Corporate Bond Selection with Option Information

by

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Abstract

When markets are efficient all available information is quickly incorporated into all asset prices. Markets are, however, not efficient due to disturbances such as transaction costs, liquidity constraints or regulations. The factor investing literature illustrates this market inefficiency by finding significant premiums in asset markets that are different from the traditional asset class premiums. This research contributes further to this literature by applying information from options to construct profitable trading strategies with corporate bonds. This shows that not all available information from the option market is incorporated in the corporate bond market. Furthermore, many insights are provided as to what kind of information can be obtained from the option market. The results of this research reinforce the notion of the option market as an important source of information for investors.

Keywords: Market Efficiency, Corporate Bond Market, Option Information, Implied Volatility
JEL classifications: G11, G12, G14

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Contents

1 Introduction

The financial market as a whole is an intricate system of several separate markets such as the stock market, option market and corporate bond market. Each of these markets have their own distinct characteristics offering investors a wide variety of investment opportunities. Accordingly, informed investors have to make a decision in which market to trade such that they can gain the most benefit out of their information. A rather peculiar market is the option market, as this market would effectively be redundant under complete and efficient market circumstances in the sense that investors would be indifferent between trading in the option market or in the stock market. The financial markets are, however, not perfect and there are reasons for informed investors to trade in the option market instead of the stock market. A reason is for example that higher leverage and therefore higher profits can be obtained by trading in options. Other reasons include the built-in downside protection of options and also less issues with short selling constraints that are present in the stock market. So there are reasons to believe that the option market can contain information for future prices that is different from other markets as a result of informed trading.

The literature has certainly confirmed the option market to be an informative source for future stock prices. Easley et al. (1998) develop an information model where informed investors can trade in either the option market or stock market. With this model they find that particular types of option trading volumes lead stock price changes. The option volume is also linked to the price discovery process between options and stocks by Chakravarty et al. (2004). They find significant price discovery in the option market indicating that new information about stock prices is first reflected in option prices and this occurs especially when the option volume is high. DeMiguel et al. (2013) apply option implied information on portfolio selection with a large number of stocks. The performances of their portfolios improve substantially when information of the volatility risk premium and the option implied skewness is incorporated in their portfolio selection methodology.

Most studies focus on the information content of the option market with respect to the stock market, because there is a direct relation between these markets since a option is a derivative of a stock. As equity and debt are on the same side of the balance sheet, there should also be a relation, albeit indirectly, between options and corporate bonds. Nevertheless, little research has been done on the informational role of options for corporate bonds. A reason might have been the lack of data availability of corporate bonds up until the launch of Transaction Reporting and Compliance Engine (TRACE) in 2002. With the introduction of TRACE all transaction data in publicly issued U.S. corporate bonds were henceforth made available to the public, which has lead to fundamental changes in the corporate bond market. Bessembinder and Maxwell (2008) state that post-TRACE the transparency of the market increased resulting in substantially lower transaction costs. Furthermore, the availability of more timely and bigger data opened up opportunities for algorithmic trading and quantitative investment strategies. Houweling and Van Zundert (2014) find that the traditional factor strategies value, size, momentum, and low risk yield significant returns in the corporate bond market. Other studies have also confirmed the existence of factor strategies in the corporate bond market (Correia et al., 2012; Frazzini and Pedersen, 2014; Jostova et al., 2013, amongst others), however, the amount of research is relatively scarce compared to the equity factor literature.

The purpose of this research is to fill this gap in the literature and shed more light on the information content of the option market with respect to the corporate bond market. Various measures mainly based on option implied volatilities are used to implement trading strategies. Most of these option measures have been proven in the literature to generate significant returns in the stock market, but none have been investigated in a trading strategy setting applied to the corporate bond market. The portfolio results based on these option measure show that significant returns can also be obtained for corporate bonds. Furthermore, several interpretations of the option measures are explored more in depth, as it is not always clear what particular piece of information is embedded in the option measures. These results provide useful insights as to what kind of information can be obtained from the option market.

This is the first research to investigate corporate bond trading strategies that are constructed using option information, whereas other studies in the literature use specific bond information or balance sheet information. In a sense this research challenges the efficient market hypothesis which states that all available information should be incorporated into the prices of all markets. The hypothesis implies that all option information should be already priced in the corporate bonds and therefore the option based trading strategies should not be able to outperform the market. This, however, is found to be not the case, as some trading strategies yield significantly higher returns than the market assuming the correctness of the evaluation models.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive overview of the literature that has investigated the information content of the option market. The data and the option measures are presented in Section 3, and the portfolio construction methodology is explained in Section 4. A brief analysis on the predictive ability of several volatility measures for future volatility can be found in Section 5. The portfolio results based on the option measures are discussed extensively in Section 6. This section also provides more in depth analyses for each individual option measure. The robustness of the results is checked in Section 7, after which a conclusion is given in Section 8.

2 Literature Overview

2.1 Option Implied Volatility

Christensen and Prabhala (1998) state that the volatility implied in an option's price is widely regarded as the option market's forecast for future stock return volatility over the remaining life of the relevant option. This means that the implied volatility should include the information contained in all other variables in the market information set in explaining future volatility. They find that the implied volatility has more predictive power than historical volatility for the S&P100 index, partly because the implied volatility subsumes the information contained in historical volatility. In a later study, Christensen and Hansen (2002) reinvestigate the information content of implied volatility of different types of options on a larger data set. They reconfirm the results of Christensen and Prabhala (1998) that implied volatility is an unbiased and efficient forecast of future volatility.

Mayhew (1995) provides an extensive review of the literature of implied volatility. He states that the general consensus is that implied volatility is more useful for forecasting volatility than volatility computed from historical data. He also reviews a branch of literature that uses a weighted average of implied volatilities to incorporate the information of more options. Ederington and Guan (2002) state that using a weighing scheme reduces the error caused by market imperfections. They investigate a multitude of weighted implied volatility measures for the S&P500 index and find that the choice of the weighing scheme matters very little. This is due to the fact that the S&P500 index is a very liquid asset such that the noise is too insignificant to average out. They state that for illiquid assets, however, averaging out the errors can be worthwhile.

Although there are merits in using the information of multiple options, nearly all studies focus on the information content of the implied volatility of a single option. Jiang and Tian (2005) mention that these studies fail to incorporate the information contained in other options stating that the use of a single option is not sufficient to extract all relevant information. They generalize and simplify the model of Britten-Jones and Neuberger (2000) of which a model-free implied volatility measure can be obtained. This measure is entirely derived from no-arbitrage conditions and it uses the information of all available options. They find that their measure subsumes the information of the historical volatility and also the Black and Scholes (1973) implied volatility. Furthermore, efficient and accurate forecasts for future realized volatility are obtained with their measure.

The previous studies all examine the information content of option index markets. Taylor et al. (2010) are the first to investigate implied volatilities of individual stock options on a large sample of U.S. stocks. They make comparisons between the historical volatility, implied volatility and model-free implied volatility. Again, the results indicate that the option implied volatilities are more informative than the historical volatility. A concerning finding is, however, that the model-free volatility only outperforms the other two volatility measures for about one-third of their sample of firms, while this measure should theoretically be better than the other measures. Possible explanations include overall illiquidity issues and an unreliable implementation of the model-free volatility due to lack of data.

2.2 Option Implied Volatility Skew

One of the first studies documenting the implied volatility skew is that of Rubinstein (1985). He found that option prices systematically deviate from the Black and Scholes (1973) model in the sense that the implied volatilities differ across strike prices and maturities, while they should be the same according to the option pricing model. Xing et al. (2010) are the first to examine individual stock options on the information content of their implied volatility skews measured as the difference between the implied volatilities of out-of-the-money put options and at-the-money call options. They demonstrate that the implied volatility skew exhibits statistically significant predictability for future equity returns in the cross section. This predictability is shown to persist for at least six months indicating that the stock market is slow in reacting to information in the option market. Furthermore, a trading strategy based on the volatility skew shows that stocks with steeper volatility skews underperform those with flatter volatility skews. The returns are shown to be significant even after controlling for the Fama and French (1996) risk factors. They conclude that option traders have a superior informational advantage over stock traders.

Other studies that find profitable trading strategies based on the implied volatility skew include Bali and Hovakimian (2009), Cremers and Weinbaum (2010), and Doran and Krieger (2010). All these studies, however, do not take liquidity constraints and transaction costs of stocks into account such that the trading strategies might not be feasible or unexploitable in practice. Baltussen et al. (2012) use an investible universe of highly liquid stocks to investigate several strategies based on option implied volatility skew measures that are also used in the aforementioned studies. The strategies are shown to produce economically and statistically significant returns and even higher returns can be obtained by combining the volatility skew measures in a single strategy. This strategy, however, becomes unprofitable when transaction costs are incorporated. They show that significant net returns can be obtained by applying several simple transaction cost reducing adjustments. Lastly, they find that the option strategies are of a different nature than other well-known stock selection strategies such as momentum, size, and value strategies.

2.3 Credit Spreads

Most studies in the literature focus on the relations between the option market and the underlying stock market. However, the option market is also connected to the credit market; for instance, Merton (1974) made a simple link between the equity market and credit market by observing that the equity of a firm is an option on the assets with the face value of debt as strike price. Subsequently, Hull et al. (2004) developed an implementation of the Merton model that uses information from the option market to obtain credit spreads. They test their methodology on the credit default swap market and find that their method is an improvement over the more traditional implementation of Jones et al. (1984) that uses information from the stock market as opposed to the option market. Culp et al. (2014) also use the insights of Merton to develop a model-free methodology in order to obtain option implied credit spreads that only depend on observable market prices. The resulting credit spreads are comparable to real corporate bond credit spreads and are also found to be an improvement over the traditional Merton model.

The information contained in individual options also includes the assessment of the market on the expected volatility risk of the corresponding stocks. This particular piece of information is relevant for evaluating the credit risk of firms. Cremers et al. (2008a) find that incorporating option implied jump risk premiums in a structural jump diffusion firm value model improves the fit of predicted credit spreads. In another study, Cremers et al. (2008b) investigate to what extent the variation in credit spreads can be explained by implied volatilities and implied volatility skews. They find that individual options certainly contain information about credit risk both over time and across firms with higher explanatory power compared to historical measures of volatility.

3 Data

3.1 Data Description

Option data of the last trading day of each month is extracted from the OptionMetrics Ivy DB U.S. database from January 1996 to August 2014, which is the most recent available data set. The database provides end-of-day information such as bid and ask quotes, open interests, and trading volumes. Additionally, it also contains option implied volatilities and other option Greeks that are computed with the binomial tree model of Cox et al. (1979). Since all options are American style options, this option pricing model takes into account the possibility of early exercise. Furthermore, discrete dividend payments are also incorporated into the model.

Several filters are applied to the data to ensure that only the most informational relevant options are used for the analysis. Firstly, as most trading activity is concentrated in options with a short maturity, mainly options that mature in the following month are used unless otherwise mentioned.

Since the data only includes options at the end of each month, the time-to-maturity of the options are all approximately three weeks, as there are always options expiring at the third Friday of the month. This ensures that there is no bias between the options due to maturity differences and there are also no unwanted expiration effects in options that are extremely close to maturity as documented by Ni et al. (2005). Secondly, options with mid quotes, i.e. the average bid and ask quote, less than $0.125 are removed from the data set, because these prices may not reflect the true price of the options due to the fact that these quotes are close to the tick size. Finally, only options with positive open interest are retained, since these options have contracts outstanding in the market and are therefore a better reflection of the market compared to options with zero open interest. Furthermore, Bhuyan and Chaudhury (2005) find that open interest contains valuable information that is attractive for trading purposes.

For the construction of the option measures it is required that the options are separated into at-the-money (ATM) options and out-of-the-money (OTM) options. This will be based on the ratio of the strike price to the stock price, i.e. the moneyness of the option. Following the conventions in the literature, e.g. Baltussen et al. (2012), Xing et al. (2010), amongst others, the ATM option is defined as the option with moneyness closest to 1, but between 0.95 and 1.05. The OTM put option has moneyness closest to 0.95, but the moneyness is bounded between 0.80 and 0.95. The reason for these definitions is to ensure that all ATM and OTM options fall in approximately the same moneyness category for better comparability.

The option data is merged with corporate bond data consisting of the Barclays U.S. Corporate Investment Grade index and the Barclays U.S. Corporate High Yield index. The bond data set is sampled monthly and it contains characteristics such as the time-to-maturity, credit ratings and credit spreads. Furthermore, the bond returns reflect the expected recovery rate whenever a firm defaults, thus making the data set survivorship bias free. Following Houweling and Van Zundert (2014) the analysis is focused on the excess returns of the corporate bonds versus duration-matched Treasuries. This way the focus of the research lies on the default premium of corporate bonds instead of the term premium which can be obtained by simply investing in government bonds.

One representative bond is chosen per firm with the seniority, age and size as the selection criteria.[1] First, the corporate bonds with the highest seniority are chosen, as these bonds are found to be less volatile compared to subordinated bonds. Next, the most liquid bonds are chosen based on their age and size as liquidity proxies, thus younger and larger bonds are preferred over other bonds. A total of 2253 firms remain in the sample with over $230,000$ observations after merging the option and corporate bond data sets. The Investment Grade (IG) universe has approximately $135,000$ observations and the High Yield (HY) universe has approximately $95,000$ observations.

[1] See Haesen et al. (2013) for a detailed explanation of the representative bond selection procedure.

This sample of firms with options is a small fraction out of the original 6360 number of firms in the indexes, thus sample selection bias can be a potential issue and care must therefore be taken in generalizing the results. A closer inspection of the data shows that there can be a small bias with respect to the firm sizes, as the mean (median) market capitalization of the original sample of firms is \$5.6 (\$1.6) billion and it is \$6.2 (\$1.9) billion for the sample of firms with options. Thus, the firms that issue options tend to be bigger in size compared to firms that do not issue options. The difference is, however, not considerably large and the distribution of the firms with respect to size stays relatively the same.

All stock related data is obtained from the CRSP database and all financial statement data is gathered from the Compustat database. Lastly, the risk-free rate is downloaded from the Kenneth French library[2].

3.2 Option Measures

This section describes a total of five option based measures or option factors that are investigated on whether they contain relevant information for corporate bonds. Each option measure has a different interpretation or information content about the relevant firm that are either proven by theory or empirically. The literature has shown that several of these option measures do contain information for stocks, but very little or no studies have examined the information content of these measures with respect to corporate bonds.

3.2.1 Realized-Implied Volatility Spread

The realized volatility is computed using historical data and is therefore a backward looking measure, whereas the implied volatility is inherently a forward looking measure. As a consequence, these two volatility measures are often found to be different from each other. This gives rise to the realized-implied volatility spread which is found to bear a negative risk premium by Bakshi and Kapadia (2003). In other words, investors buying stocks with high realized-implied volatility spreads are not rewarded for the extra volatility risk that they take. Bali and Hovakimian (2009) find that stocks with higher realized-implied volatility spreads bear higher volatility risk and those stocks indeed give lower returns compared to the stocks with lower realized-implied volatility spreads. This research investigates whether similar effects spill over to the corporate bond market. The realized-implied volatility spread is defined as

$$RVIV_{i,t} = RV_{i,t} - IV_{i,t}^{ATM}, \tag{1}$$

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

where $RV_{i,t}$ is the realized volatility of stock i measured at month t using daily returns over the past three months. This horizon is chosen to capture the most relevant information while minimizing the noise. The implied volatility $IV_{i,t}^{ATM}$ is taken to be the average implied volatilities of the ATM call and put options on stock i at month t. ATM options are overall the most liquid options and are therefore often the best representation of the market.

3.2.2 Put-Call Implied Volatility Spread

The put-call parity, originally derived by Stoll (1969), defines a no-arbitrage relation between European put and call options with the same strike price and maturity (henceforth referred to as pairs of put and call options). This relation, however, does generally not hold in practice due to market imperfections. Cremers and Weinbaum (2010) show as a consequence of the put-call parity that the implied volatilities of pairs of put and call options should be identical to each other regardless of the correctness of the chosen option pricing model. Thus, they investigate the impact of deviations of the put-call parity on stock prices by examining the differences in implied volatility of pairs of put and call options. Emphasis is put on the fact that their data consists of American style options and therefore the put-call parity is no longer a strict no-arbitrage relation. Regardless, they find relevant information about future stock prices in the deviations of the implied volatilities. This research investigates whether deviations of the put-call parity also reveal information about corporate bond prices. Likewise, the put-call implied volatility spread is used:

$$PUTCALL_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \left(IV_{i,t}^{PUT_j} - IV_{i,t}^{CALL_j} \right), \tag{2}$$

where $IV_{i,t}^{PUT_j}$ and $IV_{i,t}^{CALL_j}$ denote the implied volatility of respectively the put option and the call option of pair j on stock i at month t. The pairs are made over all available maturities and strike prices with the total number of pairs of put and call options denoted as $N_{i,t}$. Multiple pairs of put and call options are used to capture information from more options and to average out noise.

3.2.3 Implied Volatility Skew

Many studies have found the implied volatility skew to be informative with respect to stocks such as Baltussen et al. (2012), Doran and Krieger (2010), amongst others. This research investigates whether the implied volatility skew also contains information for future corporate bond prices. For this purpose the volatility skew measure of Xing et al. (2010) is used:

$$SKEW_{i,t} = IV_{i,t}^{OTMP} - IV_{i,t}^{ATMC}, \tag{3}$$

where $IV_{i,t}^{OTMP}$ and $IV_{i,t}^{ATMC}$ denote the implied volatility of respectively an OTM put option and an ATM call option on stock i at month t. This implied volatility skew measure is thought to reflect the expectations of future price movements. More precisely, it is the negative expectations that are measured, as investors with pessimistic perceptions about a firm tend to buy put options for either hedging or speculation purposes. When this happens the demand in put options increases, thus raising the prices and implied volatilities of put options which results in a steeper implied volatility skew. More leverage can be obtained in OTM options, thus investors who are more certain in the future downfall are more inclined to buy OTM put options. So the OTM put option is chosen as opposed to other put options, because it captures the severity of the negative expectations better. The ATM call option is chosen as the benchmark for the general market expectations reflected in the implied volatility skew, because this option is one of the most liquid option traded on the market.

3.2.4 Implied Variance Term Slope

The previous implied volatility skew measure captures the implied volatility skew in the moneyness dimension, however, the implied volatility is also found to vary in the maturity dimension; the so-called term structure of implied volatility. The slope of this implied volatility term structure reflects the differences in expectations of the market for volatility over different future horizons. Related to this term structure is the expectation hypothesis derived by Campa and Chang (1995) that states that there should be a rational consistency between the current long-term implied variance and the expected future short-term implied variance. Although the literature has found mixed results regarding this hypothesis, Mixon (2007) finds the slope of the implied variance over several different maturities to contain predictive power for future implied variance of short-term options. This research investigates whether the slope of the implied variance term structure contains information for corporate bonds. The implied variance term slope is defined as

$$TERMSLOPE_{i,t} = \frac{1}{M_{i,t}} \sum_{j=1}^{M_{i,t}} \left(V_{i,t}^{2MC_j} - V_{i,t}^{1MC_j} \right), \tag{4}$$

where $V_{i,t}^{2MC_j}$ and $V_{i,t}^{1MC_j}$ denote implied variances of the put options on stock i at month t that have the same strike price with a two month maturity and an one month maturity respectively. The total number of available pairs of put options with the same strike price is denoted by $M_{i,t}$. The put options are restricted within the ATM moneyness bounds for comparability in both the cross-section and throughout time. The reason for only including the options with these short maturities is that each firm with options is legally required to have these maturities outstanding, whereas there are less strict requirements for longer maturities. So the coverage is by far the largest for these options.

3.2.5 Option Implied Value Factor

One of the most well-known approaches in assessing the credit risk of a firm is the model of Merton (1974). His insights made it quite straightforward to obtain credit risk measures such as credit spreads from simple balance sheet information as described in Appendix A. Unfortunately, the total asset value is often an unobserved variable making the model difficult to implement in practice. Hull et al. (2004) developed a methodology that uses option information to obtain these parameters in order to implement the Merton model, thus linking the credit market to the option market. Their methodology requires information from two options, however, in Appendix A an adapted methodology is described that requires only one single option. Option implied credit spreads from the Merton model are used to construct a value factor that is in the same spirit as in Houweling and Van Zundert (2014). This factor compares the market credit spread with the fundamental credit spread assuming the correctness of the Merton model. At each point in time the market credit spreads are cross-sectionally regressed on a constant and the option implied credit spread, then the fitted credit spreads are used to construct the value factor as

$$VALUE_{i,t} = \frac{SPREAD_{i,t}^{MARKET}}{SPREAD_{i,t}^{FIT}}, \tag{5}$$

where $SPREAD_{i,t}^{MARKET}$ and $SPREAD_{i,t}^{FIT}$ are respectively the market credit spread and the fitted credit spread of bond i at month t. The model credit spreads are not directly used to construct this factor, because model credit spreads are often considerably lower than observed market credit spreads, which is known as the credit spread puzzle (Amato and Remolona (2003)). The regressions are applied to alleviate this problem by making the credit spreads more comparable.

3.3 Descriptive Statistics

Table 1 presents summary descriptive statistics of the option measures, where the statistics are first computed over the cross-section and then averaged over time, i.e. the time-series average of the cross-sectional statistics. The mean $RVIV$ of -0.73% shows that the implied volatility is on average higher than the realized volatility. The implied volatilities of put options are on average higher than call options which can be deduced from the mean $PUTCALL$ of 0.88%. There is a positive implied volatility skew in the moneyness dimension with a mean $SKEW$ of 6.57%, but the mean $TERMSLOPE$ of -0.17% indicates a slight negative implied variance slope in the maturity dimension. The mean $VALUE$ of 98.58% shows that the fitted credit spreads and market credit spreads are on average approximately equal. All option measures exhibit quite some cross-sectional variability with average standard deviations ranging between 5.02% and 63.87%. The percentiles show that for every option measure 98% of the observations are within three or four standard deviations from their mean.

Table 1: Descriptive statistics

This table shows the time-series average of the cross-sectional means, the standard deviations and the 1st, 50th, and 99th percentiles for each option measure over the sample period from January 1996 to August 2014.

	Mean	St. Dev.	1%	50%	99%
RVIV (%)	−0.73	9.65	−24.66	−0.97	26.90
PUTCALL (%)	0.88	5.02	−10.74	0.61	15.84
SKEW (%)	6.57	7.00	−4.85	5.17	32.55
TERMSLOPE (%)	−0.17	5.12	−15.74	0.11	10.26
VALUE (%)	98.58	63.87	22.86	84.99	270.23

In a factor strategy the portfolios are constructed by selecting assets based on sorting variables, thus the ranking of the variables is essentially what matters the most. Table 2 shows the time-series average of the cross-sectional Spearman rank correlations between the option measures. All in all, the correlations between the variables are quite low with the highest average correlation of 0.39 being observed between $RVIV$ and $TERMSLOPE$. The low correlations indicate that there is little information overlap between the option measures, or in other words, each option measure appears to contain distinct information.

Table 2: Spearman correlations

This table shows the time-series average of the cross-sectional Spearman rank correlations between the option measures over the sample period from January 1996 to August 2014.

	RVIV	PUTCALL	SKEW	TERMSLOPE	VALUE
RVIV	1.00				
PUTCALL	0.03	1.00			
SKEW	0.05	0.38	1.00		
TERMSLOPE	0.39	-0.07	-0.06	1.00	
VALUE	0.04	0.05	-0.02	0.10	1.00

Table 3 presents coverage statistics for both the IG and HY universe. The average number of observations per month, and also the number of observations at the begin and end of the sample are shown in the table. A first observation is that the coverage of each option measure increases over the sample for both universes. The option measure with the lowest coverage is $SKEW$ with an average number of observation of 79 in the HY universe. The reason for this is because in this sample there are less OTM options available than ATM options. This also explains why $VALUE$, which is constructed with OTM put options, also has a similar low coverage. Nevertheless, the option measures seem to have overall adequate coverage.

Table 3: Coverage statistics

This table shows the average number of observations, and the total number of observations at the begin and end of the sample for each option measure over the sample period from January 1996 to August 2014.

	RVIV	PUTCALL	SKEW	TERMSLOPE	VALUE
I. Investment Grade					
Average	341	399	162	261	182
Start	263	321	61	115	67
End	444	476	215	388	225
II. High Yield					
Average	171	266	79	116	109
Start	50	94	12	26	17
End	339	428	181	261	200

4 Portfolio Construction Methodology

A portfolio trading strategy approach is applied in order to assess whether the option measures contain information for corporate bonds. At the end of each month the option measures are constructed using data of the latest trading day. Then equally weighted corporate bond portfolios are constructed by sorting the bonds on the option measures into five quintile portfolios. The first quintile (Q1) contains the bonds with the highest option measure values and the last quintile (Q5) holds the bonds with the lowest values of the option measure. The portfolios are held for twelve months using the methodology of Jegadeesh and Titman (1993). This trading procedure entails that a new portfolio is formed at each month and held for the next twelve months, while the position in the portfolio that was formed twelve months ago is closed out. The longer holding period is chosen to investigate whether the option information is persistent in the corporate bond market. Furthermore, this is also a more realistic setting for real investors, as the corporate bond market is not as liquid as the the stock market and it is therefore not feasible to rebalance complete corporate bond portfolios on a frequent basis without incurring large transaction costs.

The returns are adjusted for risk with the Fama and French (1993) five factor model with an addition of the Carhart (1997) momentum factor to investigate whether the option measures contain different information compared to these well-known factors in the literature. The following regression is performed to obtain the abnormal return α_j of portfolio j

$$R_{j,t} = \alpha_j + \beta_{1j} RMRF_t + \beta_{2j} SMB_t + \beta_{3j} HML_t + \beta_{4j} MOM_t + \beta_{5j} TERM_t + \beta_{6j} DEF_t + \varepsilon_t, \quad (6)$$

where $R_{j,t}$ is the return of portfolio j, $RMRF_t$ is the equity market premium, SMB_t is the small-minus-big equity size premium, HML_t is the high-minus-low equity value premium, MOM_t is the equity momentum premium, $TERM_t$ is the risk-free term interest rate premium, and DEF_t is the default premium. The white noise residuals are denoted by ε_t. The four equity factors in the regression are downloaded from the Kenneth French library[3]. The two bond factors follow the same construction as in Houweling and Van Zundert (2014); the $TERM$ factor is the total return of the Barclays U.S. Treasury 7-10 year index minus the risk-free rate. This Treasury index is chosen to match the maturities of the corporate bonds in the sample, which has an average maturity of 9.3 years. The $DEFAULT$ factor is the excess return of the corporate bond market versus duration matched Treasuries. The interest rate risk is eliminated by matching the durations so that this factor only captures the default premium.

Following Houweling and Van Zundert (2014) the portfolio strategies are applied separately for the IG and HY universes. This is done because according to market conventions these two universes should be regarded as two distinct asset classes. This can be seen in the two separate Barclays corporate bond indexes for the IG universe and HY universe that are used in this research. Furthermore, Chen et al. (2014) provide evidence for the segmentation of the corporate bond market showing that credit ratings have significant effects on bond prices, bond holdings and bond trading activity. Moreover, the results do show noteworthy discrepancies between the universes to warrant this separation. Note that due to this separation there is a separate bond market for both the IG and HY universe and therefore the $DEFAULT$ factor will be different for each universe. The markets of the universes are defined to only consist of bonds of which option data is available for a more fair comparison, as this market definition effectively describes the investible universe.

The market performance can be seen as the benchmark to beat, thus the Opdyke (2007) test is employed to test whether a Sharpe ratio is significantly higher than the corresponding market Sharpe ratio. In this test the returns are assumed to be only stationary and ergodic, whereas the traditional Jobson and Korkie (1981) Sharpe ratio test assumes that the returns are normally distributed. This normality assumption is often found to not hold in practice, thus the easy implementable and less restrictive Opdyke (2007) test is the preferred test. Additionally, the 6-factor alphas are statistically tested on significance with t-tests to investigate whether abnormal returns can be generated that are different from the traditional factor premiums. The t-tests are corrected for heteroscedasticity and autocorrelation with Newey and West (1987) standard errors. The widely used Bartlett kernel is applied and the number of lags is determined by the plug-in procedure introduced by Newey and West (1994). More specifically, the number of lags is computed as $4(T/100)^{2/9}$ with T as the total sample size. These same settings are applied for every Newey and West (1987) standard error in this research. Lastly, it is tested whether there is a monotonically decreasing return pattern in the portfolios with the test of Patton and Timmermann (2010) (PT test). This monotonicity test is entirely nonparametric and is implemented via bootstrapping. A detailed description of this test procedure is given in Appendix B.

[3]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

5 Volatility Analysis

In this section several analyses are shown to shed light on the differences between the standalone realized volatility and implied volatility. These two volatility measures are closely related, but intuitively the implied volatility should be able to predict future returns better as opposed to the realized volatility. This is due to the fact that the implied volatility reflects the market expectation for future volatility and is therefore a forward looking measure, while the realized volatility is computed from historical data making it a backward looking measure. Thus, the implied volatility can contain more information that is relevant for the future. It is investigated whether this supposition becomes apparent in the performances of the trading strategies based on these volatility measures. The realized volatility is computed over an one month horizon with daily returns. This horizon is chosen to match the approximately one month maturity of the options of which the implied volatility is extracted. Furthermore, only ATM call options are considered, as these options are often the most liquid options and are therefore a better representation of market expectations. The portfolio results are presented in Table 4 which shows the average annualized return, the annualized volatility, the Sharpe ratio and the annualized 6-factor alpha.

The results show that bonds with lower volatility measures generally experience higher returns compared to bonds with higher volatility measures. These results are in line with the low volatility effect as documented by Frazzini and Pedersen (2014) and are especially pronounced in the HY universe, where significant Sharpe ratios are obtained for the Q5-Q1 portfolios. The PT test indicates that the return pattern of the realized volatility portfolios in the HY universe is significantly monotonically increasing with a p-value of 0.04, while the PT test for the implied volatility portfolio returns gives a p-value of 0.07 . Furthermore, the Opdyke (2007) test shows that the Q5-Q1 Sharpe ratio obtained with the implied volatility is significantly higher than the Q5-Q1 Sharpe ratio that is generated using realized volatility. The results in the HY universe show that the trading strategy based on implied volatility generally outperforms the realized volatility trading strategy. This finding, however, is not really observed in the IG universe.

This analysis only considers the information from one single option, while there are a multitude of various options available in the option market. The model-free implied volatility of Britten-Jones and Neuberger (2000) incorporates information from all available options and should theoretically contain more information compared to the implied volatility from a single option. The detailed estimation procedure of this model-free implied volatility can be found in Appendix C. The portfolio results based on the model-free implied volatility are presented in panel *III* of Table 4. The general conclusion that can be made is that these portfolio results are slightly worse compared to the portfolios constructed with implied volatility. For example, the Q5-Q1 Sharpe ratio obtained with

Table 4: Portfolio results based on volatility measures

This table presents the results of the trading strategies based on several volatility measures over the sample period of January 1996 to August 2014 in both the Investment Grade and High Yield. The methodology of Jegadeesh and Titman (1993) is employed with a holding period of twelve months to construct the portfolios. The first quintile Q1 contains the bonds with the highest values of the sorting variable and the last quintile Q5 holds the bonds with the lowest sorting variable values. The average annualized return, the annualized volatility, the Sharpe ratio and the annualized 6-factor alpha are shown in the table. Opdyke (2007) tests are employed to test whether the Sharpe ratios of the portfolios are significantly higher than the corresponding market Sharpe ratio. The 6-factor alphas are tested on significance with t-tests corrected with Newey and West (1987) standard errors.

	Investment Grade						High Yield					
	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Q1	Q2	Q3	Q4	Q5	Q5-Q1
I. Realized Volatility												
Returns (%)	0.28	0.68	0.62	0.45	0.37	0.09	−3.22	−0.49	0.53	1.49	2.11	5.51
Volatility (%)	5.83	4.73	4.52	4.07	3.90	3.29	15.13	11.20	9.54	8.17	7.10	11.79
Sharpe Ratio	0.05	0.14	0.14	0.11	0.10	0.03	−0.21	−0.04	0.06	0.18	0.30	0.47**
6F Alpha (%)	−0.18	0.17	0.07	−0.23	−0.44	−0.08	−4.03	−1.67	−1.11	0.12	0.91	7.20**
II. Implied Volatility												
Returns (%)	0.24	0.73	0.50	0.48	0.46	0.23	−4.61	−0.65	1.15	1.98	2.52	7.48
Volatility (%)	5.88	4.63	4.73	4.01	3.79	3.37	15.78	11.53	9.25	8.17	6.84	13.18
Sharpe Ratio	0.04	0.16	0.11	0.12	0.12	0.07	−0.29	−0.06	0.12	0.24	0.37*	0.57***
6F Alpha (%)	−0.24	0.16	0.00	−0.18	−0.33	0.10	−4.83	−2.09	−0.71	0.53	1.39	8.97**
III. MF Implied Volatility												
Returns (%)	0.15	0.69	0.61	0.53	0.42	0.19	−3.90	−1.06	1.00	1.70	2.39	6.56
Volatility (%)	5.76	4.75	4.57	4.05	3.86	3.10	15.40	11.21	9.60	8.33	6.93	12.54
Sharpe Ratio	0.03	0.15	0.13	0.13	0.11	0.06	−0.25	−0.09	0.10	0.20	0.34*	0.52***
6F Alpha (%)	−0.34	0.15	0.09	−0.14	−0.38	0.07	−4.41	−2.16*	−0.58	0.11	1.08	8.00**

***, ** and * show significance at the 1%, 5% and 10% level respectively.

the model-free implied volatility is found to be significantly lower than the Q5-Q1 Sharpe ratio that is generated with the implied volatility trading strategy. Other statistics also point towards the fact that the model-free implied volatility does not perform the best, while this volatility measure should theoretically contain more information.

Next, it is investigated which volatility measure is a better predictor for future volatility following the methodology of Christensen and Prabhala (1998). They run univariate and multivariate regressions to determine which volatility measure is an unbiased estimator for future volatility. All volatility measures are annualized and transformed with the natural log function to smooth out outliers. The log realized volatility, log implied volatility and log model-free implied volatility are denoted by LRV, LIV and $MFIV$ respectively. Since the univariate regressions are simply restricted versions of the multivariate regression, only the multivariate regression equation is described:

$$LRV_{i,t} = \theta_i + \theta_i^{LRV} LRV_{i,t-1} + \theta_i^{LIV} LIV_{i,t-1} + \theta_i^{MFIV} MFIV_{i,t-1} + \epsilon_{i,t}, \tag{7}$$

where the subscripts i and t denote the firm and month respectively. The white noise residuals are denoted by $\epsilon_{i,t}$. The regressions are performed for each firm with at least 50 observations resulting in 596 eligible firms. For the univariate regressions a joint hypothesis is tested on whether the constant equals zero and the slope coefficient equals one with the Wald test adjusted with Newey and West (1987) standard errors. A significance level of 5% is adopted for the test. If this hypothesis holds to be true, then the volatility measure is an unbiased estimator for future volatility. A summary of the results is presented in Table 5 which shows the average coefficients, the average adjusted R2, the average number of observations per regression and the number of times the null hypothesis is not rejected.

Table 5: Volatility predictability results

This table presents summary results of univariate and multivariate regressions as specified by Equation 7. The regressions are performed on firms with at least 50 observations resulting in 596 eligible firms. The average of the coefficients, the average adjusted R2 and the average number of observations of all regressions are shown in the table. Furthermore, the number of times the null hypothesis $\theta = 0$ and $\theta^j = 1$ with $j = LRV, LIV, MFIV$ is not rejected with the Wald test is reported as Test A. The null hypothesis of $\theta^{LRV} = 0$, $\theta^{LIV} = 1$ and $\theta^{MFIV} = 0$ is also tested with the Wald test and the number of times this null hypothesis is not rejected is reported as Test B. All tests use Newey and West (1987) standard errors and a significance level of 5%.

	θ	θ^{LRV}	θ^{LIV}	θ^{MFIV}	Adj. R2	#Obs	Test A	Test B
1	-0.43	0.63			0.41	102	36	
2	-0.12		0.97		0.53	102	205	
3	-0.33			0.82	0.39	102	181	
4	-0.13	0.17	0.82	-0.04	0.54	102		331

The univariate regressions show that the implied volatility provides the best fit with an average adjusted R2 of 0.53. Additionally, the Wald tests show that the implied volatility is an unbiased estimator in 205 cases, while the realized volatility is found to be a biased predictor in most cases. Surprisingly, the model-free implied volatility performs the worst in terms of fit. The multivariate regression results indicate that the implied volatility subsumes the other two volatility measures, as the coefficients of the realized volatility and model-free implied volatility decrease towards zero, while the implied volatility coefficient stays close to one. Furthermore, the average adjusted R2 of 0.54 is only a minor improvement over the average adjusted R2 of the univariate regressions with implied volatility as the explanatory variable. The joint null hypothesis of $\theta^{LRV} = 0$, $\theta^{LIV} = 1$ and $\theta^{MFIV} = 0$ is tested to statistically determine whether the implied volatility subsumes the information contained in the other volatility measures. The results show that this null hypothesis holds for 331 cases, which is approximately 55% of all tested firms. So the implied volatility is an efficient estimator of future volatility for a majority of firms.

Jiang and Tian (2005) recognize that the implied volatility and model-free implied volatility can potentially be endogenous variables. Their reasoning is that the implied volatility can contain measurement errors due to misspecification errors of the option pricing model. Thus, two-stage least squares (TSLS) regressions are employed to investigate whether endogeneity is an issue. In the first stage the implied volatility and model-free implied volatility are individually regressed on instrumental variables. Following Jiang and Tian (2005) the lagged realized volatility and lagged implied volatility are chosen to be the instrumental variables for the implied volatility. The same instrumental variables are chosen for the model-free implied volatility with as addition the lagged model-free implied volatility. In the second stage the same univariate and multivariate regressions are performed as before, except with the fitted values of the first stage regressions as the explanatory variables. A summary of the TSLS regression results can be found in Table 6.

The first stage regressions show that the explanatory variables provide a good fit judging from the average adjusted R2s. The Hausman (1978) test is conducted with auxiliary regressions to determine whether the volatility measures are endogenous. The tests show that the implied volatility and the model-free implied volatility are endogenous for respectively 99% and 83% of the cases with a significance level of 5%. Thus, endogeneity is an issue for the regressions that are performed earlier, which is exactly what is addressed in the second stage of the TSLS regression. The univariate regressions, however, point toward the same conclusions as before. The multivariate regressions do show significant different results, namely, the implied volatility does not seem to subsume the information contained in the realized volatility and model-free implied volatility anymore, as the joint null hypothesis of $\theta^{LRV} = 0$, $\theta^{LIV} = 1$ and $\theta^{MFIV} = 0$ only holds for 46 cases now. These results indicate that the implied volatility is not always an efficient forecast for future volatility.

Table 6: Two-stage least squares regression results

This table presents summary results of both two-stage least squares regression stages. In the first stage the dependent variable is indicated by the left column and the explanatory variables are all lagged by one month. The second stage regressions are specified by Equation 7. The regressions are performed on firms with at least 50 observations resulting in 596 eligible firms. The average of the coefficients, the average adjusted R2 and the average number of observations of all regressions are shown in the table. Furthermore, the number of times the null hypothesis $\theta = 0$ and $\theta^j = 1$ with $j = LRV, LIV, MFIV$ is not rejected with the Wald test is reported as Test A. The null hypothesis of $\theta^{LRV} = 0$, $\theta^{LIV} = 1$ and $\theta^{MFIV} = 0$ is also tested with the Wald test and the number of times this null hypothesis is not rejected is reported as Test B. All tests use Newey and West (1987) standard errors and a significance level of 5%.

	θ	θ^{LRV}	θ^{LIV}	θ^{MFIV}	Adj. R2	#Obs	Test A	Test B
I. First Stage								
LIV	-0.29	0.18	0.56		0.56	117		
$MFIV$	-0.27	0.14	0.56	0.00	0.49	99		
II. Second Stage								
1	-0.42	0.65			0.42	98	25	
2	-0.06		1.02		0.37	98	244	
3	0.00			1.11	0.37	98	123	
4	-0.17	0.43	0.24	0.23	0.45	98		46

Nonetheless, the univariate regressions suggest that the implied volatility is a better standalone unbiased estimator for future volatility compared to the realized volatility and model-free implied volatility, which is in line with the found portfolio results. A surprising result is that the model-free implied volatility does not perform the best out of all the volatility measures. A possible explanation is that there is not enough data to have an accurate estimate of the model-free implied volatility. This lack of data is mostly contributed to the filtering of the options. Taylor et al. (2010) found the model-free implied volatility to also perform poorly and pointed to the potential mispricings of OTM options as an explanation.

6 Option Measure Analyses

This section discusses the portfolio results of the trading strategies based on the option measures. Furthermore, each individual option measure is analyzed more in depth to gain more insight on their information content. The portfolio results are presented in Table 7 which shows the average annualized return, the annualized volatility, the Sharpe ratio and the annualized 6-factor alpha.

6.1 Realized-Implied Volatility Spread

Panel I of Table 7 shows that bonds with higher values of $RVIV$ experience higher returns compared to bonds with lower $RVIV$ values in both the IG and HY universe. The Q1 portfolio in the IG universe has an average annualized return of 0.73% decreasing to 0.24% in portfolio Q5.

Table 7: Portfolio results based on option measures

This table presents the results of the trading strategies based on the option measures over the sample period of January 1996 to August 2014 in both the Investment Grade and High Yield universe. The methodology of Jegadeesh and Titman (1993) is employed with a holding period of twelve months to construct the portfolios. The first quintile Q1 contains the bonds with the highest values of the sorting variable and the last quintile Q5 holds the bonds with the lowest sorting variable values. The average annualized return, the annualized volatility, the Sharpe ratio and the 6-factor annualized alpha are shown in the table. Opdyke (2007) tests are employed to test whether the Sharpe ratios of the portfolios are significantly higher than the corresponding market Sharpe ratio. The 6-factor alphas are tested on significance with t-tests corrected with Newey and West (1987) standard errors.

	Investment Grade						High Yield					
	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Q1	Q2	Q3	Q4	Q5	Q1-Q5
I. RVIV												
Returns (%)	0.73	0.70	0.47	0.44	0.24	0.48	1.09	1.86	1.92	1.86	0.42	0.67
Volatility (%)	4.79	4.53	4.26	4.39	4.58	1.00	10.18	8.62	8.46	8.71	9.81	2.46
Sharpe Ratio	0.15	0.16	0.11	0.10	0.05	0.48***	0.11	0.22	0.23	0.21	0.04	0.27
6F Alpha (%)	0.19	0.05	−0.19	−0.22	−0.37**	0.57**	−0.32	0.25	0.27	0.53	−0.83	0.50
II. PUTCALL												
Returns (%)	0.80	0.52	0.49	0.52	0.53	0.27	1.62	1.98	1.81	2.28	1.86	−0.23
Volatility (%)	4.80	4.48	4.44	4.42	4.73	0.90	11.71	9.77	9.34	9.08	10.49	2.92
Sharpe Ratio	0.17	0.12	0.11	0.12	0.11	0.30*	0.14	0.20	0.19	0.25	0.18	−0.08
6F Alpha (%)	0.15	−0.12	−0.25	−0.14	0.12	0.04	−1.17	0.38	−0.02	0.63	−0.16	−1.21
III. SKEW												
Returns (%)	0.19	0.54	0.49	0.45	0.63	−0.44	1.35	0.21	0.72	0.08	1.14	0.21
Volatility (%)	5.37	4.56	4.33	4.27	4.51	2.22	10.27	9.65	9.29	9.29	9.34	2.90
Sharpe Ratio	0.03	0.12	0.11	0.11	0.14	−0.20	0.13	0.02	0.08	0.01	0.12	0.07
6F Alpha (%)	−0.20	−0.11	−0.22	−0.25	0.06	−0.26	−0.21	−1.18	−0.66	−1.48	0.14	−0.48
IV. TERMSLOPE												
Returns (%)	0.61	0.44	0.45	0.35	0.25	0.36	0.72	1.75	1.41	0.64	−0.70	1.43
Volatility (%)	4.72	4.36	4.38	4.36	4.73	0.77	10.80	8.57	8.60	9.26	11.26	2.74
Sharpe Ratio	0.13	0.13	0.12	0.11	0.07	0.47**	0.15	0.20	0.25	0.16	−0.02	0.66***
6F Alpha (%)	−0.10	−0.20	−0.24	−0.22	−0.31	0.20	−0.86	0.31	−0.34	−0.87	−2.32	1.60
V. VALUE												
Returns (%)	1.92	0.64	0.18	0.01	−0.21	2.13	2.64	1.07	0.87	0.69	−0.51	3.17
Volatility (%)	5.88	5.14	4.95	4.20	3.13	3.57	11.69	10.01	9.58	8.95	8.83	5.44
Sharpe Ratio	0.33***	0.13	0.04	0.00	−0.07	0.60***	0.23	0.11	0.09	0.08	−0.06	0.58***
6F Alpha (%)	1.55***	0.08	−0.55***	−0.72***	−0.82***	2.30***	0.60	−0.62	−0.62	−0.69	−1.34	1.69

***, ** and * show significance at the 1%, 5% and 10% level respectively.

The PT test indicates that the portfolios have a significant monotonically declining return pattern. Although the Q1-Q5 portfolio generates relatively low returns, it's volatility is considerably lower compared to the individual portfolios resulting in a highly significant Sharpe ratio of 0.48. Furthermore, the significant annualized 6-factor alpha of 0.57% indicates that this portfolio differs from the traditional factor strategies. Similar results are found in the HY universe, though portfolio Q1 does not gain the most returns despite the higher risk it takes compared to the other portfolios as indicated by the volatilities. As a result, the Q1-Q5 portfolio has an insignificant Sharpe ratio of 0.27 and an insignificant annualized 6-factor alpha of 0.50%, but the portfolios do show a decreasing, though insignificant, return pattern starting from portfolio Q2 to Q5. So this strategy shows significant results in the IG universe and similar, though less convincing, results in the HY universe.

The literature has found the realized-implied volatility spread to bear a negative risk premium for stocks, that is, stocks with high values of $RVIV$ are shown to gain less returns compared to stocks with lower $RVIV$ values. These findings are not consistent with the corporate bond results where the opposite return effect is observed, though the Q1 portfolio in the HY universe does hint towards this negative risk premium. This portfolio contains bonds with the highest values of $RVIV$ and has lower returns compared to the other individual portfolios. The other portfolios, however, do not show evidence in favour of the negative risk premium. Thus, a different interpretation for the $RVIV$ option measure is given next to explain the portfolio results.

The realized-implied volatility spread compares the historical volatility with the market expectation of future volatility. Thus, a supposition for the interpretation of the realized-implied volatility spread is that it describes a trend in the volatility. If for example the current implied volatility is low compared to the historical volatility, then the volatility is expected to decline in the future, thus a positive $RVIV$ can be associated with a declining volatility trend. Fama-MacBeth regressions with an ARX(1)-like structure are employed to test this conjecture on the cross-sections of the data. At each point in time the following cross-sectional regression is performed:

$$VOL_{i,t} = \phi_{1t} + \phi_{2t} VOL_{i,t-1} + \phi_{3t} RVIV_{i,t-1} + \eta_{i,t}, \tag{8}$$

where $VOL_{i,t}$ is the realized volatility of stock i at month t computed using daily return data of the previous month. This choice of the horizon ensures that there is no overlap between the dependent and explanatory variables. The additional explanatory variable of interest is the realized-implied volatility spread $RVIV_{i,t-1}$ of firm i at month $t-1$. Finally, the white noise residuals are denoted by $\eta_{i,t}$. The coefficients of the cross-sectional regressions are averaged over time and tested on significance with t-tests. The standard errors for the tests are adjusted for heteroscedasticity and autocorrelation with Newey and West (1987) corrections. Table 8 presents the results of the Fama-MacBeth regressions.

Table 8: Fama-MacBeth regression results

This table presents the results of Fama-MacBeth regressions specified by Equation 8. Additionally, the table also presents the results of the same regressions performed with Z-scores of the variables which are winsorized at ±3. The average coefficients with t-stats between parentheses, the average adjusted R2 and the number of months are shown in the table. The t-stats are computed with Newey and West (1987) standard errors.

	Standard		Z-Scores	
	1	2	3	4
Constant	0.13	0.11	0.23	0.21
	(27.16)	(26.69)	(25.03)	(25.21)
VOL	0.60	0.64	0.82	0.85
	(42.16)	(49.75)	(65.17)	(72.33)
RVIV		-0.27		-0.15
		(-19.99)		(-17.65)
Adj. R2	0.35	0.39	0.37	0.39
#Months	224	224	224	224

The first regression in the table shows that the standard AR(1) specification for VOL provides a good fit with an average adjusted R2 of 0.35. The second regression includes the $RVIV$ as an explanatory variable. The $RVIV$ has a significant negative coefficient of -0.27 and it contains some explanatory power, as the average adjusted R2 increases by 0.04 to a total of 0.39. Furthermore, the addition of $RVIV$ does not heavily influence the other coefficients of the first regression. This means that when there is a positive difference between the historical volatility and implied volatility, i.e. an expected decline in volatility, then the future volatility is indeed adjusted downwards. The same inference can be made for a negative realized-implied volatility spread to adjust the future volatility upwards.

As a robustness check the same procedure is performed with Z-scores of the variables. At each point in time the corresponding cross-sectional medians are subtracted from the variables and then divided by the corresponding median absolute deviations. The explanatory variables are winsorized at ±3 to limit the influence of outliers. The third and fourth regression in Table 8 show the results of this robustness check. Even though the coefficient of $RVIV$ of -0.15 has increased more towards zero, it remains significant and the same conclusions can be made as before. The same analysis is also done with three, six and twelve month historical volatilities as the VOL variable with the appropriate lags such that there is no overlap between the dependent variable and explanatory variables. The results presented in Table 9 all show similar outcomes as before. Statistical evidence is therefore found with this brief investigation for the conjecture that the realized-implied volatility spread describes a trend in volatility.

Table 9: Fama-MacBeth regression results for different horizons

This table presents the results of the Fama-MacBeth regressions specified by Equation 8 for different historical horizons for the VOL variable with the appropriate lags such that there is no overlap between the dependent variable and explanatory variables. The variables are transformed into Z-scores and are winsorized at ±3. The coefficients with t-stats between parentheses, the average adjusted R2 and the number of months are shown in the table. The t-stats are computed with Newey and West (1987) standard errors.

	3 Months		6 Months		12 Months	
Constant	0.17	0.15	0.16	0.15	0.18	0.17
	(17.82)	(16.38)	(12.02)	(11.63)	(9.68)	(9.66)
VOL	0.93	1.03	0.97	1.01	0.98	0.99
	(73.61)	(81.43)	(65.18)	(68.71)	(50.06)	(50.89)
RVIV		-0.26		-0.13		-0.05
		(-40.86)		(-18.58)		(-6.30)
Adj. R2	0.51	0.55	0.56	0.58	0.55	0.56
#Months	224.00	224.00	224.00	224.00	224.00	224.00

This interpretation of $RVIV$ as a volatility trend is also in agreement with the portfolio results. The highest values of this option measure are sorted in portfolio Q1, thus the implied volatilities are lower compared to the realized volatilities indicating a decline in future volatilities. This can imply that the firms in this portfolio are becoming less risky which raises the future bond prices. Evidence for this reasoning is provided by Campbell and Taksler (2003) who find the equity volatility to be positively related to yields on corporate bonds relative to Treasury bonds. In normal circumstances yields on Treasury bonds are relatively stable, thus it follows that corporate bond yields will drop as volatilities decline resulting in a rise in future bond prices. The higher bond prices in the future result in positive returns for this portfolio. The volatility in portfolio Q1 is expected to decline the most and therefore, ceteris paribus, the bond prices are expected to rise the most resulting in the portfolio with the highest average annualized return. So this interpretation of the realized-implied volatility spread as a trend in volatility is backed by statistical and economical evidence.

6.2 Put-Call Implied Volatility Spread

Panel II of Table 7 presents the portfolio results based on the $PUTCALL$ option measure which shows different outcomes depending on the universe. The results in the IG universe suggest that bonds with higher $PUTCALL$ values generally experience higher returns compared to bonds with lower values. Thus, bonds with relatively expensive put options outperform bonds with relatively expensive call options. The Q1 portfolio has an average annualized return of 0.80% decreasing to 0.53% in portfolio Q5, though the PT test indicates that there is no significant decreasing return pattern. The Q1-Q5 portfolio has a lower return compared to the individual portfolios, but the Sharpe ratio of 0.30 is significant, though only marginally. The annualized 6-factor alpha of 0.04% is, however, not significant indicating that this strategy is not different from the other traditional factor strategies. In the HY universe there is no concise pattern in the returns and Sharpe ratios of the portfolios which is also confirmed with the PT test. This is also reflected in the Q1-Q5 portfolio with an average annualized return of -0.23%, an insignificant Sharpe ratio of -0.08 and an insignificant annualized 6-factor alpha of -1.21%. So only the portfolio results in the IG universe suggest that this option measure might contain relevant information for the corporate bond market with the only concern being an insignificant 6-factor alpha. As the option measure is constructed out of a wide variety of options with different strikes and maturities, it is suspected that noise can be a disturbing factor. An attempt to capture more relevant information is done next.

Deviations from the put-call parity are argued by Cremers and Weinbaum (2010) to be caused by informed trading in the options market. Related to this is the sequential trade model of Easley et al. (1998) that is developed to determine where informed investors will trade. Their model suggests that informed investors will trade more in options when the option market is more liquid. Chakravarty et al. (2004) find evidence supporting this suggestion, that is, they find that the option market contains more information when the option trading volume is high. Intuitively, informed investors want to hide their trading intents to gain the most out of their information. This can be done by strategically camouflaging their trades depending on the liquidity of the market; so-called stealth trading. Anand and Chakravarty (2007) investigate the price discovery in the option market in the light of stealth trading and find that informed traders prefer to trade in more liquid options. All of this suggests that the information content of the $PUTCALL$ option measure should increase when the options are more liquid.

This is investigated by sorting the available pairs of put and call options in three groups based on the average bid-ask spread as a liquidity measure. Three groups are made such there is a group with liquid options, a group with illiquid options and a middle neutral group. The liquid options group are the options with the lowest bid-ask spreads and vice versa. This separation of options is done for each individual $PUTCALL$ option measure and a prerequisite is that there are at least three pairs of put and call options to ensure that each group contains at least one observation. Then for each liquidity group the $PUTCALL$ option measure is computed and the same portfolio strategy as before is applied to examine whether more information is captured by more liquid options. Table 10 presents the portfolio results for the liquid options group and the illiquid options group in the IG universe.

Table 10: Liquidity effects in the Investment Grade universe

This table presents the results of the trading strategies based on the *PUTCALL* option measure in the Investment Grade universe over the sample period of January 1996 to August 2014. All available pairs of put and call options are separated into three liquidity groups based on the average bid-ask spread. The liquid options group are the options with the lowest bid-ask spreads and vice versa. The *PUTCALL* option measure is then constructed with the options for each group and the methodology of Jegadeesh and Titman (1993) is employed with a holding period of twelve months to construct the portfolios. The first quintile Q1 contains the bonds with the highest values of the sorting variable and the last quintile Q5 holds the bonds with the lowest sorting variable values. The average annualized return, the annualized volatility, the Sharpe ratio and the annualized 6-factor alpha are shown in the table. Opdyke (2007) tests are employed to test whether the Sharpe ratios of the portfolios are significantly higher than the corresponding market Sharpe ratio. The 6-factor alphas are tested on significance with t-tests corrected with Newey and West (1987) standard errors.

	Q1	Q2	Q3	Q4	Q5	Q1-Q5
I. Liquid Options						
Returns (%)	0.70	0.47	0.46	0.54	0.40	0.30
Volatility (%)	4.84	4.45	4.48	4.46	4.72	0.82
Sharpe Ratio	0.14	0.11	0.10	0.12	0.08	0.36**
6F Alpha (%)	0.09	−0.18	−0.26	−0.10	−0.02	0.11
II. Illiquid Options						
Returns (%)	0.61	0.49	0.50	0.49	0.47	0.14
Volatility (%)	4.82	4.45	4.44	4.42	4.83	0.93
Sharpe Ratio	0.13	0.11	0.11	0.11	0.10	0.15
6F Alpha (%)	0.07	−0.15	−0.16	−0.19	−0.03	0.11

** shows significance at the 5% level.

The results show a clear difference between using liquid options and illiquid options. When the *PUTCALL* option measure is based on liquid options, then the Q1-Q5 portfolio has an average annualized return of 0.30% with a significant Sharpe ratio of 0.36. However, when illiquid options are used, then the Q1-Q5 portfolio has a lower average annualized return of 0.14% with an insignificant Sharpe ratio of 0.15. The Opdyke (2007) test shows that this Sharpe ratio is significantly lower than the Sharpe ratio obtained with liquid options. Furthermore, the average annualized return, Sharpe ratio and annualized 6-factor alpha of the Q1-Q5 portfolio based on liquid options are an improvement over the unfiltered Q1-Q5 portfolio results that uses all options. The 6-factor alpha, however, remains insignificant showing again that no abnormal returns can be gained with this strategy. Nevertheless, these results suggest that liquid options contain more information compared to illiquid options. Next, Table 11 shows the portfolio results in the HY universe.

The results when illiquid options are used to construct the *PUTCALL* option measure show a complete reversal of returns compared to the IG universe. Now portfolio Q1 has the lowest returns with an average annualized return of 1.01% and it increases to 2.15% in portfolio Q5. The Q1-Q5 portfolio has a negative annualized return of −1.11% with an insignificant Sharpe ratio of −0.27 and an annualized 6-factor alpha of −2.01% that is insignificant. Also, the results using liquid options are not an improvement over the results that uses all options indicating that there might be other noises involved in the construction of this option measure. Nevertheless, the Opdyke (2007) test here also indicates that the Sharpe ratios based on the liquid and illiquid options are significantly different from each other. So the results do suggest that options contain different information depending on their liquidity. Most findings, however, indicate that this option measure does not contain much relevant information for corporate bonds.

Table 11: Liquidity effects in the High Yield universe

This table presents the results of the trading strategies based on the *PUTCALL* option measure in the High Yield universe over the sample period of January 1996 to August 2014. All available pairs of put and call options are separated into three liquidity groups based on the average bid-ask spread. The liquid options group are the options with the lowest bid-ask spreads and vice versa. The *PUTCALL* option measure is then constructed with the options for each group and the methodology of Jegadeesh and Titman (1993) is employed with a holding period of twelve months to construct the portfolios. The first quintile Q1 contains the bonds with the highest values of the sorting variable and the last quintile Q5 holds the bonds with the lowest sorting variable values. The average annualized return, the annualized volatility, the Sharpe ratio and the annualized 6-factor alpha are shown in the table. Opdyke (2007) tests are employed to test whether the Sharpe ratios of the portfolios are significantly higher than the corresponding market Sharpe ratio. The 6-factor alphas are tested on significance with t-tests corrected with Newey and West (1987) standard errors.

	Q1	Q2	Q3	Q4	Q5	Q1-Q5
I. Liquid Options						
Returns (%)	1.78	1.27	1.63	1.76	1.59	0.19
Volatility (%)	11.42	10.20	9.34	9.46	10.31	2.72
Sharpe Ratio	0.16	0.12	0.17	0.19	0.15	0.07
6F Alpha (%)	−1.17	−0.33	−0.14	0.13	−0.28	−1.10*
II. Illiquid Options						
Returns (%)	1.01	1.31	1.42	2.04	2.15	−1.11
Volatility (%)	12.32	9.90	9.53	9.00	10.26	4.15
Sharpe Ratio	0.08	0.13	0.15	0.23	0.21	−0.27
6F Alpha (%)	−1.62	−0.49	−0.20	0.32	0.17	−2.01

* shows significance at the 10% level.

This option measure is based on the put-call parity that only holds for European options, while the stock options are all in American style. Thus, the early exercise premium included in American options can introduce disturbing noises to this option measure. This is investigated by constructing the *PUTCALL* option measure with only ATM options that expire in one month. This way the early exercise premium of American options is reduced, as there are less incentives to exercise ATM options and the premium is by definition less for options that have a shorter maturity. The portfolio results based on this new *PUTCALL* option measure are presented in Table 12. The general finding is that there are no significant improvements over the results based on the original *PUTCALL* option measure. This confirms again that deviations from the put-call parity does not reveal information relevant for corporate bonds.

Table 12: Portfolio results with modified *PUTCALL* option measure

This table presents the results of the trading strategies based on a modified $PUTCALL$ option measure over the sample period of January 1996 to August 2014 in both the Investment Grade and High Yield. The modified $PUTCALL$ option measure is defined similarly as $PUTCALL$, but only ATM options with an one month maturity are included in the construction. The methodology of Jegadeesh and Titman (1993) is employed with a holding period of twelve months to construct the portfolios. The first quintile Q1 contains the bonds with the highest values of the sorting variable and the last quintile Q5 holds the bonds with the lowest sorting variable values. The average annualized return, the annualized volatility, the Sharpe ratio and the annualized 6-factor alpha are shown in the table. Opdyke (2007) tests are employed to test whether the Sharpe ratios of the portfolios are significantly higher than the corresponding market Sharpe ratio. The annualized 6-factor alphas are tested on significance with t-tests corrected with Newey and West (1987) standard errors.

	Q1	Q2	Q3	Q4	Q5	Q1-Q5
I. Investment Grade						
Returns (%)	0.53	0.49	0.49	0.39	0.39	0.14
Volatility (%)	4.87	4.36	4.35	4.33	4.59	0.64
Sharpe Ratio	0.11	0.11	0.11	0.09	0.08	0.22
6F Alpha (%)	−0.02	−0.21	−0.30	−0.30	−0.08	0.04
II. High Yield						
Returns (%)	0.97	0.43	0.38	0.82	1.03	−0.06
Volatility (%)	10.93	9.85	9.42	9.25	9.92	3.08
Sharpe Ratio	0.09	0.04	0.04	0.09	0.10	−0.02
6F Alpha (%)	−0.84	−1.14	−1.14	−0.67	−0.66	−0.32

An intentional decision that is made is to not use option trading volume as a liquidity measure. This is because Easley et al. (1998) find the stand-alone option trading volumes to contain no information about future stock prices. However, when they decompose the option trading volume into positive trades (buying calls and selling puts) and negative trades (selling calls and buying puts), then these volumes are found to have informational content. Pan and Poteshman (2006) also investigate the predictive ability of option trading volumes for future stock prices. They find that option trading volumes that are initiated to open new positions contain significant information. So the standalone option trading volume can be decomposed into components based on different information signals. When this is not done it is possible to bias the results by naively sorting on standalone option trading volume. Due to lack of data to perform this decomposition it is opted to not choose the option trading volume as the liquidity measure.

6.3 Implied Volatility Skew

Panel *III* of Table 7 shows the portfolio results of the $SKEW$ based trading strategies. The results in the IG universe indicate that bonds with higher values of $SKEW$ underperform compared to bonds with lower values. The Q1 portfolio has an average annualized return of 0.19% increasing to 0.63% in portfolio Q5. The PT test indicates that this increasing pattern is, however, not significant. The Q1-Q5 portfolio has an insignificant Sharpe ratio of −0.20 and an insignificant annualized 6-factor alpha of -0.26%. The portfolios in the HY universe do not give a significant return pattern resulting in a low and insignificant Sharpe ratio of -0.07 and an insignificant annualized 6-factor alpha of -0.48% for the Q1-Q5 portfolio. This outcome is possibly due to the lower coverage in the HY universe. Regardless, these portfolio results indicate that this option measure contains little to no information for corporate bond prices.

Despite the weak results, the portfolios in the IG universe do exhibit the correct return pattern according to the interpretation of the $SKEW$ option measure. That is, high values of the $SKEW$ imply that implied volatilities of OTM put options are relatively higher compared to those of ATM call options. According to Garleanu et al. (2009) this indicates that there is a relatively high demand for OTM put options, as they document theoretical and empirical evidence that high demand pressures increase the implied volatilities of options. The reasons for investors to buy OTM put options are either to hedge or speculate for future price drops. Thus, the high demand for these options suggests that informed investors have bad expectations for the future health of the relevant firms. This corresponds with the fact that the Q1 portfolio in the IG universe has the lowest return out of all the portfolios, though this interpretation does not hold in the HY universe. This interpretation of the $SKEW$ option measure is investigated further.

Pooled regressions of the market credit spread on the $SKEW$ option measure and other control variables are performed to investigate whether the $SKEW$ contains information regarding the health of a firm. The market credit spreads are in basis points and are chosen as the indicator for the degree of riskiness or health of a firm. The regressions are not contemporaneous, but the explanatory variables are all lagged by one month in order to investigate the predictive power of $SKEW$. The chosen control variables are similar to those used by Cremers et al. (2008b) who also investigated the explanatory power of option information for corporate bond credit spreads. Other studies have also found that these variables contain information for credit spreads.

The essential firm specific volatility control variables include the historical return volatility, historical return skew and option implied volatility. Other natural firm specific control variables are the leverage and stock return. The leverage is undoubtedly an important measure for the credit risk of firms and the stock return reflects the overall health of the firm. Cremers et al. (2008b) also add the corresponding market based variables due to concerns of measurement errors in the firm specific variables. The S&P500 index is chosen as the proxy for the market, as the firms in the data set are all U.S. listed. The market variables include the historical return volatility, historical return skew, option implied volatility, option implied skew, and return. All historical measures and returns are computed with a six month horizon on a daily frequency.

Furthermore, the 5-year yield of Treasury bonds and the difference between the 10-year and 2-year Treasury yields are included to control for respectively the level and the slope of the term structure of interest rates. The BAA corporate bond yield rate is also added to capture the overall market credit risk. These specific data series are downloaded via Datastream. Lastly, the time-to-maturity of the bonds is also used as a control variable, as Cremers et al. (2008b) find significant different regression results depending on whether the bonds have a short maturity or long maturity.

The sample is split between the IG and HY universe in order to examine whether the $SKEW$ variable shows different effects depending on the universe, as this is the case for the portfolio results. Additionally, the regressions are only performed on bonds with at least 25 month observations. Driscoll and Kraay (1998) standard errors are used to correct for heteroscedasticity, auto-correlation and cross-sectional correlation. These standard errors are a generalization of the Newey and West (1987) standard errors for pooled regressions. Table 13 presents the results of the regressions.

As argued before, a high value of $SKEW$ indicates relatively high distress of a firm, thus the $SKEW$ variable should be positively related to credit spreads. This interpretation corresponds with the regression results, as the coefficients of $SKEW$ are significantly positive in each regression. Remarkably, the coefficients in the HY universe are more significant and of a higher magnitude compared to the IG universe. This suggests that the $SKEW$ variable has substantial predictive power for future credit spreads or the future risk of a firm, thought the portfolio results in the HY universe do not reflect this finding. A possible reason might be that the information contained in the $SKEW$ option measure is already priced in the bonds. Another reason can be that the information is only relevant for a short period. If this is the case, then the portfolios with a twelve month holding period will incorporate old irrelevant information. But the results with an one month holding period in the robustness check do not show any significant improvements indicating that there is little information in the $SKEW$ option measure for future corporate bond prices.

An interesting finding is that the maturity has a positive coefficient in the IG universe and a negative coefficient in the HY universe. Intuitively, bond yields should be higher for bonds with longer maturities, as investors want a premium for holding the bonds due to the risks that they take such as interest rate risk or default risk. So the maturity has the intuitive effect in the IG universe, but not in the HY universe. The negative coefficient of the maturity, which indicates a downward sloping yield curve, suggests that there are already negative expectations about the future of these bonds. As a consequence, the $SKEW$ variable, which tries to indicate future distress, does possibly not contain any extra information that is already known to the market. So the information contained in $SKEW$ is perhaps already incorporated into the prices of the bonds which explains the insignificant portfolio results.

Table 13: Pooled regression results

This table presents the results of pooled regressions with the credit spreads in basis points as the dependent variable over the sample period of January 1996 to August 2014. The explanatory variables are indicated by the first column. The coefficients with t-stats between parentheses, the adjusted R2, the total number of observations and the total number of bonds are shown in the table. The t-stats are computed with Driscoll and Kraay (1998) standard errors.

	Investment Grade			High Yield		
	1	2	3	4	5	6
SKEW	318.21	218.84	151.80	434.56	348.82	332.26
	(3.39)	(4.23)	(4.24)	(3.87)	(4.64)	(5.67)
Firm Hist. Skew	6.88	5.22	1.72	12.82	12.20	4.26
	(4.42)	(6.36)	(4.49)	(5.04)	(5.36)	(2.46)
Firm Impl. Volatility	364.75	279.65	278.42	556.31	425.78	474.89
	(3.11)	(5.63)	(12.78)	(5.05)	(6.58)	(10.38)
Firm Hist. Volatility	144.43	47.84	81.13	158.82	109.24	148.52
	(2.38)	(1.63)	(3.99)	(2.64)	(3.36)	(4.44)
Firm Return	-7.59	1.27	1.31	-36.85	-29.53	-17.05
	(-1.02)	(0.71)	(1.56)	(-2.08)	(-1.90)	(-2.35)
Market Impl. Skew		-674.41	-325.17		-1130.41	-716.01
		(-1.71)	(-1.76)		(-2.08)	(-2.47)
Market Hist. Skew		-14.50	-29.61		-16.39	-36.67
		(-0.84)	(-2.50)		(-0.65)	(-2.89)
Market Impl. Volatility		209.02	-153.25		621.14	80.14
		(1.18)	(-2.12)		(2.80)	(0.74)
Market Hist. Volatility		253.99	-14.32		195.66	-252.23
		(2.09)	(-0.15)		(1.04)	(-2.12)
Market Return		-84.12	32.36		102.81	87.85
		(-1.25)	(0.72)		(1.00)	(1.84)
Leverage			76.02			229.45
			(9.94)			(6.67)
5Y Yield			-84.16			-103.78
			(-6.95)			(-7.95)
10Y Yield - 2Y Yield			-32.98			-15.04
			(-3.35)			(-1.49)
BAA Rate			89.10			102.79
			(5.78)			(6.11)
Maturity			0.71			-3.42
			(3.28)			(-2.24)
Constant	-23.99	-10.43	-231.10	66.92	54.71	-246.24
	(-0.85)	(-0.28)	(-4.56)	(2.22)	(1.15)	(-4.30)
Adj. R2	0.26	0.31	0.43	0.27	0.31	0.44
#Obs	30971	30971	30971	11693	11693	11693
#Bonds	439	439	439	243	243	243

Multicollinearity is a possible complication for these regressions, especially for the historical and implied volatilities, as these volatility measures are most likely highly correlated. However, a brief inspection of the correlation matrix shows that the correlations between the historical volatilities and option implied volatilities in the IG and HY universe are lower than 0.40. These correlations are reasonably low such that multicollinearity is not a big problem for these volatility variables. Other variables of interest also show acceptable correlations such that that there are no multicollinearity problems.

Since the point of this analysis is to investigate the effects of $SKEW$ on credit spreads, only the noteworthy results of the other variables will be discussed briefly. The fact that several market variables are significant indicates that the variables on a firm level are not their true values and therefore contain measurement errors as is reasoned by Cremers et al. (2008b). An economically counter-intuitive result are the positive coefficients for the firm historical skew for all regressions, as this suggests that credit spreads decline when returns become more negatively skewed. Cremers et al. (2008b) also find this result and they argue that the historical skew is too slow to incorporate the relevant information for credit spreads as opposed to the implied skew that is less persistent and mean-reverts more quickly. Most other results are in line with the findings of the literature, thus I refer to Campbell and Taksler (2003), Collin-Dufresne et al. (2001) and Cremers et al. (2008b) for a more in depth discussion of these regression results.

6.4 Implied Variance Term Structure

Panel IV of Table 7 presents the portfolio results of the trading strategies based on $TERMSLOPE$. In general, bonds with higher values of $TERMSLOPE$ experience higher returns than the bonds with lower values. This can be seen in the IG universe, where portfolio Q1 has an average annualized return of 0.61% decreasing to 0.25% in portfolio Q5, as well as in the HY universe with an average annualized return of 0.72% in portfolio Q1 decreasing to −0.70% in portfolio Q5. The PT test indicates that this decreasing return pattern is significant in the IG universe, but in the HY universe the test shows insignificant results. The Q1-Q5 portfolio in the IG universe has the lowest volatility out of all the strategies resulting in a highly significant Sharpe ratio of 0.47, but it has an insignificant annualized 6-factor alpha of 0.20%. The highest Sharpe ratio out of all the option strategies is observed for the Q1-Q5 portfolio in the HY universe. This portfolio has an average annualized return of 1.43% with a highly significant Sharpe ratio of 0.66, but again an insignificant annualized 6-factor alpha of 1.60%. These portfolio results show that the $TERMSLOPE$ option measure does contain some information for corporate bonds.

As for as I know, the literature did not investigate the term structure of the implied variance in a trading strategy setting for any asset market yet. A possible reason might be that this option measure has little economic interpretation regarding the state of the corresponding firm. What is known in the literature is that the term structure of the implied variance is linked to the future implied variance with the expectations hypothesis. The hypothesis is based on the linearity of variance with respect to time and states that the future short-term implied variance is determined by the current slope of the implied variance term structure. Campa and Chang (1995) show based on the stochastic volatility option pricing model of Hull and White (1987) that the following relation should hold at current time t_0:

$$E_{t_1}\left[(t_2 - t_1)V_{t_1}^{t_2}\right] = E_{t_0}\left[t_2 V_{t_0}^{t_2}\right] - E_{t_0}\left[t_I V_{t_0}^{t_1}\right] + \xi_{t_1}, \qquad t_0 \leq t_1 \leq t_2, \tag{9}$$

where V_t^T denotes the implied variance of an option at time t that expires at time T and ξ_{t_1} is white noise that becomes known at time t_1. This relation shows that the future implied variance should follow a rational consistency with the current implied variance term structure and is referred to as the expectations hypothesis. The majority of the literature, e.g. Byoun et al. (2003), Campa and Chang (1995), Mixon (2007), amongst others, test this hypothesis with simple linear regressions. The regression equation can be obtained by manipulating the previous relation and is as follows:

$$V_{t_1}^{t_2} - V_{t_0}^{t_2} = \lambda_1 + \lambda_2\left(\frac{1}{t_2/t_1 - 1}\right)\left(V_{t_0}^{t_2} - V_{t_0}^{t_1}\right) + \xi, \tag{10}$$

where the expectations hypothesis holds when $\lambda_1 = 0$ and $\lambda_2 = 1$. Note that the $TERMSLOPE$ option measure appears on the right hand side of the equation when t_2 and t_1 are set to the expiration times that are respectively two months and one months from the current time. Accordingly, the variables on the left hand side of the equation are defined as such to match the $TERMSLOPE$ option measure resulting in the following regression equation:

$$\frac{1}{L_{i,t+1}}\sum_{j=1}^{L_{i,t+1}} V_{i,t+1}^{1MC_j} - \frac{1}{M_{i,t}}\sum_{j=1}^{M_{i,t}} V_{i,t}^{2MC_j} = \lambda_{1i} + \lambda_{2i} TERMSLOPE_{i,t} + \xi_i, \tag{11}$$

where $V_{i,t+1}^{1MC_j}$ is the implied variance of the put option with an one month maturity on stock i at month $t+1$. The put options are restricted within the ATM bounds and the strike prices are matched to those of $TERMSLOPE$ for comparability. The number of eligible options is denoted by $L_{i,t+1}$. The second term on the left hand side of the regression is the first term of the $TERMSLOPE$ option measure. Finally, the white noise residuals are denoted by ξ_i. When the expectations hypothesis holds, this equation states that changes in the implied variance of the options that expire in two months are fully correlated with $TERMSLOPE$ at any point in time.

The regression is performed for each firm with at least 50 month observations resulting in 336 eligible firms. The hypotheses $\lambda_1 = 0$ and $\lambda_2 = 1$ are tested individually with t-tests and also jointly with a Wald test, where in both tests Newey and West (1987) corrections are applied and a significance level of 5% is adopted. A summary of the results is presented in Table 14 which shows the average coefficients, the average adjusted R2, the average number of observations per regression and the number of times the null hypothesis is not rejected.

Table 14: Expectations hypothesis regression results

This table presents summary results of the regressions as specified by Equation 11. The regressions are performed on a firms with at least 50 observations resulting in a total of 336 firms. The average and the standard deviation of the coefficients, the average adjusted R2 and the average number of observations of all regressions are shown in the table. Furthermore, the number of times the null hypotheses $\lambda_1 = 0$ and $\lambda_2 = 1$ are not rejected is also reported. The null hypothesis are tested with t-test corrected with Newey and West (1987) standard errors and a significance level of 5% is adopted.

	λ_1	λ_2	Adj. R2	#Obs
Mean	-0.008	0.154	0.04	84
St. Dev.	0.011	0.784		
Test	261	141		

The mean constant of all the regressions is -0.008 and in line with this statistic is that in 261 of cases the t-test fails to reject the hypothesis of $\lambda_1 = 0$. Most of the t-tests reject the $\lambda_2 = 1$ hypothesis with only 141 failing to reject this hypothesis. This is also reflected in the mean slope coefficient of 0.154. The joint Wald test shows that a total of 96 firms conform with the expectations hypothesis, which is approximately 29% out of all the tested firms. Similar findings are found when the put options are substituted for call options. It is safe to conclude that the expectations hypothesis does generally not hold for this sample. Nevertheless, the $TERMSLOPE$ does have predictive power for future implied variances judging from the average adjusted R2 of 0.04. Additionally, a t-test shows that the average coefficient of $TERMSLOPE$ is significantly larger than zero. So $TERMSLOPE$ does predict the correct direction of the change in the future implied volatility, though it underestimates the change compared to what the expectations hypothesis indicates. This finding can be used to explain the portfolio results.

The highest values of $TERMSLOPE$ are sorted in portfolio Q1, thus this portfolio contains the bonds with the largest expected positive changes in future option implied variance according to the expectations hypothesis. This of course has to be incorporated in the prices in all markets including the corporate bond market. This expected rise in implied variance indicates that the firm is expected to be more risky in the future resulting in a downward adjustment of the current corporate bond prices. As the previous tests show, the realized change in implied variance is only a fraction of what was expected. So when the market observes in the future that the actual change in implied variance did not change as much as expected, then the prices are adjusted upwards resulting in positive returns. Portfolio Q1 contains the observations with the largest overreactions in the future risk increase and therefore also the highest returns. The opposite can be reasoned for portfolio Q5 where the firms are expected to decrease in risk, but the overreaction to this expectations results in current prices that are too high resulting in low returns.

What is peculiar is that the $TERMSLOPE$ option measure only captures the really short end of the implied variance term structure. So the information content of this option measure should only be relevant for a short time period, though the portfolio results with a holding period of twelve months indicate otherwise. The portfolio results with an one month holding period in the later robustness check indicate that higher returns and higher 6-factor alphas can be generated with a shorter holding period, though the volatilities of the portfolios are higher resulting in similar Sharpe ratios. Nevertheless, the findings indicate that most returns are generated in the first month after portfolio formation.

6.5 Value Factor

Panel V of Table 7 shows that bonds with higher values of $VALUE$ typically experience higher returns compared to bonds with lower values. The Q1 portfolio in the IG universe has an average annualized return of 1.92% decreasing to −0.21% in portfolio Q5. The same return pattern can be seen in the HY universe with an average annualized return of 2.64% in portfolio Q1 decreasing to −0.51% in portfolio Q1. This decreasing return pattern in the HY universe is monotonically significant according to the PT test, while the return pattern in the IG universe is found to be insignificant. The Q1-Q5 portfolios in both universes have by far the highest volatility compared to other Q1-Q5 portfolios, but the portfolios are adequately compensated with higher returns. The Q1-Q5 portfolio in the IG universe has an average annualized return of 2.13% with a highly significant Sharpe ratio of 0.60 and a highly significant annualized 6-factor alpha of 2.30%. The highest returns are observed for the Q1-Q5 portfolio in the HY universe with an average annualized return of 3.17% and a highly significant Sharpe ratio of 0.58, but an insignificant annualized 6-factor alpha of 1.69%. Next, a brief analysis is done on the option implied credit spread that is part of the $VALUE$ factor.

Apart from implementing the Merton model with option data, it is also possible to do so with equity data as described in Appendix A. This equity implied implementation is found by Hillegeist et al. (2004) to provide more information about the probability of bankruptcy than accounting based measures. They do state, however, that it doesn't reflect all market based information such as the returns and size of the firms. The option implied implementation, however, has not been investigated much in the literature. While the data sources of both implementations are different, the approaches are quite similar in the sense that both require to solve a non-linear system of equations to obtain the parameters of the Merton model. Thus, it is possible to investigate which data source contains more information by comparing both implementations. This is exactly done by Hull et al. (2004) and they find the option implied implementation to provide a better fit for CDS spreads.

A similar analysis is done to compare both implementations with corporate bond spreads as opposed to CDS spreads. For this purpose, pooled regressions of the market bond spread are performed on a model implied credit spread as the explanatory variable. All credit spreads are in basis points and the equity implied credit spread and option implied credit spread are denoted by $SPREAD^{Equity}$ and $SPREAD^{Option}$ respectively. The regressions are only performed on bonds with at least 50 month observations. The results of the regressions are presented in Table 15. Hull et al. (2004) state that the errors of regressions are unlikely to be normally distributed due to the nature of the models generating the credit spreads, thus only the standard errors are reported.

Table 15: Pooled regression results

This table presents the results of pooled regressions with the credit spreads in basis points as the dependent variable over the sample period of January 1996 to August 2014. The explanatory variables are indicated by the first column. Furthermore, the same pooled regressions with firm dummies and month dummies are also presented. The coefficients with standard errors between parentheses, the adjusted R2, the total number of observations and the total number of bonds are shown in the table.

	Standard		Firm Dummies		Month Dummies	
	1	2	3	4	5	6
Constant	215.82	199.75	219.27	211.65	115.97	108.35
	(1.03)	(1.01)	(22.32)	(21.16)	(6.76)	(6.58)
$SPREAD^{Equity}$	0.17		0.14		0.12	
	(0.00)		(0.00)		(0.00)	
$SPREAD^{Option}$		0.22		0.19		0.16
		(0.00)		(0.00)		(0.00)
Adj. R2	0.15	0.23	0.44	0.49	0.36	0.39
#Obs	41934	41934	41934	41934	41934	41934
#Bonds	464	464	464	464	464	464

The average market credit spread is approximately 216 and 200 basis points higher than respectively the equity and option implied credit spread as indicated by the constants in the first two regressions. So even though the credit spread puzzle still crops up for both models, it is less pronounced for the option implied credit spreads. Furthermore, the option implied credit spreads also provide a better fit with an adjusted R2 of 0.23 compared to 0.15 of the regression with the equity implied credit spread as the explanatory variable. Also important to note is that both model credit spreads are positively related with the market spread as is expected.

The same regressions are also done with firm dummies and month dummies to control for cross-sectional variations and time variations respectively. These results are also presented in Table 15. In both cases the adjusted R2 increases quite substantially indicating that the model credit spreads do not explain the entire cross-section and time variation of market credit spreads. Although the coefficients of the model credit spreads decrease slightly, the same conclusion can be made that the option implied credit spread is a better fit for the market spreads than the equity implied credit spreads as is indicated by the adjusted R2s.

Overall the regressions indicate that the model credit spreads are not a spectacularly good fit of the observed market credit spreads. The Merton model is of course not always an exact replication of the reality. Firms also issue other types of bonds with different maturities and seniorities besides the assumed discount bond, and interest rates do not remain constant over time. Furthermore, many important frictions are left out of the model such as taxes, bankruptcy costs, agency costs, moral hazard and so on. Over time many developments of the Merton model have emerged addressing these shortcomings; an extensive review of these extensions is provided by Sundaresan (2013). So the fact that the credit spreads obtained from the traditional Merton model do not fit the observed market credit spreads well is not a surprise. However, the results do indicate that information from options can help explain credit spreads better than stock information.

7 Robustness

The literature that investigates the information content of options via trading strategies often use a short holding period. One reason is because most studies apply the strategy on stocks which is a more liquid asset class compared to corporate bonds. While it is possible to completely change stock portfolios on a frequent basis without incurring relatively high transaction costs, it is simply not possible to do so for corporate bond portfolios. A theoretical oriented motivation for using a short holding period is that the information contained in options is a snapshot of market expectations. It is possible that expectations of the market change in the short-term such that older information becomes irrelevant. If this is the case, then it is quite difficult to determine whether options contain relevant information when the portfolios are held for a long period. This is a reason to apply a shorter holding period of one month to the strategies as a robustness check.

Only the general findings from this robustness check are briefly discussed, but the detailed portfolio results can be found in Table 16. The performance of the Q1-Q5 portfolios based on $RVIV$, $TERMSLOPE$ and $VALUE$ are generally higher than the Q1-Q5 portfolios with a twelve month holding period indicating that the information contained in these option measures is more relevant in the short term, but it is also quite persistent for a longer period. The portfolio results of the $PUTCALL$ and $SKEW$ option measures do not show significant improvements compared to the twelve month holding period results. This confirms that there is little evidence for $PUTCALL$ and $SKEW$ to contain relevant information for corporate bonds prices.

Table 16: Portfolio results with an one month holding period

This table presents the results of the trading strategies based on the option measures over the sample period of January 1996 to August 2014 in both the Investment Grade and High Yield universe. The methodology of Jegadeesh and Titman (1993) is employed with a holding period of one month to construct the portfolios. The first quintile Q1 contains the bonds with the highest values of the sorting variable and the last quintile Q5 holds the bonds with the lowest sorting variable values. The average annualized return, the annualized volatility, the Sharpe ratio and the annualized 6-factor alpha are shown in the table. Opdyke (2007) tests are employed to test whether the Sharpe ratios of the portfolios are significantly higher than the corresponding market Sharpe ratio. The 6-factor alphas are tested on significance with t-tests corrected with Newey and West (1987) standard errors.

	Investment Grade						High Yield					
	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Q1	Q2	Q3	Q4	Q5	Q1-Q5
I. RVIV												
Returns (%)	1.13	0.92	0.99	0.46	−0.18	1.32	3.20	3.11	3.10	2.36	2.34	0.84
Volatility (%)	4.92	4.57	4.14	4.26	4.66	2.00	9.62	8.14	7.78	8.41	9.38	4.66
Sharpe Ratio	0.23*	0.20	0.24*	0.11	−0.04	0.66***	0.33	0.38**	0.40**	0.28	0.25	0.18
6F Alpha (%)	0.49**	0.15	0.29	−0.26	−0.34	0.83*	1.87*	1.82*	1.75**	0.97	0.23	1.79
II. PUTCALL												
Returns (%)	0.60	0.36	0.58	0.74	0.53	0.07	2.46	2.55	2.78	2.73	1.75	0.70
Volatility (%)	5.08	4.62	4.30	4.48	4.79	2.00	11.70	9.24	8.97	8.83	10.80	4.95
Sharpe Ratio	0.12	0.08	0.14	0.17	0.11	0.03	0.21	0.28	0.31	0.31	0.16	0.14
6F Alpha (%)	0.09	−0.25	−0.16	−0.08	0.31	−0.20	−0.27	1.30*	1.08	1.25**	−0.09	−0.18
III. SKEW												
Returns (%)	0.35	0.87	0.80	0.80	0.90	−0.55	4.01	1.88	2.62	2.82	2.61	1.36
Volatility (%)	5.32	4.73	4.29	4.03	4.74	2.65	9.10	8.81	8.75	8.21	8.90	5.33
Sharpe Ratio	0.07	0.18	0.19	0.20	0.19	−0.21	0.44***	0.21	0.30	0.34*	0.29	0.26
6F Alpha (%)	−0.03	−0.06	0.29	0.11	0.15	−0.13	2.81**	−0.06	1.26	1.06	1.20	1.81
IV. TERMSLOPE												
Returns (%)	0.95	0.96	0.97	0.36	−0.07	1.02	4.36	1.90	2.61	1.66	0.24	4.12
Volatility (%)	5.10	4.07	4.36	4.35	4.92	2.56	10.06	7.92	8.00	8.72	11.09	6.00
Sharpe Ratio	0.19	0.24*	0.22	0.08	−0.01	0.40**	0.43***	0.24	0.33	0.19	0.02	0.69***
6F Alpha (%)	0.18	0.16	0.41	−0.33	−0.26	0.41	2.79***	0.23	1.07	−0.12	−0.99	4.13***
V. VALUE												
Returns (%)	3.27	1.24	0.28	−0.31	−1.02	4.33	7.90	4.45	2.82	1.27	−2.35	10.50
Volatility (%)	6.30	5.21	4.80	4.14	3.12	4.09	10.92	9.23	8.72	8.26	7.84	6.95
Sharpe Ratio	0.52***	0.24*	0.06	−0.07	−0.33	1.06***	0.72***	0.48***	0.32	0.15	−0.30	1.51***
6F Alpha (%)	3.13***	0.48	−0.52**	−1.12***	−1.73***	4.86***	5.25***	3.78***	1.30	−0.08	−3.21***	8.50***

***, **, and * show significance at the 1%, 5%, and 10% level respectively.

8 Conclusion

This research investigates whether it is possible to extract information from options that is relevant for corporate bonds. This is done by employing corporate bond trading strategies based on various option based measures. These option measures are confirmed by the literature to contain information for stocks and the portfolio results of this research do indicate that several option measures also contain relevant information for corporate bond prices. Some option measures, however, are found to contain little to no information. Besides employing these trading strategies, more in-depth analyses are also performed for individual option measures in order to gain insights as to what kind of information can be obtained from the option market. A summary of the findings is given next.

Statistical and economical evidence is found that the realized-implied volatility spread describes a trend in volatility. Related to predicting future volatility is the expectations hypothesis that links the current implied variance term structure to future implied variances. It is shown that the expectations hypothesis does generally not hold for this sample of options, but the results do indicate that the market overreacts to the information contained in the implied variance term slope. It is also found that the implied volatility skew has predictive power for future credit spreads, though this does not translate into significantly profitable trading strategies. Lastly, option implied credit spreads are shown to provide a better fit for observed market credit spreads compared to equity implied credit spreads.

All in all, it can be concluded that the option market does certainly contain relevant information for corporate bonds. An immediate question that follows is whether this information can be used to construct profitable and feasible portfolios in practice. This automatically means that transaction costs becomes an important factor that has to be incorporated into the strategies. Since the implied volatility is a snapshot of market expectations, it can change drastically from month to month resulting in high turnovers. As a consequence, transaction costs will be high especially in the illiquid corporate bond market. This issue is possibly an interesting topic for future research.

A completely different approach in assessing the information content of the option market with respect to the corporate bond market is to develop a Kyle (1985) model. This is a a sequential trading model that determines an equilibrium between inside traders, random noise traders and market makers. Back and Crotty (2015) investigate the information conveyed in the order flows of stocks and corporate bonds by developing a Kyle (1985) model with traders who can trade in either the stock market or corporate bond market. A possibly interesting extension is to include the option market as an additional market to this model to investigate the trading dynamics between these markets.

A Merton Model

Merton (1974) developed a model to obtain credit risk measures from simple firm balance sheet information. In his model the firm assets are assumed to follow a geometric Brownian motion:

$$dA_t = \mu A_t dt + \sigma_A A_t dW_t, \tag{12}$$

where A_t is the total asset value of the firm, μ is the continuously compounded return on the assets, σ_A is the constant asset volatility and W_t is a standard Wiener process. Furthermore, the firm only has equity and debt as liabilities, where the debt is a single pure discount bond with payment D at time T. As recognized by Merton, the equity price E_t of the firm at time t is the price of a European call option on the assets A_t with strike price D and maturity T, which can be formulated with Black and Scholes (1973) as

$$E_t = A_t N(d_1) - De^{-r(T-t)} N(d_2), \tag{13}$$

where

$$d_1 = \frac{\ln\left(\frac{A_t e^{r(T-t)}}{D}\right)}{\sigma_A\sqrt{T-t}} + \frac{1}{2}\sigma_A\sqrt{T-t}; \qquad d_2 = d_1 - \sigma_A\sqrt{T-t}.$$

The risk-free rate r is assumed to be constant and N is the cumulative standard normal distribution. The equity E_t is set to the stock price of the firm. The debt payment D is defined to be the total liabilities divided by the total shares outstanding and the maturity T is matched to the maturity of the bond. Thus, the remaining unknown variables are the asset value and the asset volatility. When these variables are known, then the credit spreads implied by the Merton model can be obtained in a straightforward manner. First, define the market value of debt B_t as the assets minus the equity:

$$B_t = A_t - E_t = A_t\left(N(-d_1) + \frac{De^{-r(T-t)}}{A_t}N(d_2)\right), \tag{14}$$

where the definition of equity as a call option is used. The definition of the yield to maturity y of a discount bond can also be used to define the market value of debt as

$$B_t = De^{-y(T-t)}. \tag{15}$$

Subsequently, by setting both definitions of B_t equal to each other the credit spread s derived from the Merton model can be computed as

$$s = y - r = -\frac{\ln\left(N(d_2) + \frac{A_t}{De^{-r(T-t)}}N(-d_1)\right)}{T-t}. \tag{16}$$

A popular approach to obtain the asset value and asset volatility is given by Jones et al. (1984). They make use of the fact that equity is a function of asset value and apply Ito's lemma to obtain the following relation between the asset volatility and equity volatility:

$$\sigma_E = \frac{\partial E_t}{\partial A_t}\frac{A_t}{E_t}\sigma_A. \tag{17}$$

It can be shown with the Black-Scholes option formula that $\frac{\partial E_t}{\partial A_t} = N(d_1)$. So substituting this and the definition of equity as a call option results in

$$\sigma_E = \frac{\sigma_A N(d_1)}{N(d_1) - \frac{De^{-r(T-t)}}{A_t} N(d_2)}. \tag{18}$$

This relation along with the definition of equity as a call option on the assets can be used to form a system of equations to solve for the asset value A_t and asset volatility σ_A. This research sets the equity volatility σ_E as the historical return volatility of the stock measured with daily returns over a horizon of twelve months.

Another approach to obtain the asset value and asset volatility is to make use of the fact when the Merton model holds, then the option on the equity E_t is a compound option, i.e. an option on an option. Hull et al. (2004) utilize this fact in order to implement the Merton model. They use the model of Geske (1979) who derived an analytical formula of the compound option in continuous time with no-arbitrage conditions. The derived formula for the value of an European put option $P_t(\tau, K)$ with strike price K and maturity $\tau < T$ is

$$P_t(\tau, K) = De^{-r(T-t)} M\left(-a_2, d_2; \sqrt{\frac{\tau - t}{T - t}}\right) - A_t M\left(-a_1, d_1; \sqrt{\frac{\tau - t}{T - t}}\right) + Ke^{-r(\tau - t)} N(-a_2), \tag{19}$$

where

$$a_1 = \frac{\ln\left(\frac{A_t e^{r(\tau - t)}}{A_\tau^*}\right)}{\sigma_A \sqrt{\tau - t}} + \frac{1}{2}\sigma_A \sqrt{\tau - t}; \qquad a_2 = a_1 - \sigma_A \sqrt{\tau - t}$$

and M denotes the bivariate cumulative normal distribution function with the first two parameters as the upper integral limits and last parameter as the correlation coefficient. A_τ^* is the asset value for which the equity equals the strike price K at time τ, that is, it is the solution to the following equation

$$E_\tau^* \equiv A_\tau^* N(d_1^*) - De^{-r(T-\tau)} N(d_2^*) = K, \tag{20}$$

where

$$d_1^* = \frac{\ln\left(\frac{A_t^* e^{r(T-\tau)}}{D}\right)}{\sigma_A \sqrt{T - \tau}} + \frac{1}{2}\sigma_A \sqrt{T - \tau}; \qquad d_2^* = d_1^* - \sigma_A \sqrt{T - \tau}.$$

One can also interpret A_τ^* as the value for which the call option is exactly at-the-money at time τ, thus the holder of this option is indifferent between exercising and not exercising the option. This is an important observation used by Geske (1979) in deriving the formula of the option, because this allowed him to partition the value of the compound option over the asset value of the firm. If the asset value is lower than A_τ^*, then the put option will be exercised and vice versa.

Instead of formulating the put option as a compound option, it is also possible to use the traditional Black and Scholes (1973) formula:

$$P_t(\tau, K) = Ke^{-r(\tau - t)} N(-\hat{d}_2) - E_t N(-\hat{d}_1), \tag{21}$$

where

$$\hat{d}_1 = \frac{\ln\left(\frac{E_0 e^{r(\tau-t)}}{K}\right)}{\sigma_E\sqrt{\tau-t}} + \frac{1}{2}\sigma_E\sqrt{\tau-t}; \qquad \hat{d}_2 = \hat{d}_1 - \sigma_E\sqrt{\tau-t}.$$

Here too the equity E_t is assumed to follow a geometric Brownian motion with constant option implied volatility σ_E. The moneyness κ of this put option at time t is the strike price divided by the equity price, i.e. $\kappa = K/E_t$. A system of two non-linear equations can now be set up to solve for the asset value A_t and the asset volatility σ_A by setting the two formulas of the call option, i.e. the compound option definition and the Black-Scholes definition, equal to each other and using the following alternative relation of equity:

$$\kappa E_t = E^*_\tau. \tag{22}$$

As inputs this system of equations requires information of a single put option on the stock of the firm which will give the strike price K, time to maturity τ and the implied volatility σ_E. Note that the derivations are made assuming European options, but in practice the options on stocks are American options. OTM put options with a short maturity are used to reduce the errors caused by this discrepancy, as these options are less likely to be exercised early.

B Monotonic Relation Test

There are instances in finance where one wants to test whether returns are monotonically increasing. For example, the Capital Asset Pricing Model implies that expected stock returns should show an increasing pattern when sorted on their market betas. Another example is to test whether there is an increasing return pattern in the portfolios of a factor strategy. Consider $N+1$ assets with expected returns $\boldsymbol{\mu} = (\mu_0, \mu_1, ..., \mu_N)'$ and one wants to prove the following relation:

$$\mu_N > \mu_{N-1} > ... > \mu_0. \tag{23}$$

Patton and Timmermann (2010) developed a nonparametric method to test for this monotonicity in returns. They use the return differentials of adjacent pairs of securities denoted as $\Delta_i = \mu_i - \mu_{i-1}$ to test this relation. It is assumed that there is a flat or weakly decreasing return pattern under the null hypothesis.

$$H_0 : \Delta_i \leq 0, \qquad \forall i = 1, 2, ..., N \tag{24}$$

The alternative hypothesis is that there is a strict increasing return pattern.

$$H_1 : \Delta_i > 0, \qquad \forall i = 1, 2, ..., N \tag{25}$$

So the monotonically increasing return pattern is proved by rejecting the null hypothesis. It is also possible to test for monotonically decreasing returns by simply reversing the order of the assets. Next, Patton and Timmermann (2010) recognize that if the smallest value of Δ_i is larger than zero, then it must be that $\Delta_i > 0$ for every $i = 1, 2, ..., N$ when the alternative hypothesis holds. Thus, the alternative hypothesis can be rewritten as

$$H_1 : \min_{i=1,2,...,N} \Delta_i > 0. \tag{26}$$

This motivates the use of the following test statistic:

$$J = \min_{i=1,2,...,N} \hat{\Delta}_i, \tag{27}$$

where $\hat{\Delta}_i = \hat{\mu}_i - \hat{\mu}_{t-1}$ with $\hat{\mu}=\frac{1}{T}\sum_{t=1}^{T} r_{i,t}$. These are the observed sample estimates of Δ_i and μ_i of the time series of returns $\{r_{i,t}\}_{t=1}^{T}$ of asset i.

Since the distribution of the test statistic is unknown, Patton and Timmermann (2010) implement the test by means of bootstrapping. This approach has the advantage of not imposing any distributional assumptions, but it can be less optimal in situations where more information of the distribution is available. The stationary bootstrap method of Politis and Romano (1994) is used to randomly draw samples from the observed return set $\{r_{i,t} \mid i = 0, 1, ..., N; t = 1, 2, ..., T\}$, where i denotes the asset and t the time index. Instead of drawing from the sample of returns, however, the bootstrap method is applied on the set of time indexes $\{1, 2, ..., T\}$ to draw return samples $\{r^b_{i,\tau(t)} \mid i = 0, 1, ..., N; \tau(1), \tau(2), ..., \tau(T)\}$, where $\tau(t)$ denotes the randomly drawn time index. The drawing of the time index is done only once per bootstrap b and is common across all returns to preserve any cross-sectional dependencies in the returns. The bootstrapping method has many similarities to a moving block bootstrap algorithm, but there are several alterations in order to have stationary sampled series[4]. These alterations are that the block length and the starting point are both randomly drawn, as opposed to deterministically fixing them beforehand. The block length and starting point are drawn from a geometric distribution and an uniform distribution respectively. The parameters of the geometric distribution are set such that the average length of a block is six.

The bootstrapped return samples are used to obtain a bootstrap distribution of the test statistic J under the null hypothesis. This is done by first choosing a point in the null space least favourite to the alternative hypothesis which is $\Delta_i = 0$ for every $i = 1, 2, ..., N$. Then for each return sample a bootstrapped test statistic is computed as

$$J^b = \min_{i=1,2,...,N} (\hat{\Delta}^b_i - \hat{\Delta}_i), \tag{28}$$

where $\hat{\Delta}^b_i$ is the is the bootstrapped estimate of $\hat{\Delta}_i$. This is done for $B = 10000$ bootstraps and will give a distribution of the test statistic under the null hypothesis. The p-value is simply computed as the percentage of times when J^b is larger than J. This approach is similar to the Reality Check test of White (2000).

[4] See Politis and Romano (1994) for more details

C Model-Free Implied Volatility

The traditional way to price options is to specify a price process of the underlying asset and then derive the option prices with the parameters of this price process. For example, one of the key assumptions in the option model of Black and Scholes (1973) is that the underlying price process follows a geometric Brownian motion. The Black-Scholes option price formulas can then be derived via several approaches such as with Martingale theory or with the Feynman-Kac formula. A completely different take on this standard approach in option pricing theory is done by Britten-Jones and Neuberger (2000). They assume that the option prices are a given of which they extract as much information as possible about the underlying price process. This results in a characterization of all continuous price processes that are consistent with the current option prices of the market. Subsequently, they derive the implied volatility that is commonly shared by all of these consistent processes via no-arbitrage conditions. Since only option prices are required to compute this implied volatility and thus no specific model, this implied volatility measure is seen as a model-free implied volatility. The simplified implementation of this model-free implied volatility developed by Jiang and Tian (2005) is described next.

Let $C(T, K)$ denote a call option that expires at time T with strike price K. Then the integrated variance[5] between the current date 0 and future date T of the underlying forward price process F_t is given by the following equation:

$$E_0^F\left[\int_0^T \left(\frac{dF_t}{F_t}\right)^2\right] = 2\int_0^\infty \frac{C^F(T,K) - \max(F_0 - K, 0)}{K^2}dK, \tag{29}$$

, where a superscript F denotes the forward probability measure. The model-free implied volatility is obtained by dividing this integrated variance by T and taking the square root. Next, the forward asset price is translated to the asset spot price S_t as $F_t = e^{rT}S_t$, where r is the risk-free interest rate. Similarly the forward call price is defined as $C^F(T,K) = e^{rT}C(T,K)$. A simple change of variables results in

$$2\int_0^\infty \frac{C^F(T, e^{rT}K) - \max(S_0 - K, 0)}{K^2}dK. \tag{30}$$

As can be observed from this equation is that the integral is taken over an infinite range of strike prices. This requires that call options exist for a continuous range of strike prices which is not the case in practice. Only a limited range of strike prices are actually traded on the market and thus numerical methods are required in order to compute the integral. Following Jiang and Tian (2005) the integral is approximated with the trapezoidal rule over the truncated bounds K_{min} and K_{max}.

$$2\int_0^\infty \frac{C^F(T, e^{rT}K) - \max(S_0 - K, 0)}{K^2}dK \approx \sum_{i=1}^{N}\Big[g(T, K_i) + g(T, K_{i-1})\Big]\Delta K, \tag{31}$$

[5]See Britten-Jones and Neuberger (2000) for a detailed derivation of this integrated variance.

where N is the number of subintervals and $\Delta K = (K_{max} - K_{min})/N$ is the size of the subintervals. The function in the summation is defined as

$$g(T, K_i) = \frac{C^F(T, K_i) - \max(F_0 - K_i, 0)}{K_i^2}, \tag{32}$$

where $K_i = K_{min} + i\Delta K$. The reason for truncating the bounds is because in practice the options do not span the strike prices from zero to infinity. Jiang and Tian (2005) provide theoretical upper bounds of the errors that result from truncating the integral. They find that in general when the truncation bounds are more than two standard deviations from the current stock price then the truncation errors become negligible. Accordingly, the truncation bounds are set to be at least two standard deviations from the current stock price whenever possible.

The approximation of the integral requires that there are option prices available for every strike price K_i. In practice, however, the strike prices only span a small set of discrete values. This issue is solved by using estimated option prices by means of interpolation. First, the available option prices are transformed into implied volatilities with the Black and Scholes (1973) model and then a smooth function is fitted between these implied volatilities with the cubic spline interpolation. The reason for not directly interpolating between the available option prices is because there will be numerical complications due to the non-linear relationship between the option price and the strike price. Finally, the implied volatilities are transformed back into option prices for every strike price K_i, again with the Black-Scholes model. It is important to note that the Black-Scholes model is not assumed to be the true pricing model, but it is simply used as a mapping tool between the option prices and implied volatilities. This interpolation method cannot be used to obtain option prices outside the bounds of the available option prices. Jiang and Tian (2005) show that extrapolating these options as the option prices of the maximum and minimum available strike prices reduces the estimation errors as compared to simply truncating the bounds.

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