Exploiting Uncertainty with Market Timing in Corporate Bond Markets

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Abstract

The purpose of this article is to show the usefulness of technical analysis in credit markets. We document that an application of a simple moving average timing strategy to U.S. high yield and U.S. investment grade corporate bond portfolios sorted by option-adjusted spread generates investment timing portfolios that substantially outperform the corresponding benchmark. For portfolios with high uncertainty, as measured by the option-adjusted spread, the abnormal returns generate economically and statistically significant returns relative to the capital asset pricing model (CAPM) and the Carhart 4-factor model. Our results remain robust to different moving average formation periods, transaction costs, long-short portfolio construction techniques and alternative definitions of information uncertainty.

Keywords: Market efficiency, market timing, predictability, behavioral finance, technical analysis

JEL Classification Codes: G11, G12, G14

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1 Introduction

The ultimate goal of many financial market participants is to earn money and for the majority of fund managers to outperform their respective benchmarks. Fundamental analysis, which is based primarily on accounting data, and technical analysis, which is based on historical performance or other past statistics, are often employed to reach these goals. Despite its widespread acceptance by practitioners, academics have been sceptical about the added value of technical analysis. For instance, Malkiel (1981) states that *"technical analysis is anathema to the academic world"* (p.139). The main reason for this point of view is that the theoretical basis for technical analysis is scarce. Since the majority of financial models assumes a random walk for prices, any profitability from technical trading is per se ruled out (see Fama, 1995). However, during the last couple of years evidence has grown steadily in the favour of technical analysis. For example, Brock et al. (1992) and Lo et al. (2000) or more recently Zhu and Zhou (2009), Moskowitz et al. (2012) and Han et al. (2013) document strong evidence of profitability from such kind of trading strategies. Furthermore, Covel (2005) and Schwager (2012) show how successful hedge funds rely solely on technical analysis without taking into account any fundamental indicators.

Manifold studies investigate the value of fundamental (Harvey et al., 2016 count more than 300 factors) and technical analysis (see Brock et al., 1992, Zhu and Zhou, 2009 or Han et al., 2013) for equity portfolios. While some recent papers on the value added of fundamental analysis for investing in corporate bonds exist (see Crawford et al., 2015, Chordia et al., 2016 or Bektic et al., 2016), similar studies about the impact of technical analysis on corporate bonds are surprisingly rare. Thus, despite the fact that the market for corporate bonds has increased monotonically over the last 30 years[1], we know fairly little about the profitability of technical analysis in this asset class. Therefore, a detailed examination of the usefulness of technical analysis in corporate bond markets is crucial to understanding the true return potential to investors' portfolios.[2]

In this paper, we attempt to close that gap and analyze the profitability of technical analysis in corporate bond portfolios at the example of moving average strategies.[3] In fact, mov-

[1]The U.S. bond market is considered as the largest security market in the world and according to Federal Reserve data, the total market value of U.S. corporate bonds had a growth rate of 8.5% per year from 1990 to 2014.

[2]Since government bond yields are on historically low levels, the demand for credit securities plays a much larger role than in the past. Usually, institutional investors such as pension funds, mutual funds and insurance companies invest in these securities.

[3]For instance, Brock et al. (1992), Lo et al. (2000) and Han et al. (2013) use simple moving average schemes to forecast the equity market.

ing average strategies represent so-called trend-following strategies and their profitability depends heavily on whether there are pronounced trends in the cross section of the corporate bond market. To this end, we focus on returns of moving average strategies in a universe of U.S. investment grade (IG) and high yield (HY) corporate bonds. Thus, we try to answer the following question: Can past information be used to predict future returns in corporate bond markets? If these market were efficient in the sense that current prices reflect all past information, the answer would be clearly no. Barberis and Thaler (2003) argue that the existence of profitable investment strategies builds on two main pillars: (i) (some) investors deviate from perfect rationality, for instance due to behavioral biases and (ii) limits to arbitrage prevent that this irrationality is fully exploited by other market participants (see Shleifer and Vishny, 1997).

Indeed, we find that past information does help to predict future returns under certain circumstances, that relate to both behavioral biases and limits to arbitrage. More precisely, our results indicate that moving average strategies can be profitable, especially if they are applied to portfolios with a high degree of informational uncertainty. The key idea, which was suggested for equity portfolios by Han et al. (2013), states that (i) behavioral biases – which could lead to mispricing – should be stronger for portfolios with high degrees of uncertainty and (ii) assets with a high degree of uncertainty typically face stronger limits to arbitrage. For stock markets, Zhang (2006) argues that price continuation is predominantly due to underreaction to public information by investors, and investors will underreact stronger in case of greater information uncertainty. Since returns of equity and bonds of the same entity should be related, according to structural credit risk models like Merton's (1974), this idea translates to returns of corporate bonds. Merton introduces in his seminal paper the notion that corporate debt and equity both represent claims on the firm value. In that framework, corporate debt reflects a risk-free bond in combination with a short put option on the firm's equity. Therefore, yield spreads on corporate debt should widen if equity volatility increases because the put option will become more valuable if equity volatility increases. Consequently, the correlation between equity volatility and yield spreads on corporate debt is expected to be positive and sorting bonds on either of these two variables should lead to similar results. In line with that thought, Campbell and Taksler (2003) find that both, equity volatility and credit risk have explanatory power for the movement of yield spreads of corporate bonds. Consequently, we apply moving average strategies to portfolios of corporate bonds sorted by equity volatility and option-adjusted spreads (OAS). We then analyze the profitability of moving average strategies for portfolios with high and low levels of informational uncertainty.

Our results are surprisingly strong. For instance, we find that our strategy generates a monthly alpha of 0.42% (t = 3.05) for IG corporate bonds and even 1.33% (t = 2.70) for HY corporate bonds against their respective benchmarks for portfolios with a high degree of uncertainty, contrasting 0.04% (t = 0.55) and 0.06% (t = 1.14) for portfolios with low degrees of uncertainty. These results are insensitive to measures of uncertainty used to construct the portfolio. In addition, our results are robust to different time lags used to create the moving average strategy.

We find that cumulative returns, one would have obtained by following such a moving average strategy, are substantial for portfolios with a high degree of informational uncertainty. For example, the cumulative excess return (over duration-matched U.S.Treasuries) for the moving average strategy applied to a portfolio of IG corporate bonds in the highest quintile with respect to their OAS are about 111% over the time period from December 1996 to November 2016 assuming 30 bps round-trip transaction costs, while the benchmark delivered only 20% over the same period. For high yield corporate bonds, the effect is even stronger with more than 784% for the strategy over the time period from December 1996 to November 2016 assuming 50 bps round-trip transaction costs versus about 97% for the benchmark.

Technical analysis is based on the belief that prices of securities are influenced by sentiment-affected investment decisions of investors, such as herding behavior. Daniel, Hirshleifer, and Subrahmanyam (1998; 2001) and Jiang et al. (2005) show that the impact of biased investment decisions, and therefore, the profitability of technical analysis, should be stronger for higher degrees of information uncertainty since psychological biases are more pronounced if information uncertainty is greater. The findings presented in this paper are consistent with the idea that the profitability of technical strategies is driven by irrational investors and therefore particularly pronounced if information uncertainty is strong and arbitrage is limited. Moreover, we find that profitability is stronger for HY bonds (which manifest more uncertainty) compared to IG bonds. Finally, most HY bonds exhibit equity-like behavior which links our results neatly to the findings of Han et al. (2013).[4]

[4] See, for example, Hong et al. (2012) reporting that stocks lead HY bonds and to a lesser degree IG bonds as well or Bao and Hou (2014), who show that the comovement between equities and bonds is stronger for firms with higher credit risk for a variety of measures of this firm characteristic.

Recent literature on technical analysis focuses exclusively on equity markets (see Brock et al., 1992, Lo et al., 2000, Han et al., 2013 or Neely et al., 2014) and government bonds (Goh et al., 2013 show that technical indicators predict the bond market much better than fundamental factors). Moskowitz et al. (2012) examine the profitability of futures and forward contracts on equity indexes, currencies, commodities as well as government bonds. None of these studies considers credit markets. Given the recent interest in studying technical indicators in the major asset classes, analysis of the profitability of technical indicators in corporate bond markets seems warranted.

We contribute to the literature in several important ways. First, our paper provides the first study on cross-sectional profitability of technical analysis in corporate bond markets. Unlike existing literature that applies technical analysis to either market indices or individual securities, we apply it to corporate bond portfolios sorted by measures that reflect information uncertainty, namely OAS and equity volatility of the corresponding firm. The rationale behind our analysis is that many investors and fund managers use technical analysis to make trading decisions and that proponents of this investment approach use the most widespread indicator, moving averages, to time investments. Second, we provide empirical evidence for behavioral finance theories suggesting that asset prices can display patterns of predictability that cannot be explained with risk-based expectation theories of price formation.[5] However, previous literature on this topic does not include credit markets (see Daniel and Hirshleifer, 2015). Third, our results contribute to the debate whether well-known strategies from equity markets can be extended to corporate bond markets. While factors based on fundamental data deliver inconclusive results at best for corporate bonds implying market segmentation (see Chordia et al., 2016, Choi and Kim, 2016, and Bektic et al., 2016), we show that technical analysis almost fully translates to the realm of credit markets. Finally, these findings provide important insights for corporate bond investors, hedgers and speculators.

The remainder of the paper is structured as follows: In section 2 we describe our data and empirical methodology. Section 3 provides evidence for the profitability of the moving average timing strategy and Section 4 documents the robustness of our findings. Section 5 concludes.

[5]Chordia et al. (2016) state that sophisticated institutions, who in fact dominate corporate bond markets, price risk in the neoclassical sense.

2 Data and Methodology

2.1 Data

Our analysis is based on an extensive Bank of America Merrill Lynch (BAML) data set of U.S. HY and IG corporate bonds between December 1996 and November 2016 on a monthly frequency. We focus on senior debt only as junior debt is usually an unsecured form of debt and has different payout characteristics compared to standard senior coupon bonds. In addition, we differentiate between IG and non-investment grade (or HY) corporate bonds rated by at least one of the following rating agencies: S&P, Moody's or Fitch. In the spirit of Merton (1974), bonds with varying credit risks exhibit different market behavior and according to Chen et al. (2007) they also manifest different transaction costs. This segmentation is also widespread in practice as index providers offer either HY or IG indexes. Within IG, there are AAA, AA, A and BBB rated securities whereas HY covers all bonds below BBB-. In addition, all bonds have a fixed coupon schedule and a minimum remaining time to maturity of 12 months which is a standard cut-off for most fixed-income indexes. Table 1 provides summary statistics on the average duration, spread and rating characteristics of our data set over time.

[Please insert Table 1 here]

Since our main uncertainty measure is based on OAS, all traded firms from our U.S. corporate HY & IG indexes are considered in this analysis. For our alternative measure, equity volatility, only publicly traded companies are considered. This provides a further robustness check to our results since the universe almost halves when taking into account listed firms only. Our resulting sample includes 1,076,376 unique bond-month observations (236,280 for U.S HY and 840,096 for U.S. IG). Table 2 reports the basic characteristics of the quintile portfolios.

[Please insert Table 2 here]

Our key variables are OAS and equity volatility, respectively. Equity volatility is the standard deviation of the firm's stock and OAS is the fixed spread in addition to the Treasury curve where the corporate bond's discounted payments matches its traded market price (including possible option features). BAML provides total returns as well as excess returns, which are equal to total returns minus the return of a duration-matched Treasury. Since the main purpose of investing in corporate bonds is to earn the default premium besides the term premium, only excess returns should be considered to evaluate unbiased corporate bond returns (see Houweling and van Zundert, 2016, Israel et al., 2016 and Bektic et al., 2016).

2.2 Methodology

As common in academic literature (see Frazzini and Pedersen, 2014 or Jacobs, 2016), we investigate the existence of market timing strategies in corporate bond markets according to uncertainty measures via quintile analysis. That is, issuers are ranked and grouped into five quintiles according to their OAS and equity volatility score, respectively. To ensure that the resulting quintile portfolios are not dominated by single large issuers, we weigh each issuer equally rather than employing a market-capitalization weighting scheme (see Baker and Wurgler, 2012, Choi and Kim, 2016 or Bektic et al., 2016). Accordingly, we use equal-weighted benchmarks. The quintile portfolios are rebalanced on a monthly basis. Given the weighting scheme and monthly excess returns of each bond, the performance of each quintile for each OAS and equity volatility sorted factor portfolio and bond subsample can be computed.

Our employed moving average timing strategy works as follows: At time t we compute the moving average of excess returns of the respective portfolio under consideration over the past K months starting at *t-2*:

$$MA_{t-1} = \frac{1}{K} \sum_{i=2}^{K+1} r_{t-i} \tag{1}$$

Then, we compare MA_{t-1} to the excess return of the portfolio r_{t-1} in *t-1*. If and only if

$$r_{t-1} > MA_{t-1} \tag{2}$$

we will invest in the portfolio at time t and otherwise, we will hold cash. Note that the one month time lag between the computation of the investment decision criterion and the actual investment prevents any forwarded looking bias that might result from delayed data availability. Therefore, this lag ensures the practical implementability of the strategy. We apply this strategy to each of the quintile portfolios constructed from sorts on OAS and equity volatility for each rating bucket, i.e. HY and IG.

3 Empirical Analysis

We start by conducting an analysis of excess returns generated by a moving average timing strategy. In this baseline analysis, we set $K = 3$ in equation (1), i.e., we use one quarter for the computation of our moving average. We choose this length because the recency bias indicates that the value of information decays over time (see Furham, 1986).

For each combination of rating bucket and measure of uncertainty, we construct benchmark excess returns by computing the equal-weighted average of excess returns of each quintile. Therefore, we compute four benchmarks in total. To assess profitability we compute excess returns, alphas against the respective benchmark and Sharpe ratios for moving average strategies applied to each of the quintiles constructed from sorts on OAS and equity volatility. Table 3 displays the results.

Panel A shows our findings for portfolios based on OAS of the underlying bonds. For IG bonds, excess returns increase monotonically from quintile one to quintile five. The excess return over maturity matched Treasuries amounts to 35 basis points (bps) per month for quintile five with a t-statistic of 2.22. Moreover, the alpha versus the benchmark is substantial with 29 bps per month and a t-statistic of 2.66. Sharpe ratios also increase monotonically across quintiles, which indicates that excess returns increase even on a risk-adjusted basis.

For HY bonds, our results are even stronger. Excess returns increase monotonically across quintiles from 11 bps per month (t-statistic 1.86) for quintile one to 104 bps per month (t-statistic 2.58) for quintile five. Notably, alphas versus the benchmark increase from insignificant 7 bps per month to significant 86 bps per month (t-statistic 3.31). These alphas and excess returns are surprisingly large. Likewise, the Sharpe ratio increases from 0.14 to 0.31.

Results in panel B show a similar picture for portfolios based on equity volatility of listed bond issuing companies. In general, the results are weaker compared to the results in panel A, in particular for IG bonds. Nevertheless, the moving average strategy generates an alpha of 12 bps per month (t-statistic 2.11) versus the benchmark in quintile five of IG bonds. Also, note that because equity volatility is only available for publicly traded companies, the amount of bonds per quintile is smaller compared to portfolios based on OAS sorts.

For HY bonds in panel B, excess returns and alphas are smaller than in panel A, but still quite sizeable. For instance, for quintile five, the monthly excess return amounts to 68 bps per month (t-statistic 2.45) which corresponds to a monthly alpha of 49 bps (t-statistic 2.53) versus the benchmark.

[Please insert Table 3 here]

In sum, our results indicate that the profitability of the moving average strategy is particularly pronounced for quintile five, which represents a portfolio of bonds with the highest informational uncertainty. This finding is insensitive to the specific measure of uncertainty used to construct the portfolios. As higher uncertainty is usually associated with both, stronger psychological biases and stronger limits-to-arbitrage, both factors should contribute to the large abnormal returns we document. This is in line Barberis and Thaler (2003) who claim that anomalies in capital market should arise only if both psychological biases and limits-to-arbitrage are present.

3.1 Market Timing

In order to shed some light on the sources of profitability of the moving average strategy applied to the portfolios with high informational uncertainty, we analyze its market timing ability. To this end, we follow two approaches suggested by Treynor and Mazuy (1966) and Henriksson and Merton (1981), respectively. For the former, we run the following regressions for each combination of measure of uncertainty and rating bucket:

$$r_{t,\mathrm{MAQ5}} = \alpha + \beta_{\mathrm{BM}} r_{t,\mathrm{BM}} + \beta_{\mathrm{BM}^2} (r_{t,\mathrm{BM}})^2 + \epsilon \tag{3}$$

where $r_{t,\mathrm{MAQ5}}$ denotes the return of the moving average strategy applied to the fifth quintile constructed on the measure of uncertainty and $r_{t,\mathrm{BM}}$ denotes the return of the respective benchmark.

A positive and significant β_{BM^2} indicates market timing ability. Similary, we follow the approach from Henriksson and Merton (1981) and regress (again for each combination of measure of uncertainty and rating bucket):

$$r_{t,\mathrm{MAQ5}} = \alpha + \beta_{\mathrm{BM}} r_{t,\mathrm{BM}} + \beta_{\mathrm{BM}>0}(r_{t,\mathrm{BM}} \cdot I_{r_{t,\mathrm{BM}}>0}) + \epsilon \tag{4}$$

where $I_{r_{t,\mathrm{BM}}>0}$ equals one if and only if $r_{t,\mathrm{BM}} > 0$ and zero otherwise. As before, $\beta_{\mathrm{BM}>0}$ signals market timing ability. Tables 4 and 5 below illustrate our findings.

[Please insert Table 4 here]

[Please insert Table 5 here]

As Tables 4 and 5 demonstrate, both analyses show that the moving average strategy indeed exhibits market timing ability. Any combination of rating bucket and measure of uncertainty yields positive and significant coefficients $\beta_{\mathrm{BM}>0}$ and β_{BM^2}. These findings agree with the results presented in Han et al. (2013).

3.2 Cumulative Excess Returns

To assess the long-run performance of the moving average strategy presented in the previous sections, we compute cumulative excess returns over our entire sample period. To this end, we set $K = 3$ as in our baseline analysis. Then, we compute for each portfolio P under consideration

$$\text{Cumulative Excess Return(P)} = \prod_{t=1}^{T}(1 + \text{Excess Return(P)}_t) \tag{5}$$

We choose the moving average strategy applied to quintile one and five as well as the benchmark. In Figure 1, we show the resulting time series for the rating bucket IG and portfolios sorted by OAS. For the other rating bucket and measure of uncertainty combinations, results are very similar.

[Please insert Figure 1 here]

The graph shows that the moving average strategy for quintile five avoids some downside risk and therefore profits strongly in a cumulative perspective. Because of the limited downside, the higher volatility of quintile five compared to quintile one seems quite beneficial. In contrast, cumulative excess returns for the moving average strategy applied to quintile one appear rather weak. The lower volatility of this portfolio profits less and ends even weaker than the benchmark from a cumulative perspective. These findings are in line with Han et al. (2013) who also document similar results for equity portfolios.

4 Robustness Checks

4.1 Different Formation Periods

As a robustness check, we re-run our analysis with different time periods over which we compute our moving average strategy. Specifically, we set $K = 6$, $K = 9$ and $K = 12$, i.e., we compute moving averages over half a year, three quarters, and one year. Thereby, we ensure that our findings are robust with respect to the chosen time horizon used for the calculation of the moving averages. As before, we compute excess returns over duration-matched Treasuries, alpha against the respective benchmarks and Sharpe ratios.

As we focus on the impact of information uncertainty on the profitability of moving average strategies, we report results for quintile one and quintile five for a combination of rating buckets and measure of uncertainty in Table 6. Our findings indicate that results are essentially unchanged for portfolios sorted by OAS. Thus, irrespective of the time horizon that we use for computing the moving average, the strategy performs better for quintile five compared to quintile one. Furthermore, our findings remain robust across rating buckets. For instance, the moving average strategy delivers an excess return of 27 bps per month (t-statistic 2.19) for IG bonds when twelve months are used for the computation of the moving average, compared to 34 bps (t-statistic 2.04) when only three months are used.

[Please insert Table 6 here]

Looking at our second measure of uncertainty, namely equity volatility, results are weaker, however generally in line with the baseline findings. Similar to our other measure of uncertainty, results tend to be stronger for HY bonds compared to IG bonds when applying such kind of strategy. Since HY bonds are typically stronger correlated with equity[6], this is in line with Han et al. (2013).

These results corroborate the notion that information uncertainty enhances the profitability of technical analysis.

4.2 Risk-adjusted Excess Returns

To analyze the extent to which excess returns of the moving average strategy are attributable to known risk factors, we run regressions based on the Carhart (1997) model. If the moving average strategy would generate its excess returns by taking additional risk, we would expect the intercept of the regression to vanish. If, however, the intercept remains positive and significant, known risk factors would unlikely provide an explanation of the excess returns of the strategy. Table 7 below summarizes our regression results for each combination of rating bucket and measure of uncertainty. Although the intercepts vary across rating buckets and measures of uncertainty, all are positive and significant. For instance, the monthly Carhart (1997) 4-factor alpha for IG bonds and OAS as measure of uncertainty amounts to 0.31% with a t-statistics of 3.98.

[Please insert Table 7 here]

In sum, our findings suggest that the anomalous profits of the moving average strategy cannot be explained by the Carhart model.

4.3 Long-Short Portfolios and the Impact of Market Volatility

Since our main conjecture states that informational uncertainty enhances the profitability of moving average strategies, we construct long-short portfolios to underline that assumption. These portfolios offset a long position in the moving average strategy applied to quintile five with a short position in the moving average strategy applied to quintile one. We then compute the mean return of the resulting long-short portfolio and test for significance. Again, we conduct this exercise for each rating bucket and each measure of uncertainty. Table 8 displays our findings. All long-short

[6] See Hong et al. (2012) or Bao and Hou (2014).

portfolios deliver positive and significant returns ranging from 0.07% per month (t-statistic 2.24) for IG bonds and equity volatility as measure of uncertainty to 0.92% per month (t-statistic 4.55) for HY bonds with OAS as measure of uncertainty.

[Please insert Table 8 here]

In a next step, we investigate how market volatility, as measured by the VIX, affects the excess returns of our strategy. Intuitively, portfolios with high levels of informational uncertainty should be affected more strongly by increasing market volatility due to the additional informational risk they entail. Therefore, the performance of the moving average strategy applied to quintile five should outpace the performance of the moving average strategy applied to quintile one more strongly for higher levels of market volatility. Consequently, we expect the profitability of the long-short portfolio introduced above to increase as market volatility increases. Regression results shown in Table 9 support that claim. Irrespective of the rating bucket or measure of uncertainty, we find that the performance of the long-short portfolio is positively related to market volatility.

[Please insert Table 9 here]

4.4 Transaction Costs

As a final robustness test, we determine the break-even transaction costs of the moving average strategies applied to quintile one and five for each combination of rating bucket and measure of uncertainty. Following the literature (see Houweling and van Zundert, 2016), we define break-even transaction costs as the amount of transaction costs that would lead to a CAPM alpha of zero. Table 10 shows our findings. The determined break-even transaction costs are quite large. For instance, the break-even transaction for the moving average strategy applied to quintile five of IG bonds sorted by equity volatility amounts to 55 bps, which substantially exceeds assumed levels of transaction costs in the literature (see Gebhardt et al., 2005 or Jostova et al., 2013). This finding highlights the relevance of our findings also from a practitioner's perspective.

[Please insert Table 10 here]

5 Conclusion

We document strong and robust anomalous excess returns for moving average timing strategies applied to corporate bond portfolios with high levels of informational uncertainty. These strategies use a simple rule to create market timing decisions: whenever the moving average of past returns exceeds the current return, the strategy invests in the portfolio and holds cash the rest of the time. The resulting excess returns are sizeable and robust with respect to the time horizon used to construct the moving average strategy. In addition, excess returns increase with the degree of uncertainty of the underlying portfolio, irrespective of the measure of uncertainty employed.

Exposure to classical risk factors, such as Carhart's (1997) 4-factor model, is unable to explain the obtained excess returns. The variation in the return differential of moving average strategies applied to portfolios with different levels of informational uncertainty is positively related to the level of market volatility. Because high informational uncertainty tends to amplify both investor biases and limits-to-arbitrage, these two theories are likely to explain our results. The strong long-run performance of the strategy is also in line with this conjecture.

Our study complements the findings of (Han et al., 2013) who document similar results for equity markets. The fact the our results are stronger for HY bonds compared to IG bonds is also coherent with these authors. Further, we contribute to a growing strand of literature that analyzes the link between corporate bond markets and equity markets. Our findings are also relevant to practitioners who apply technical analysis. First, we show that technical analysis can be profitable in corporate bond markets and second, the profitability is likely to increase with both, the uncertainty of the underlying portfolio and the general uncertainty in the market.

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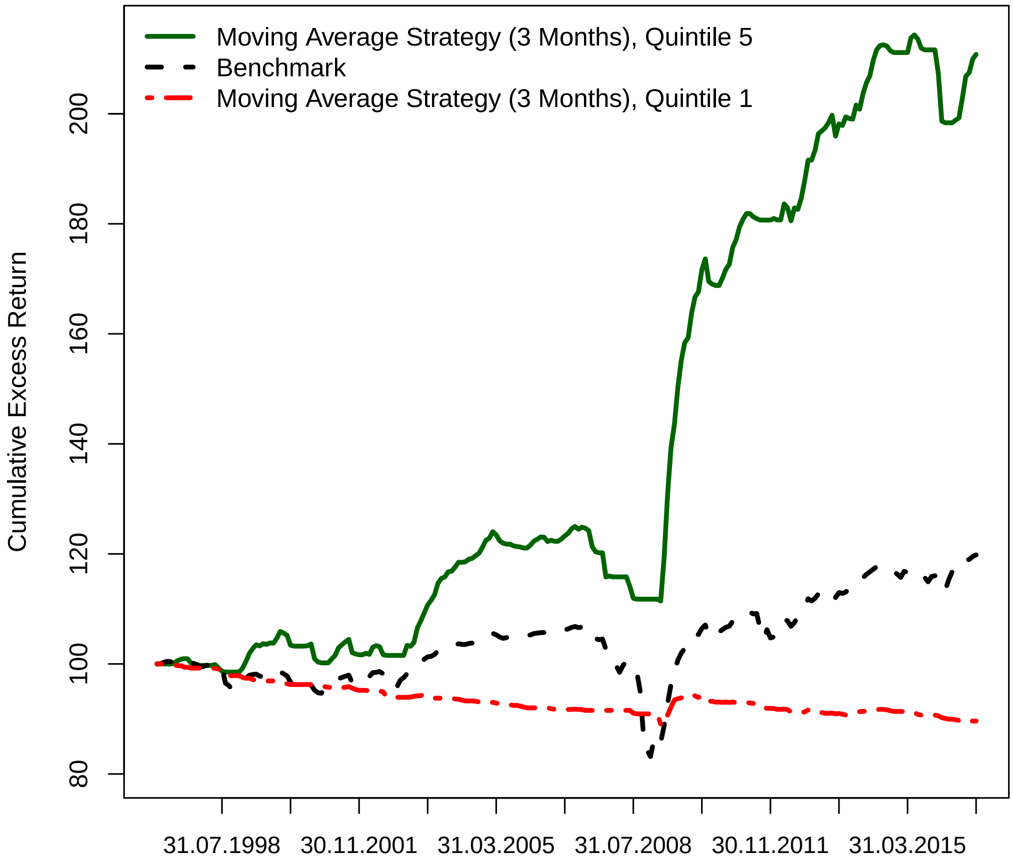
Figure 1: Cumulative Excess Returns for Moving Average Strategies Applied to Portfolios Sorted on Option Adjusted Spreads



This figure shows cumulative excess returns of moving average strategies using a moving average of three months. The moving average strategies are applied to portfolios which are constructed from sorts. For the portfolio construction, bonds are sorted into five equally sized portfolios based on their option adjusted spreads (OAS). Excess returns of the resulting portfolios over the maturity matched treasuries are computed as equally weighted averages of excess returns of all bonds contained in the respective portfolio. The moving average strategy is applied to the top and the bottom quintile portfolio constructed from this sort, denoted as quintile 5 and quintile 1, respectively. The moving average strategy works are follows: whenever the lagged portfolio value exceeds its lagged three month moving average (ranging from t-4 to t-1), the strategy invests in the respective portfolio. Whenever the lagged portfolio value is less or equal to its lagged three month moving average (ranging from t-4 to t-1), the strategy holds cash. This figure also shows the cumulative excess returns of quintile 5, quintile 1 and the benchmark. All excess returns are normalized to 100 at the beginning of the sample period. The sample period ranges from December 1996 to November 2016.

Table 1: Descriptive Statistics: Panel A

Average monthly number of total firms, public firms, private firms and bonds as well as the average duration (Avg. DUR), spread (Avg. OAS) and rating (Avg. RTG) for U.S. High Yield as well as Investment Grade corporate bonds in the period from December 1996 until November 2016.

High Yield							
Year	Firms	Public Firms	Private Frims	Bonds	Avg. DUR	Avg. OAS	Avg. RTG*
1997	333	143	190	295	4.12	290	13.72
1998	381	166	215	316	4.33	418	13.67
1999	465	207	258	376	4.39	558	13.66
2000	485	222	263	447	4.21	650	13.81
2001	501	246	255	534	3.84	1131	14.15
2002	511	270	241	645	3.89	1405	14.22
2003	615	334	282	825	4.11	780	14.16
2004	719	384	335	895	4.27	396	14.04
2005	745	396	349	889	4.14	343	14.00
2006	757	403	354	886	4.15	324	13.93
2007	709	379	329	721	4.25	321	13.71
2008	819	438	380	826	4.11	871	13.73
2009	782	464	317	936	3.7	1515	14.17
2010	876	523	353	1089	3.94	651	14.08
2011	1054	615	439	1270	4.18	600	13.94
2012	1124	677	448	1409	3.85	677	14.04
2013	1231	740	491	1570	3.89	553	14.23
2014	1314	801	513	1732	3.89	488	14.20
2015	1347	870	477	1978	3.95	760	14.19
2016	1292	875	417	2051	3.74	946	14.29

Investment Grade							
Year	Firms	Public Firms	Private Frims	Bonds	Avg. DUR	Avg. OAS	Avg. RTG*
1997	816	549	267	2474	5.59	62	6.69
1998	909	600	309	2957	5.61	100	6.83
1999	860	588	272	2931	5.59	139	6.88
2000	738	542	196	2528	5.26	179	6.90
2001	736	557	178	2686	5.16	199	7.11
2002	756	602	153	2850	5.19	204	7.25
2003	752	607	145	2943	5.39	147	7.39
2004	799	632	168	3112	5.49	98	7.45
2005	700	533	166	2336	5.70	88	7.23
2006	717	547	170	2427	5.71	100	7.23
2007	759	585	174	2237	6.06	123	7.44
2008	809	642	167	2721	5.65	330	7.48
2009	789	637	152	3026	5.41	435	7.58
2010	855	699	156	3395	5.69	192	7.60
2011	928	765	163	3894	5.86	194	7.67
2012	994	818	176	4386	5.94	219	7.78
2013	1117	922	196	5021	6.08	174	7.86
2014	1220	1000	220	5545	6.00	142	7.85
2015	1294	1055	239	6055	6.00	172	7.85
2016	1306	1053	253	6484	5.89	186	7.88

*Rating Description: AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19

Table 2: Descriptive Statistics: Panel B

Average duration (Avg. DUR), spread (Avg. OAS), rating (Avg. RTG) and annualized standard deviation (Avg. VOL) as well as the average past cumulative 12 month return (Avg. Past Cum. 12m Return) and average lag 1 month return (Avg. Lag 1m Return) of all quintiles and the corresponding market for U.S. High Yield as well as Investment Grade corporate bonds in the period from December 1996 until November 2016 sorted by option adjusted spread (OAS) and equity volatility (Eq. Vol.), respecitvely.

OAS

High Yield	Q1	Q2	Q3	Q4	Q5	Market
Avg. DUR	4.13	4.30	4.12	3.86	3.17	3.92
Avg. OAS	271.36	410.26	553.09	801.53	2391.47	885.54
Avg. RTG*	12.49	13.48	14.48	15.35	16.73	14.51
Avg. VOL	5.69%	7.27%	9.32%	12.46%	19.17%	10.25%
Avg. Past Cum. 12m Return	0.02%	2.36%	3.27%	4.41%	10.85%	3.72%
Avg. Lag 1m Return	0.01%	0.22%	0.30%	0.38%	0.72%	0.33%

Investment Grade	Q1	Q2	Q3	Q4	Q5	Market
Avg. DUR	3.84	5.41	6.18	6.52	6.29	5.65
Avg. OAS	71.33	121.35	160.47	206.68	336.06	179.18
Avg. RTG*	4.83	6.59	7.60	8.32	8.97	7.26
Avg. VOL	1.87%	2.89%	3.51%	4.18%	6.61%	3.68%
Avg. Past Cum. 12m Return	-0.53%	-0.12%	0.43%	1.10%	3.68%	0.88%
Avg. Lag 1m Return	-0.05%	-0.01%	0.04%	0.10%	0.32%	0.08%

Eq. Vol

High Yield	Q1	Q2	Q3	Q4	Q5	Market
Avg. DUR	4.17	4.13	4.09	4.03	3.85	4.05
Avg. OAS	543.03	588.80	602.51	644.69	1040.00	683.81
Avg. RTG*	13.51	13.59	13.69	13.99	15.17	13.99
Avg. VOL	6.67%	8.31%	8.60%	10.16%	15.12%	9.33%
Avg. Past Cum. 12m Return	3.83%	4.12%	4.04%	4.52%	5.96%	4.42%
Avg. Lag 1m Return	0.35%	0.37%	0.36%	0.40%	0.51%	0.40%

Investment Grade	Q1	Q2	Q3	Q4	Q5	Market
Avg. DUR	5.87	5.83	5.67	5.53	5.39	5.66
Avg. OAS	143.86	152.92	166.51	181.84	225.78	174.18
Avg. RTG*	6.90	7.11	7.35	7.60	7.99	7.39
Avg. VOL	2.90%	3.20%	3.42%	4.01%	4.75%	3.59%
Avg. Past Cum. 12m Return	0.77%	0.70%	0.94%	1.08%	1.32%	0.96%
Avg. Lag 1m Return	0.07%	0.07%	0.08%	0.10%	0.12%	0.09%

*Rating Description: AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19

Table 3: Moving Average Strategies - Baseline Results

This table reports return characteristics for a moving average strategy based on portfolios of corporate bonds sorted on measures of uncertainty, separately for the rating buckets *Investment Grade* and *High Yield*. Corporate bonds are sorted into five equally sized portfolios based on their option adjusted spread in panel A and based on their issuer's equity volatility in panel B. The table shows the equally weighted average of excess returns over maturity matched treasuries, alphas as the intercept from a regression of the time series of excess returns on the excess returns of the benchmark together with the respective t-statistics. Benchmarks for each combination of rating bucket and measure of uncertainty are computed as equally weighted average of excess returns over each quintile. Further, the table reports the Sharpe ratios of the portfolios. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Panel A: Portfolios Sorted by OAS						
	Investment Grade			High Yield		
	Excess Return	α	Sharpe Ratio	Excess Return	α	Sharpe Ratio
MA: Q1	0.01	0.00	0.02	0.11*	0.07	0.14
t-value	0.29	0.03		1.86	1.33	
MA: Q2	0.04	0.02	0.09	0.24**	0.17**	0.20
t-value	1.09	1.78		2.47	2.26	
MA: Q3	0.09*	0.07**	0.17	0.37***	0.28***	0.25
t-value	1.82	2.00		2.67	2.92	
MA: Q4	0.15**	0.12**	0.22	0.50**	0.37**	0.24
t-value	2.08	2.51		2.45	2.89	
MA: Q5	0.35**	0.29***	0.27	1.04***	0.86****	0.31
t-value	2.22	2.66		2.58	3.31	
BM	0.08		0.08	0.33		0.11
t-value	0.70			1.06		

Panel B: Portfolios Sorted by Equity Volatility						
	Investment Grade			High Yield		
	Excess Return	α	Sharpe Ratio	Excess Return	α	Sharpe Ratio
MA: Q1	0.09**	0.07**	0.20	0.31***	0.20**	0.24
t-value	2.10	2.34		2.75	2.75	
MA: Q2	0.10**	0.08**	0.20	0.36***	0.26***	0.28
t-value	2.05	2.36		3.14	3.14	
MA: Q3	0.12**	0.10***	0.22	0.40***	0.27***	0.27
t-value	2.14	2.62		2.79	2.83	
MA: Q4	0.12*	0.09**	0.20	0.43**	0.28**	0.24
t-value	1.86	2.18		2.52	2.37	
MA: Q5	0.16*	0.12**	0.20	0.68***	0.49**	0.37
t-value	1.85	2.11		2.45	2.53	
BM	0.09		0.09	0.40		0.15
t-value	0.78			1.58		

Table 4: Treynor and Mazuy (1966) Market Timing Test

We test whether the quadratic regression of Treynor and Mazuy (1966) has a significantly positive coefficient β_{BM^2}, indicating successful market timing, for long-short moving average portfolio returns for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility. Alphas are excess returns in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
Q5	0.66***	0.97***
t-stat	4.83	3.98
IG	OAS	Eq. Vol.
Q5	1.89***	3.35***
t-stat	6.43	6.39

Table 5: Henriksson and Merton (1981) Market Timing Test

We test whether the regression of Henriksson and Merton (1981) has a significantly positive coefficient $\beta_{BM>0}$, indicating successful market timing, for long-short moving average portfolio returns for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility. Alphas are excess returns in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
Q5	0.66***	0.97***
t-stat	4.83	3.98
IG	OAS	Eq. Vol.
Q5	1.89***	3.35***
t-stat	6.43	6.39

Table 6: Moving Average Strategies: Robustness Check

This table reports return characteristics for moving average strategies based on portfolios of corporate bonds sorted on measures of uncertainty, separately for the rating buckets *Investment Grade* and *High Yield* on a 6, 9 and 12 month basis, respectively. Corporate bonds are sorted into five equally sized portfolios based on their option adjusted spread in panel A and based on their issuer's equity volatility in panel B. The table shows the equally weighted average of excess returns over maturity matched treasuries, alphas as the intercept from a regression of the time series of excess returns on the excess returns of the benchmark together with the respective t-statistics. Benchmarks for each combination of rating bucket and measure of uncertainty are computed as equally weighted average of excess returns over each quintile. Further, the table reports the Sharpe ratios of the portfolios. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Panel A: 6 months						
	HY OAS			HY Eq. Vol		
	Excess Return	α	Sharpe Ratio	Excess Return	α	Sharpe Ratio
MA: Q1	0.06	0.02	0.07	0.29	0.1	0.18
t-stat	0.91	0.36		1.84	1.52	
MA: Q5	0.95**	0.77***	0.28	0.62**	0.43**	0.25
t-stat	2.19	2.71		2.25	2.23	
	IG OAS			IG Eq. Vol		
MA: Q1	0.01	0	0.03	0.09	0.06	0.16
t-stat	0.34	0.03		1.42	1.41	
MA: Q5	0.34**	0.28***	0.26	0.12	0.09	0.16
t-stat	2.04	2.59		1.46	1.43	
Panel B: 9 months						
	HY OAS			HY Eq. Vol		
	Excess Return	α	Sharpe Ratio	Excess Return	α	Sharpe Ratio
MA: Q1	0.01	-0.03	0.02	0.17	0	0.1
t-stat	0.21	0.64		1.12	0.03	
MA: Q5	0.76*	0.6*	0.24	0.53**	0.39*	0.25
t-stat	1.89	1.86		2.02	1.95	
	IG OAS			IG Eq. Vol		
MA: Q1	0	0	0.02	0.07	0.05	0.15
t-stat	0.33	0.08		1.46	1.3	
MA: Q5	0.24*	0.20**	0.22	0.12	0.09	0.16
t-stat	1.95	2.06		1.45	1.34	
Panel C: 12 months						
	HY OAS			HY Eq. Vol		
	Excess Return	α	Sharpe Ratio	Excess Return	α	Sharpe Ratio
MA: Q1	0.02	-0.02	0.03	0.13	-0.04	0.08
t-stat	0.32	0.27		0.86	0.36	
MA: Q5	0.77**	0.62**	0.26	0.45*	0.3	0.21
t-stat	2.04	2.06		1.92	1.6	
	IG OAS			IG Eq. Vol		
MA: Q1	-0.01	-0.01	-0.05	0.08*	0.06	0.18
t-stat	0.69	1.02		1.84	1.62	
MA: Q5	0.27**	0.23**	0.25	0.11	0.08	0.16
t-stat	2.19	2.27		1.52	1.28	

Table 7: Carhart (1997) 4-Factor Alpha

Alphas are estimated from the time-series regression using *MKT* as the equity market premium in addition to the Fama–French factors *SMB* (size) and *HML* (value) as well as the Carhart (1997) *UMD* (momentum) factor for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility. Alphas are excess returns over benchmark in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
Q5	0.90***	0.58***
t-stat	4.36	3.69
IG	OAS	Eq. Vol.
Q5	0.31***	0.13***
t-stat	3.98	2.63

Table 8: Long-Short Performance

We compare whether the outperformance of long-short moving average portfolio returns for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility is larger than 0. Alphas are excess returns in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
Q5-Q1	0.92***	0.37***
t-stat	4.55	2.79
IG	OAS	Eq. Vol.
Q5-Q1	0.35***	0.07**
t-stat	4.61	2.24

Table 9: Long-Short Performance vs. VIX Index

We compare VIX index returns versus long-short moving average portfolio returns for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility, repectively. Alphas are excess returns over benchmark in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
Q5-Q1	0.07***	0.03**
t-stat	2.69	1.97
IG	OAS	Eq. Vol.
Q5-Q1	0.04***	0.01**
t-stat	4.04	2.34

Table 10: Break-Even Transaction Costs

We define break-even transaction costs of a portfolio as the costs that would lower its CAPM-alpha to 0 (see Houweling and van Zundert, 2016). The costs are calculated in basis points (bps) per transaction for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility, repectively.

HY	OAS	Eq. Vol.
Q5	367	219
Q1	21	87
IG	OAS	Eq. Vol.
Q5	152	55
Q1	1	26