility and that just like the credit-implied $CIVX^{Fin,EU}$ index, the VSTOXX indexes, particularly the long-term VSTOXX 24M index, remain at slightly elevated levels all through 2013. In other words, some of the earlier mentioned discrepancy between $CIVX^{Fin,EU}$ and VIX is probably due to the different geographical focus and some is probably due to the different horizons. The latter is also confirmed by the higher sample correlations between $CIVX^{Fin,EU}$ and VSTOXX (VSTOXX 24M) at 0.53 (0.76) than between $CIVX^{Fin,EU}$ and VIX at 0.40; the long-horizon $CIVX^{Fin,EU}$ index behavior is more similar to that of the longer-horizon VSTOXX 24M than to that of the shorter-horizon VSTOXX/VIX. The impact of geography and horizon, respectively, is also demonstrated in Figure 5 where we follow Goltz et al. (2011) in showing trailing 3-year rolling window estimates of volatility index correlations. Apparently, the correlation between credit-implied and equity-implied volatilities is higher the more similar the geographical focus and forecasting-horizon is. Figure 5 also shows that the correlation level is high and positive throughout (essentially) the entire time-period. Finally, some of the remaining differences between the indexes can probably be explained by the different industry focus, and it is not surprising that the volatility of the financial firms in the $CIVX^{Fin,EU}$ index is higher than that of the (mainly) non-financial firms in the VSTOXX indexes during the recent financial crisis.

In addition to the comparison of the $CIVX^{Fin,EU}$ index with other *fear gauges* one can also compare the index to so-called *systemic risk indicators*. One example of such an indicator is the Composite Indicator of Systemic Stress (CISS) developed by the European Central Bank (Hollo et al. (2012)). In Figure 6 the $CIVX^{Fin,EU}$ index is plotted together with the CISS indicator (starting on January 5, 2007) and it is clear that the two indicators react fairly similarly to the major events occurring over the sample period. A striking difference, though, is the different signals sent by the indicators towards the end of the sample. While the CISS indicator is back to the pre-crisis levels, the $CIVX^{Fin,EU}$ index clearly is not. We are not able to explain this difference but perhaps the relative simplicity of the $CIVX^{Fin,EU}$ index, with its sole focus on volatility, is a limitation when it comes to its interpretation as a systemic risk indicator. Or perhaps its one-sided market focus should be complimented with some additional non-market factors/indicators in order to get the entire picture. Or, alternatively, it might simply be due to the long-term forward-looking properties of the CIVX index. In any case, whether the $CIVX^{Fin,EU}$ index has the properties needed of an indicator of systemic stress or not cannot be answered at this point. We just conclude that the general performance of the index is similar to that of the CISS indicator.

4.2.2. Country-Specific Fear Indexes

In this sub-section we calculate individual country fear indexes for those of the eleven European countries that are represented by enough firms in our sample. We consider three domestic firms as a necessary minimum to calculate a meaningful country index, and France, Germany, Sweden, and the UK each have four firms and Italy and Switzerland each have three firms represented in the sample. Due to the different portfolio sizes (three or four firms), and the resulting difference in diversification and volatility smoothing, the two groups' country-specific indexes are presented in separate panels in Figure 7. All the country-specific fear indexes evidently start out at volatility levels of around 30% in 2004. After a steady decline for about three years all fear indexes except $CIVX^{Fin,Sweden}$ start signaling increased fear levels in mid-2007. The Swedish fear index joins the other country indexes six months later and by March 2009, after a steady increase in the fear levels, all country-specific fear indexes reach their peaks.

With the first signs of the more Europe-centered phase of the crisis around 2010, the fear levels in the various countries start to diverge. Basically, the countries can be divided into three groups, those that reach their highest fear levels during the initial financial phase of the crisis, those that reach their peak during the euro-zone crisis some years later and those that demonstrate two similar peaks during the two phases of the crisis. $CIVX^{Fin,Switzerland}$ clearly peaks in 2009, $CIVX^{Fin,France}$, $CIVX^{Fin,Germany}$ and $CIVX^{Fin,Italy}$ all equally clearly peak in 2012 and $CIVX^{Fin,Sweden}$ and $CIVX^{Fin,UK}$, finally, both reach roughly similar peaks in 2009 and 2012. This grouping makes sense when one compares the depths of the Europe-centered (or euro-zone) phase of the crisis in the different European countries. First, there is no wonder that the fear levels were deemed relatively low in Switzerland during the euro-zone phase considering the status of Switzerland

and the Swiss Franc as safe havens during long periods of the crisis. Second, Sweden and the UK are both outside the euro-zone and none of these two countries were as deeply affected by the euro-crisis as the countries in the euro-zone. Third, finally, France, Germany and Italy are all within the euro-zone and therefore at the center of the euro-crisis. Not surprisingly these three countries are also deemed the riskiest three during the euro-crisis, according to the credit market. The fear level in Italy, represented by $CIVX^{Fin,Italy}$ is, by far, the highest and the fear level remains elevated (at around 70%) from 2011 to 2013. This is consistent with the financial and economic development in Italy during the second (euro-zone) phase of the crisis. Meanwhile, at the other extreme, the fear level in the Swedish financial sector stands out as the lowest among the six countries both before and during the financial crisis. Moreover, a pair-wise comparison of France and the UK shows how the heavy concentration of financial activity in London, the UK capital, is reflected in $CIVX^{Fin,UK}$. While $CIVX^{Fin,UK}$ and $CIVX^{Fin,France}$ follow each other both before and after the financial phase of the crisis, i.e. before 2008 and after 2010, at the height of the financial phase of the crisis the fear level in the UK is far higher than in France. Finally, among the six countries, only Sweden and Switzerland are (almost) back at the fear levels seen in 2004, and in none of the countries is the fear level even close to the trough seen in mid-2007. Also this is broadly consistent with the general development in economic/financial indicators and “animal spirits” in Europe over the last decade. Looking forward, considering the long-term forward-looking interpretation of the CIVX indexes, despite fear levels having receded somewhat from 2012 to 2013 the credit market clearly points at heightened stock market volatility in many European countries, most notably in Italy, for many years to come. This message differs from that of most traditional fear indexes, such as VSTOXX, as well as the message of well-known systemic risk indicators such as the CISS indicator. Notably, the message of the CIVX index is the message of a different, in this context mostly unheard, market constituent, namely the credit market. Regardless of which indicator will eventually turn out to have been more right, the different views of the different markets are clearly interesting in their own right.

5. Conclusion

The aim of this study has been to compute long-term stock return volatilities using credit derivatives (as described in Byström (2013)) and to demonstrate how such credit-implied volatilities can be used in different areas ranging from the valuation of employee stock options to the construction of alternative fear gauges. Considering that our credit-implied volatilities are long-term forecasts of future stock return volatilities, typically with a 5-year horizon or longer, we find them particularly suitable in applications where traditional implied volatilities do not look far enough into the future, such as in executive compensation plans. Another area where we believe that credit-implied volatilities can be useful is in the construction of credit-based volatility indexes, or “fear gauges”. We show how regional or branch-specific CIVX volatility indexes can be constructed by averaging credit-implied volatilities across firms in selected countries or industry sectors. Compared to fear gauges backed out from equity derivatives, such as the well-known VIX indexes, our fear gauges (i) are instead backed out from credit derivatives, (ii) look further into the future and (iii) cover different firms and regions.

In the empirical part of the paper we focus on the European financial sector. The empirical study can be divided into two parts. In the first part, we focus on credit-implied volatilities for individual banks and insurance companies in Europe. The implied volatilities are compared to traditional historical volatilities, and their long-term forecasting performance is studied. Overall, we find the credit-implied volatilities to be better at predicting future realized volatility than horizon-matched historical volatilities. In the second part, we construct CIVX financial sector fear gauges for the entire Europe as well as for a select set of individual European countries. The CIVX fear indexes perform very much as expected, indicating particularly high levels of fear in the financial sectors of euro-zone countries during the recent euro-zone debt crisis, and correlate with both traditional fear indexes, such as the VIX and VSTOXX volatility indexes, and with well-known systemic risk indicators such as the CISS indicator. Overall, the credit-implied volatilities demonstrate a behavior consistent with the economic and financial development both on a Europe-wide level and on country- and firm-specific levels. Furthermore, the volatility dynamics is similar to existing indexes and indicators. Differences exist, however, particularly in the high-frequency domain (i.e. day-to-day or month-to-month movements). This is not surprising considering that the credit-implied CIVX indexes contain unique forward-looking information from a unique market, i.e. the credit derivatives market.

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Table 1. Descriptive statistics for daily annualized credit-implied stock return volatilities (CI) and daily empirically observed historical stock return volatilities (HI) averaged across the 30 firms and the 2456 daily observations (June 8, 2004 to November 5, 2013).

	Mean (%)	Stdev (%)	Skewness	Kurtosis
CI	35,7	8,8	0,4	-0,6
HI 5-year	40,8	11,1	-0,2	-0,8
HI 3-year	39,9	16,0	0,1	-1,2
HI 1-year	37,6	21,8	1,2	0,7

Table 2 Ranking of the credit-implied volatilities, from lowest to highest, together with Moody's long-term ratings for the 23 banks in the study on June 27, 2012.

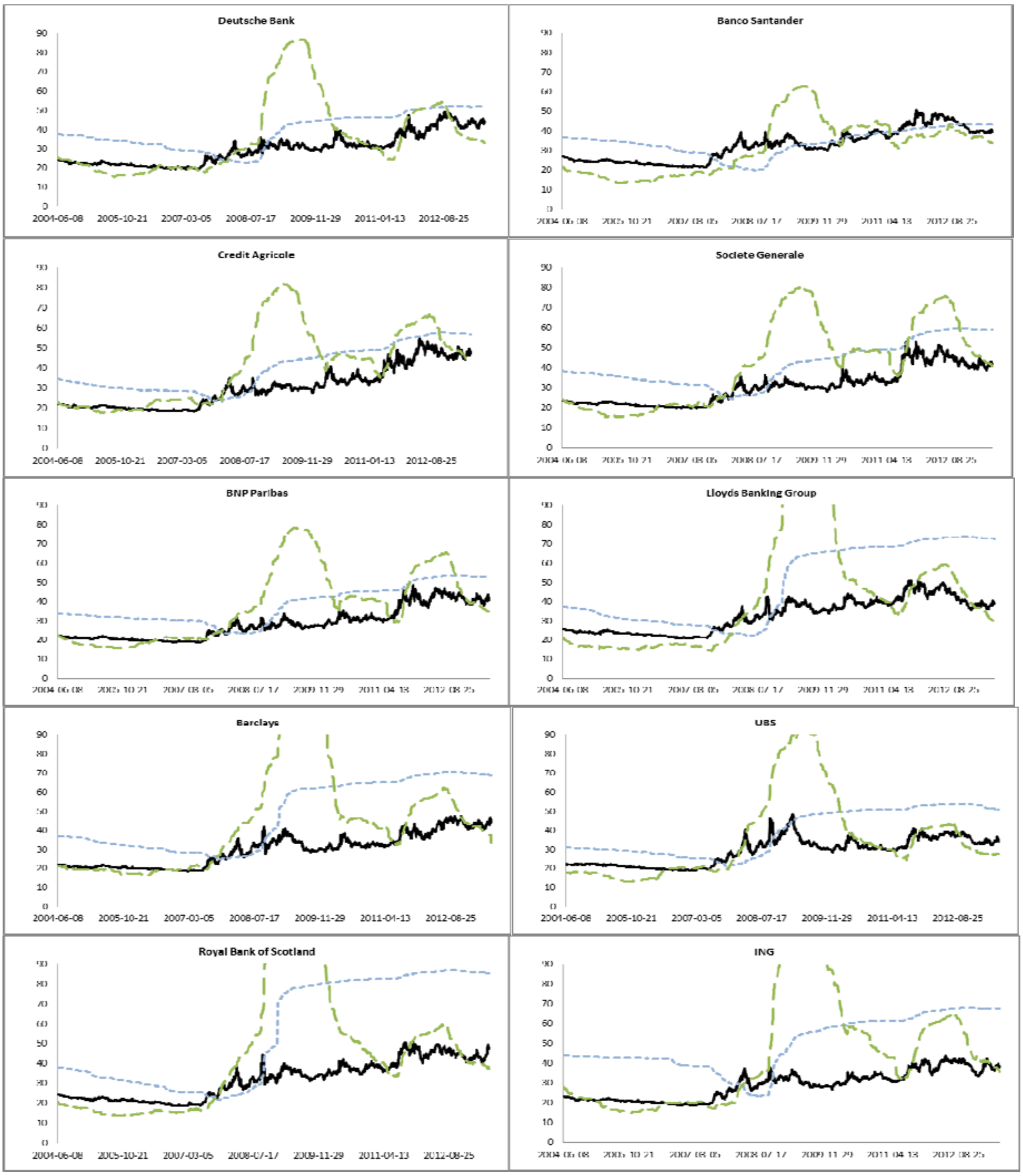
SVENSKA HANDBKN	32,9	Aa3
NORDEA BANK	36,1	Aa3
DNB	36,5	Aa3
CREDIT SUISSE GROUP	38,4	A2
UBS	38,4	A2
SWEDBANK	38,5	A2
SEB	38,7	A3
DEXIA	39,4	-
BARCLAYS	40,8	A3
ING GROEP	41,4	A3
DEUTSCHE BANK	42,9	A2
BNP PARIBAS	45,0	A2
ROYAL BANK OF SCOTLAND	46,1	Baa1
LLOYDS BANKING GROUP	46,3	A2
SOCIETE GENERALE	47,1	A2
BANCO SANTANDER	47,4	Baa2
DANSKE BANK	48,5	Baa1
CREDIT AGRICOLE	50,9	A2
KBC GROUP	51,1	A2
COMMERZBANK	52,9	A3
INTESA SANPAOLO	59,3	A3
BANCA MONTE DEI PASCHI	75,1	Baa3
BANCO POPULAR ESPANOL	75,7	Ba1

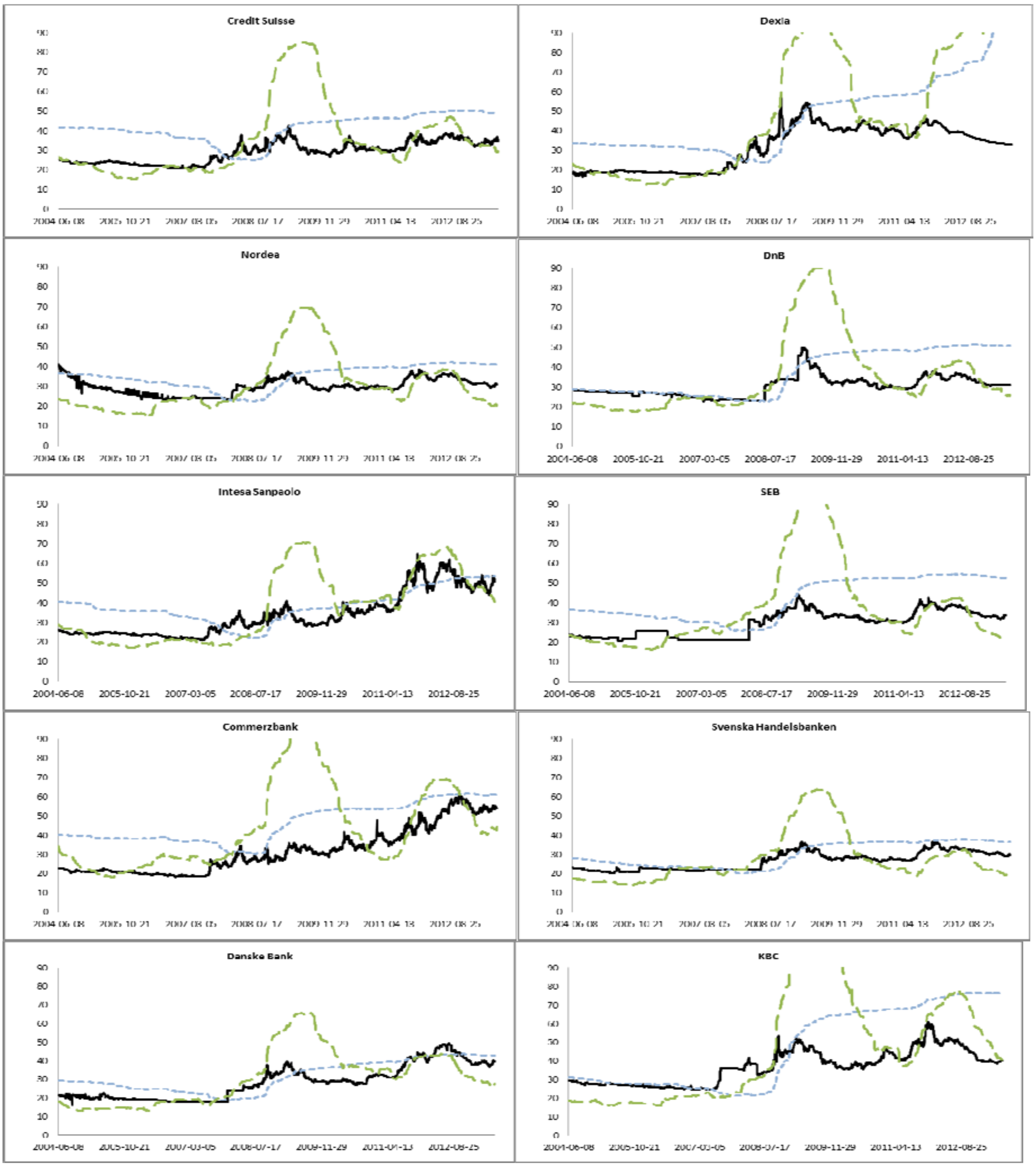
Table 3 Forecast accuracy of the credit-implied volatilities over the sample period June 8, 2004 to November 5, 2013. For each firm in the sample the median % error, the median absolute % error and 90th-percentile absolute % error over the sample period is calculated. The *Median ERROR* is then calculated by taking the median across the 30 firms' median % errors, the *Median |ERROR|* is calculated by taking the median across the 30 firms median absolute % errors and the *90% |ERROR|* is calculated by taking the median across the 30 firms 90th-percentile absolute % errors. *Fraction Positive* is the fraction (%) of the errors that are positive. *CI* is the credit-implied volatility, *HI 5-year* is the historical volatility estimated using 5 years of historical data etc. The smallest error in each category is typed in bold.

Forecasting Method	*Median ERROR* (%)	*Fraction Positive* (%)	*Median |ERROR|* (%)	*90% |ERROR|* (%)
Panel A: 5-Year Forecasting Horizon				
CI	48.3	90.8	50.3	58.2
HI 5-year	**32.4**	93.8	**32.4**	**54.6**
HI 3-year	52.3	93.9	52.3	63.1
HI 1-year	56.0	98.2	56.0	64.6
Panel B: 3-Year Forecasting Horizon				
CI	29.7	72.5	**39.2**	**66.2**
HI 5-year	21.9	61.5	42.4	68.0
HI 3-year	**16.9**	58.3	55.3	77.4
HI 1-year	31.8	67.7	52.4	89.9
Panel C: 1-Year Forecasting Horizon				
CI	**3.6**	49.3	**29.4**	**68.2**
HI 5-year	-26.0	35.2	48.9	107.0
HI 3-year	-29.0	39.2	46.1	110.1
HI 1-year	4.6	53.9	34.0	86.7
Panel D: 6-Month Forecasting Horizon				
CI	**-2.0**	42.9	**29.3**	**67.5**
HI 5-year	-34.0	31.1	53.9	116.5
HI 3-year	-26.0	36.5	44.4	121.1
HI 1-year	-6.0	45.6	31.6	77.2

Appendix The 30 European financial firms in the study.

DEUTSCHE BANK
CREDIT AGRICOLE
BNP PARIBAS
BARCLAYS
ROYAL BANK OF SCOTLAND
BANCO SANTANDER
SOCIETE GENERALE
LLOYDS BANKING GROUP
UBS
ING GROEP
CREDIT SUISSE GROUP
NORDEA BANK
INTESA SANPAOLO
COMMERZBANK
DANSKE BANK
DEXIA
DNB
SEB
SVENSKA HANDBKN
KBC GROUP
BANCA MONTE DEI PASCHI
SWEDBANK
BANCO POPULAR ESPANOL
AEGON
ALLIANZ
ASSICURAZIONI GENERALI
AVIVA
AXA
HANNOVER RUCK
SWISS RE


Deutsche Bank
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25
Banco Santander
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25
Credit Agricole
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25
Societe Generale
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25
BNP Paribas
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25
Lloyds Banking Group
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25
Barclays
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25
UBS
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25
Royal Bank of Scotland
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25
ING
0 10 20 30 40 50 60 70 80 90
2004-06-08 2005-10-21 2007-03-05 2008-07-17 2009-11-29 2011-04-13 2012-08-25


Credit Suisse
Dexia
Nordea
DnB
Intesa Sanpaolo
SEB
Commerzbank
Svenska Handelsbanken
Danske Bank
KBC
0
10
20
30
40
50
60
70
80
90
2004-06-08
2005-10-21
2007-03-05
2008-07-17
2009-11-29
2011-04-13
2012-08-25

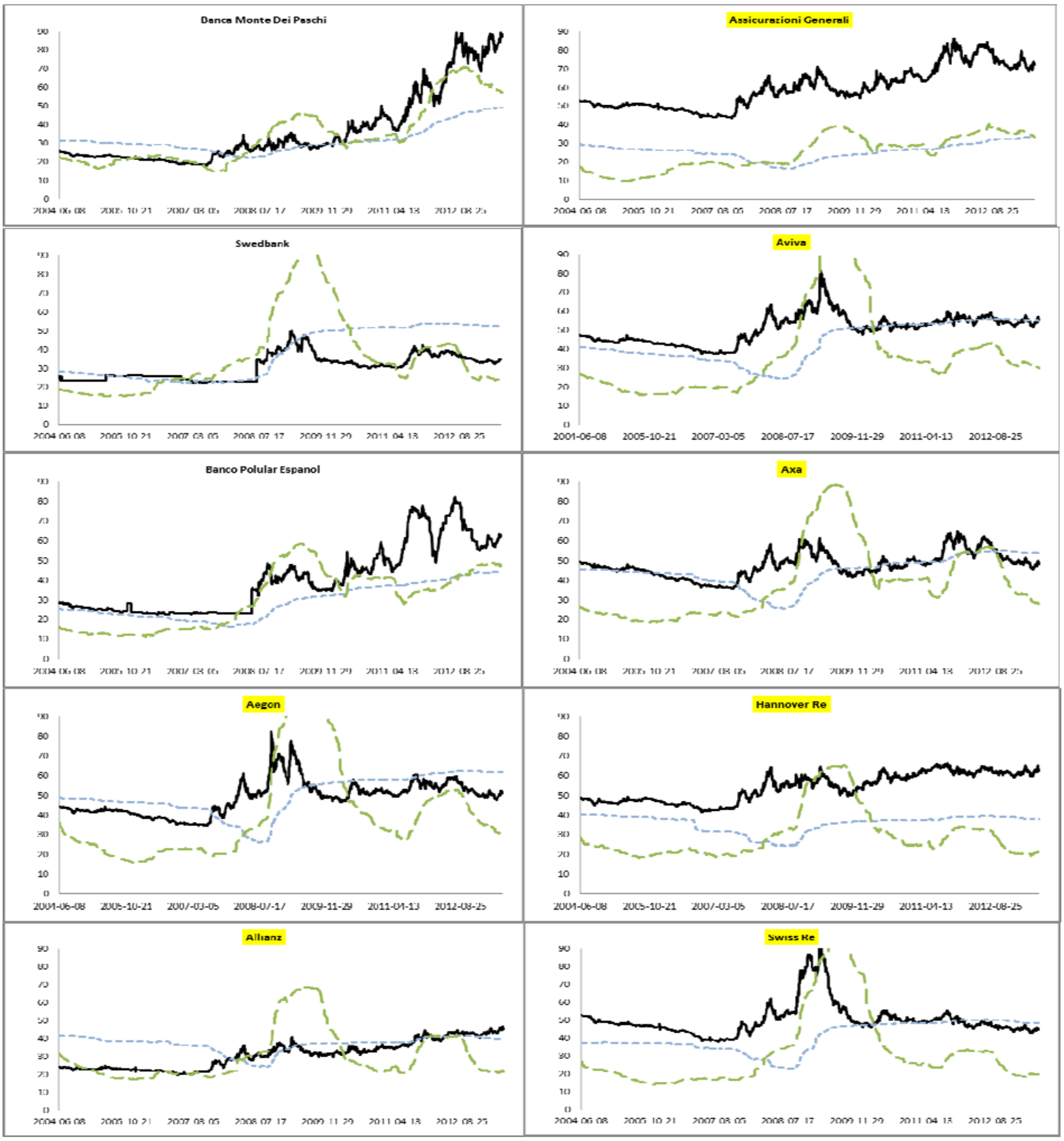


Figure 1. Daily credit-implied stock return volatilities (dark) and daily 1-year and 5-year historical stock return volatilities (pale dashed and pale dotted, respectively) for the firms in our sample over the time period June 8, 2004 to November 5, 2013. All volatilities are annualized and expressed in %.

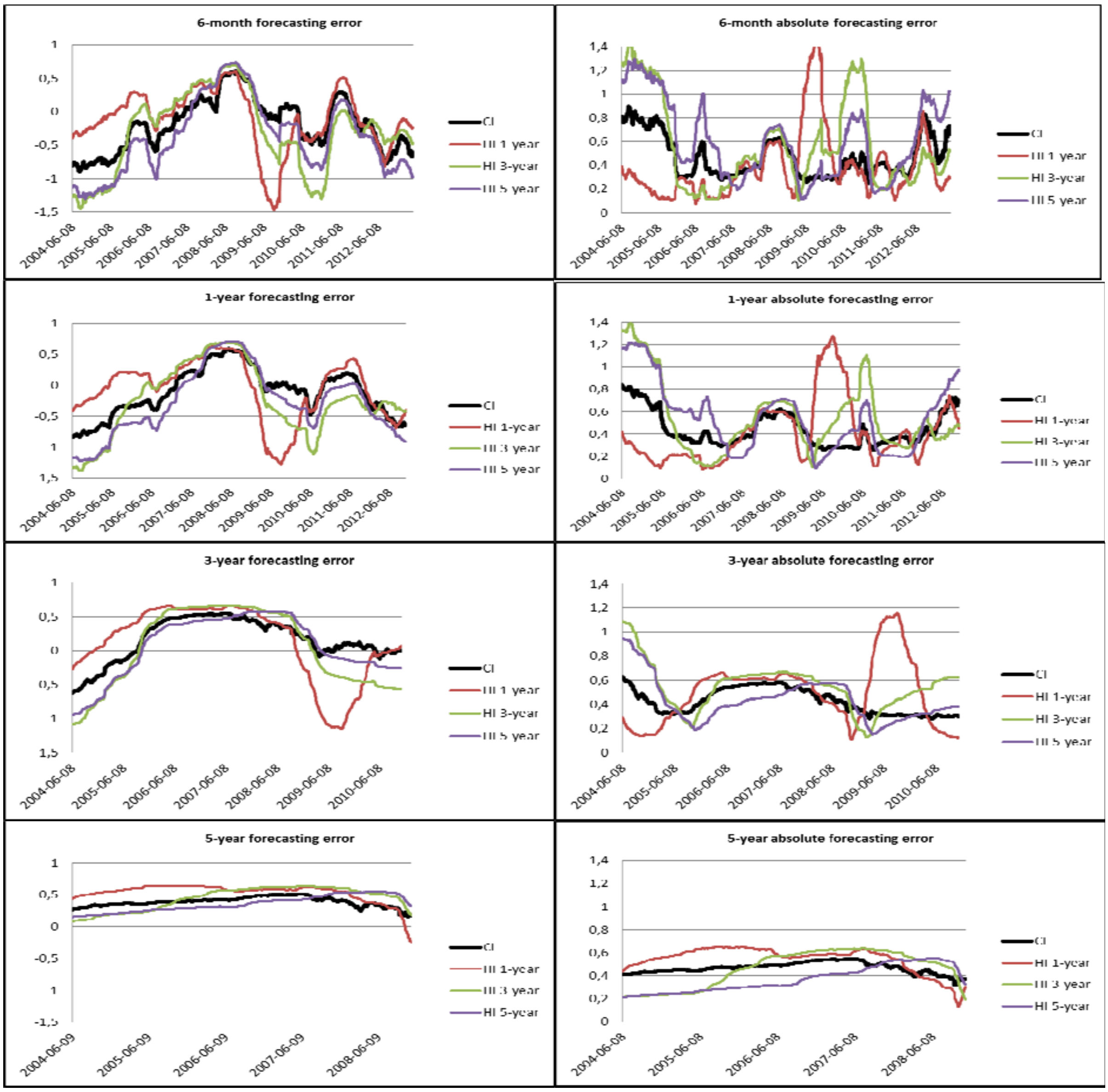


Figure 2. Daily error and absolute error averaged across the 30 firms for the four different forecast horizons over the time period June 8, 2004 to November 5, 2013.

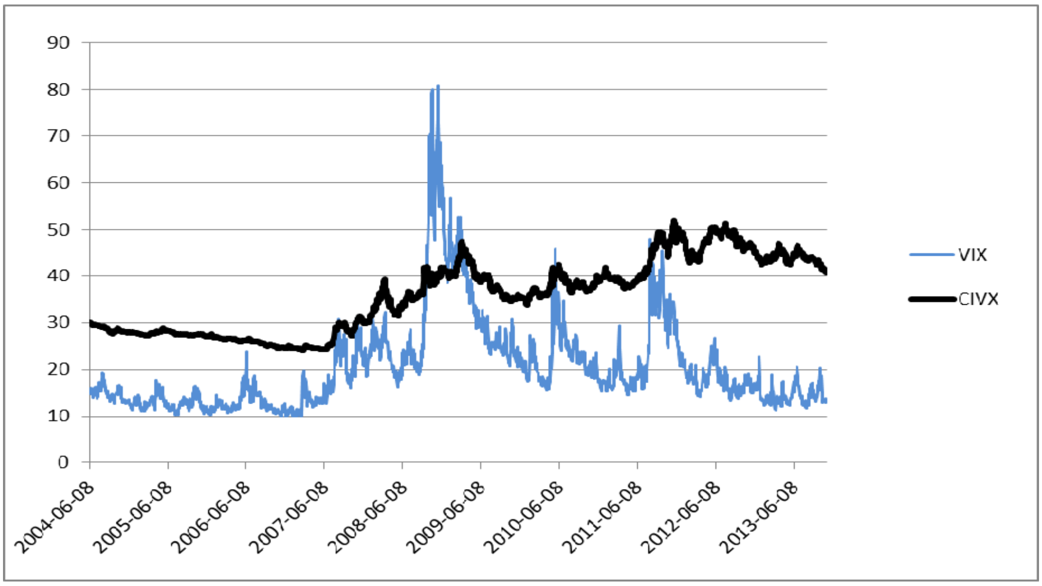


Figure 3. The $CIVX^{Fin,EU}$ index, i.e. the average credit-implied volatility for the European financial firms in our sample, together with the VIX index (the CBOE volatility index) over the time period June 8, 2004 to November 5, 2013. The volatilities are annualized and expressed in %.

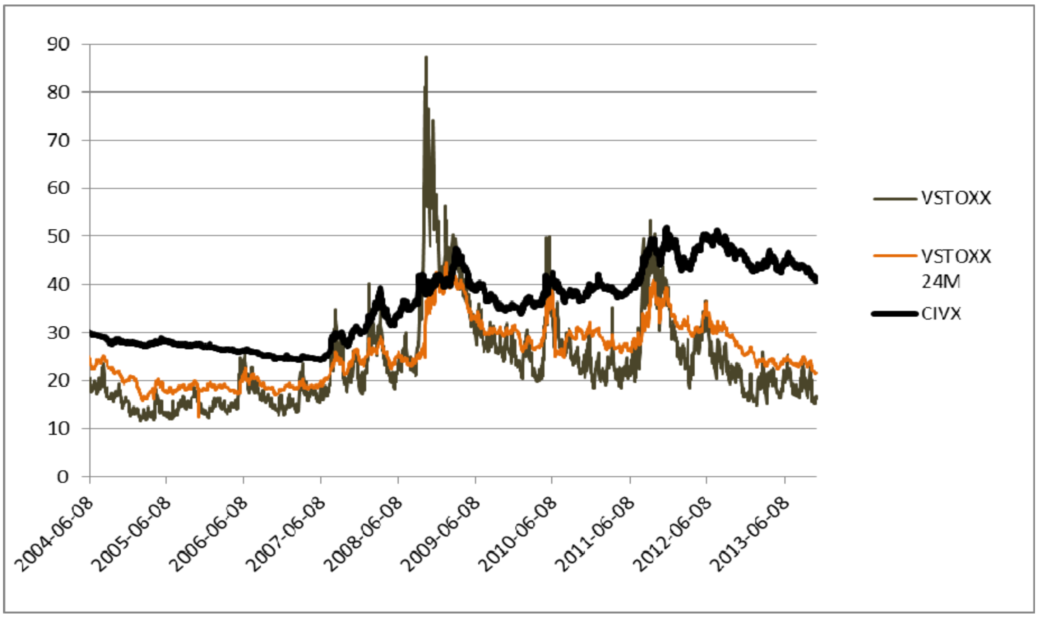


Figure 4. The CIVX^{Fin,EU} index, i.e. the average credit-implied volatility for the European financial firms in our sample, together with the VSTOXX index and the VSTOXX 24M index (the Europe-wide Eurex volatility indexes) over the time period June 8, 2004 to November 5, 2013. The volatilities are annualized and expressed in %.

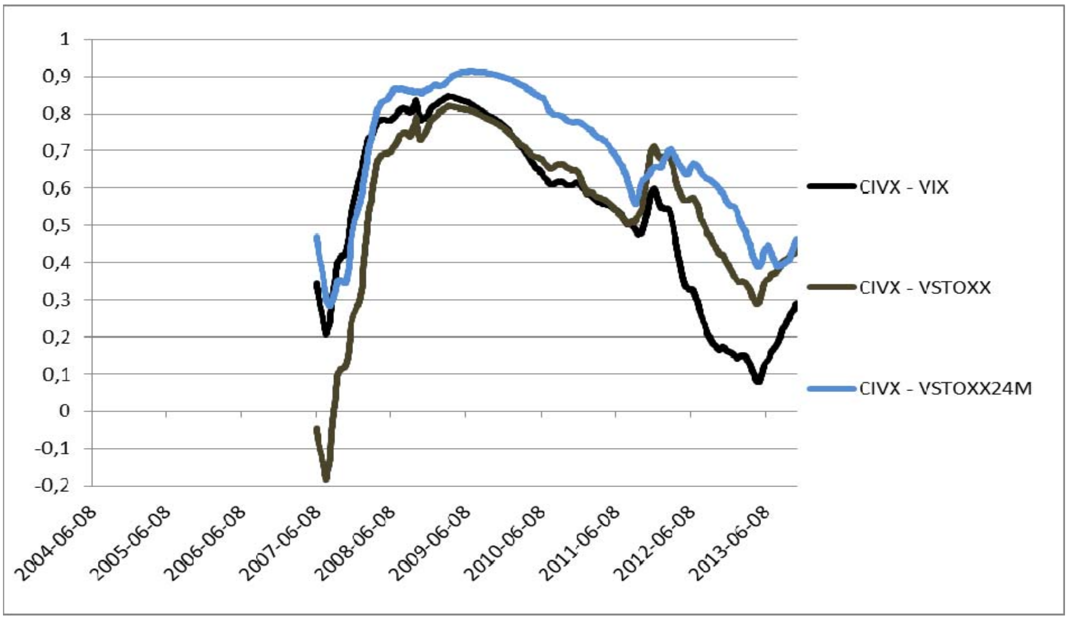


Figure 5. Trailing 3-year rolling window correlation estimates between the $CIVX^{Fin,EU}$ index and, respectively, the VIX index, the VSTOXX index and the VSTOXX 24M index over the time period June 8, 2007 to November 5, 2013.

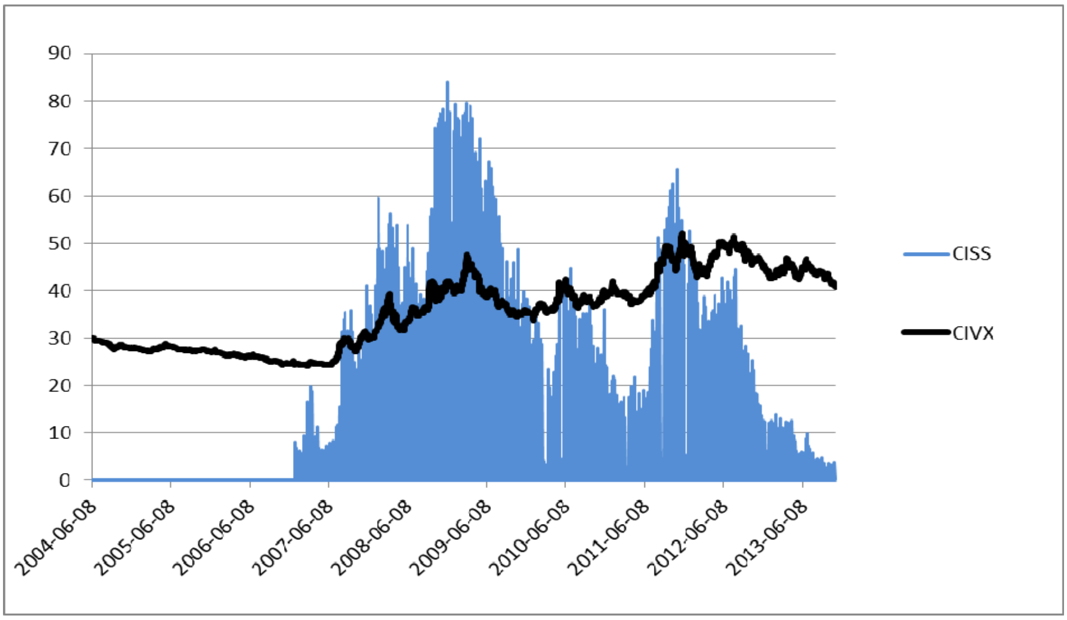


Figure 6. The $CIVX^{Fin,EU}$ index, i.e. the average credit-implied volatility for the European financial firms in our sample, together with the CISS indicator (the Composite Indicator of Systemic Stress). The $CIVX^{Fin,EU}$ index is sampled on a daily basis over the time period June 8, 2004 to November 5, 2013 and the CISS index is sampled on a weekly basis over the time period January 5, 2007 to November 5, 2013.

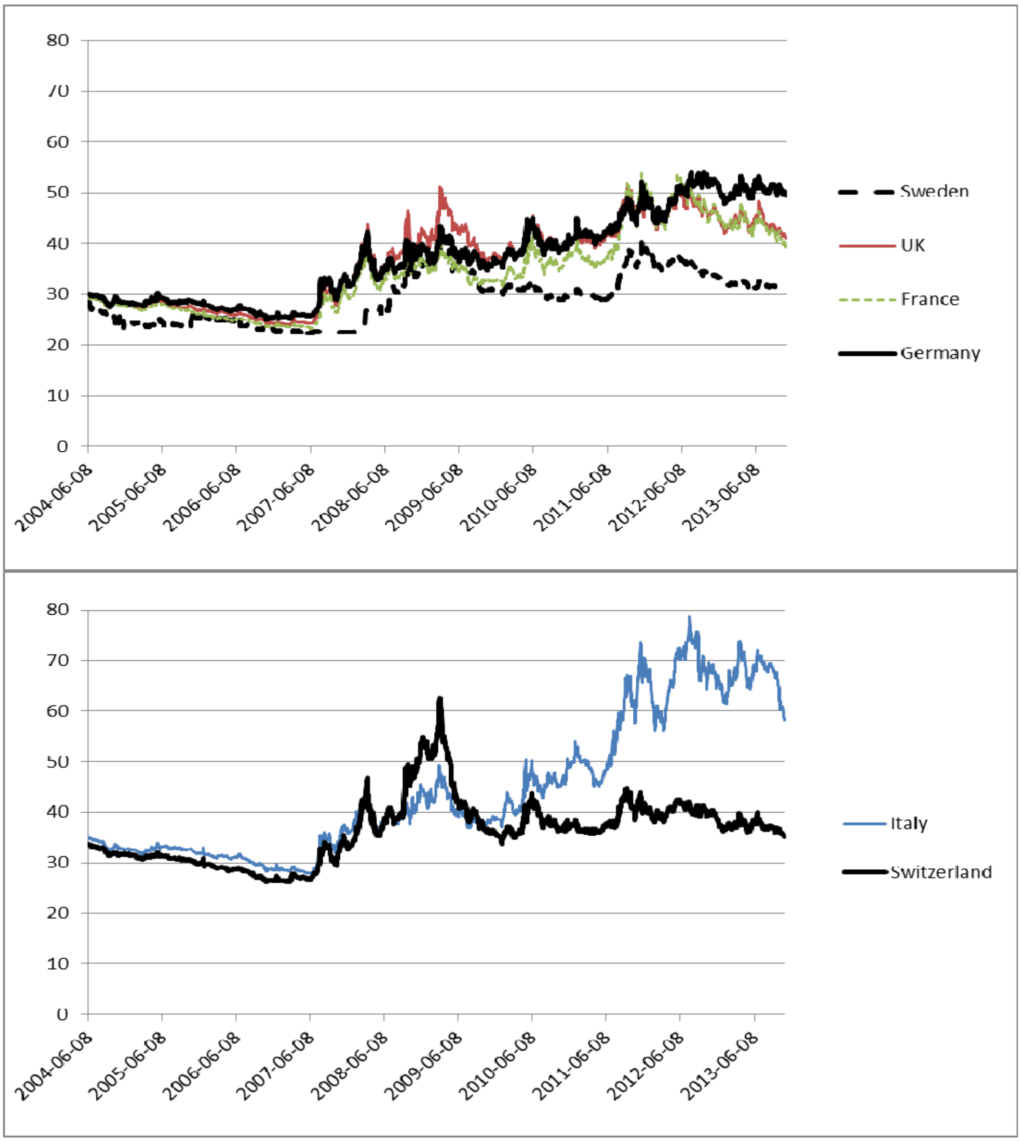


Figure 7. CIVX^{Fin,Country} indexes, i.e. average credit-implied volatilities for the French, German, Swedish and UK financial firms (upper panel) and the Italian and Swiss financial firms (lower panel) over the time period June 8, 2004 to November 5, 2013. The volatilities are annualized and expressed in %.