Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

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Volatility Timing in Corporate Bond Funds: Prevalence, Persistence and Performance

Master's thesis in Industrial Economics and Technology Management
Supervisor: Einar Belsom
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Preface

This thesis is written as the final requirement of our Master of Science at the Norwegian University of Science and Technology.

We would like to thank our supervisor Einar Belsom for interesting conversations and invaluable technical discussions regarding the development of our methods and models. Lastly, we would like to thank our friends and families for supporting and encouraging us through the research process.

Abstract

We examine various aspects of volatility timing among corporate bond funds, including general prevalence, persistence over time, and impact on performance. Using daily return data, we find that high yield funds, on average, time volatility procyclically, while investment grade funds time countercyclically. This discrepancy appears to stem from a more positive correlation between market returns and conditional market volatility in high yield markets than in investment grade markets. There appears to be persistence in the timing ability of procyclical timers, but not in that of countercyclical timers. Finally, our performance analysis yields largely inconclusive results, except for one distinct pattern; funds are more inclined to time volatility in the same direction as the funds that achieve the greatest risk-adjusted returns.

Sammendrag

Vi undersøker ulike aspekter ved timing av volatilitet blant selskapsobligasjonsfond, deriblant generelt omfang, persistens over tid og innvirkning på risikojustert avkastning. Ved bruk av daglig avkastningsdata kommer vi frem til at high yield-fond i gjennomsnitt timer volatilitet medsyklisk, mens investment grade-fond timer motsyklisk. Denne forskjellen ser ut til å komme av at korrelasjonen mellom markedsavkastning og betinget markedsvolatilitet er større i high yield-markeder enn i investment grade-markeder. Våre resultater tyder også på at det er persistens i motsyklisk timing, men ikke i medsyklisk timing. Når vi analyserer forholdet mellom timing av volatilitet og risikojustert avkastning får vi delte resultater, men det er ett tydelig mønster; de fleste fondene som timer volatilitet, timer i samme retning som de fondene som har høyest risikojustert avkastning.

Contents

1 Introduction

The purpose of this thesis is to examine the extent to which bond fund managers engage in volatility timing. To understand why a fund manager would adjust his portfolio in response to a changing market volatility outlook, it is helpful to consider the fundamentals of what fund managers are trying to achieve. Manager performance is usually quantified in some risk-adjusted metric, whether its the Sharpe ratio, the Treynor ratio or the intercept of some risk pricing model regression. For ease of interpretation, we will use the Sharpe ratio as an example, but the following arguments hold for any risk-adjusted performance measure. The Sharpe ratio is defined as

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p} \tag{1.1}$$

where R_p is the return of the fund portfolio, R_f is the risk-free return and σ_p is the volatility of portfolio returns, all in the same period. A fund manager attempting to maximize this ratio can either increase the numerator, i.e. obtain greater returns, or decrease the denominator, i.e., obtain less variable returns. The former is notoriously difficult, at least if portfolio volatility is to be held constant, while the latter should, in theory, be fairly simple. To understand why, one can neglect bond picking ability for a second, and simply consider portfolio management to be the act of deciding when to be exposed to aggregate bond market fluctuations. In this context, management performance boils down to market timing ability and volatility timing ability. In other words, a manager is skilled, simply to the extent that he is capable of predicting appreciation or depreciation in bond market value and the volatility of this appreciation or depreciation. While market returns are generally modelled as stochastic processes where an upswing is more or less as probable as a downturn, the volatility of said returns follows far more predictable processes. This is mainly due to two specific attributes of volatility time series: First, volatility tends to appear in clusters, meaning that a high-volatility day is more likely to be followed by another high-volatility day than a low-volatility day. Such a pattern is known as volatility clustering. Second, volatility is more likely to increase following a negative-return period than following a positive-return period. This is known as the leverage effect. Both of these attributes can be exploited by fund managers attempting to time volatility, while a manager attempting to time market returns has far less to work with.

Given the above discussion, how should we expect the volatility timing fund manager to behave? Busse (1999) argues that managers could increase investors' utility by reducing their market exposure when conditional market volatility rises, as long as market returns and return volatility are uncorrelated. Extensive literature suggests that this condition holds in equity markets (Campbell 1987; French, Schwert, and Stambaugh 1987; Glosten, Jagannathan, and Runkle 1993; Whitelaw 1994). In fixed income markets, on the other hand, this is not a priori clear. Cai and Jian (2008) find evidence of a negative correlation between corporate bond market excess returns and the contemporaneous excess return volatility. However, given that the correlation is negative, the incentive for fund managers to reduce portfolio volatility when market volatility increases should be even higher in bond markets than in equity markets.

To our knowledge, mutual fund volatility timing has never been studied in the fixed income universe. In the equity universe, on the other hand, Busse (1999) conducted the first extensive volatility timing study two decades ago. He finds evidence of the abovementioned expected behavior, wherein managers reduce portfolio volatility when market volatility is high. Moreover, he shows that surviving funds are more inclined to exhibit this behavior than non-surviving funds, suggesting that volatility timing positively affects fund performance. Giambona and Golec (2009) expand on his work by examining how volatility timing varies across funds with different compensation schemes. Finally, Foran and O'Sullivan (2017) find evidence of a small percentage of UK mutual funds exhibiting volatility timing behavior in the manner described above.

In this thesis, we analyse whether the conclusions drawn about volatility timing in equity funds also apply to bond funds. Our approach bears a resemblance to that of Busse (1999), in that we use his model as a starting point. We then alter it considerably in order to make it applicable to bond markets. Specifically, our focus will be on corporate bond funds in the period from 2010 to 2020. We do not impose any geographical constraints, hence the domiciles of the funds in our data set are scattered across the world.

Under the umbrella of volatility timing, we study several different aspects of fund manager behavior. First, we consider the degree to which fund managers actually use volatility timing as an active part of their investment strategy. We perform analyses based on both daily and monthly data, in order to capture market volatility changes over different time horizons. Second, we examine whether fund managers who time volatility, hereinafter referred to as volatility timers, do so consistently, both on a daily and on a monthly basis, and whether there is persistence in timing ability over time. Third, we explore the impact of volatility timing on fund performance, analysing whether volatility timers achieve greater risk-adjusted returns than non-timers.

The rest of the thesis is structured as follows: Chapter 2 lays out the methodology applied in various analyses performed. Chapter 3 presents our data sample and data sources. Chapter 4 contains our results and associated discussions, and finally, Chapter 5 concludes the thesis.

2 Methodology

In this chapter, we outline the methodology employed in the development of our models. Section 2.1 establishes a theoretical framework for interpreting our results, while Section 2.2 describes our various empirical models.

2.1 Theoretical Model

Busse (1999) and Giambona and Golec (2009) develop somewhat different theoretical models to motivate their empirical volatility timing analyses. However, both papers use the maximization of fund manager utility with respect to factor sensitivities $\beta_{1\ldots k}$ as a starting point:

$$\max_{\beta_{1\ldots k}} E_t[U(\cdot)], \tag{2.1}$$

where $E_t[\cdot]$ is the expectation conditional upon all information available at time t and $U(\cdot)$ is the fund manager utility function. From here, Busse (1999) proceeds by assuming that factors are orthogonal and that conditional fund returns are normally distributed. Under these assumptions, expected excess return and variance can be expressed as

$$E_t[R^e_{pt+1}] = \alpha_{pt} + \sum_{j=1}^{k} \beta_{jpt} E_t[R^e_{jt+1}] \tag{2.2}$$

and

$$\sigma^2_t(R^e_{pt+1}) = \sum_{j=1}^{k} \beta^2_{jpt}\sigma^2_{jt+1} + \sigma^2_t(\epsilon_{pt+1}), \tag{2.3}$$

wherein α_{pt} is the abnormal return of portfolio p at time t, β_{jpt} is the beta of portfolio p associated with risk factor j at time t, R^e_{jt} is the excess return of risk factor j at time t, R^e_{pt} is the excess return of portfolio p at time t, and $\sigma^2_t(\cdot)$ is the variance at time t.

Then, applying the first-order condition to Equation (2.1), along with the Stein (1981) lemma, the optimal factor exposure, β^*, becomes

$$\beta^*_{jpt} = \frac{1}{a}\frac{E_t(R^e_{jt+1})}{\sigma^2_{jt+1}}, \tag{2.4}$$

where $a = -E[U''_{t+1}(R_{jt+1})]/E[U'_{t+1}(R_{jt+1})]$ is the Rubinstein (1973) risk aversion measure. If a is constant, then

$$\frac{\partial\beta^*}{\partial\sigma^2_{jt+1}} = \frac{\sigma^2_{jt+1}\partial E_t[R^e_{jt+1}]\partial\sigma^2_{jt+1} - E_t[R^e_{jt+1}]}{(\sigma^2_{jt+1})^2}. \tag{2.5}$$

As long as the expression above is negative, i.e. as long as

$$\frac{\partial E_t[R^e_{jt+1}]}{\partial\sigma^2_{jt+1}} < \frac{E_t[R^e_{jt+1}]}{\sigma^2_{jt+1}}, \tag{2.6}$$

fund managers would benefit from timing volatility countercyclically. Cai and Jian (2008) find evidence of a negative relation between corporate bond market returns and contemporaneous return volatility. If this holds in general, then $\partial E[R^e_{jt+1}]/\partial\sigma^2_{jt+1} < 0$. If we further assume that $E_t[R^e_{jt+1}] > 0$, then countercyclical volatility timing is always optimal.

This approach is quite general, in that the shape of the fund manager's utility function is never specified. As a result, we find it helpful to also present the theoretical model developed by Giambona and Golec (2009). They make the assumption that fund managers' utility is linear with respect to the expected value of fees earned and the variance of said fees:

$$E[U(Fee)] = E[Fee] - \Omega Var(Fee) \tag{2.7}$$

where Ω is a constant, $Var(\cdot)$ is the variance, and Fee is defined as:

$$Fee = k_b A(1 + R^e_p + R^f). \tag{2.8}$$

Equation (2.8) is the fee earned over the next period, wherein A is the total assets under management and k_b is the fee as a percentage of total assets. By inserting Equation (2.7) into Equation (2.1) and applying the first order condition, we obtain the following optimal market exposure under the assumption that the capital asset pricing model (CAPM) holds:

$$\beta^* = \frac{E[R^{mkt}]}{2\Omega A k_b \sigma^2_{mkt}}, \tag{2.9}$$

where R^{mkt} is the excess market return, Ω is a constant, and σ_{mkt} is the market volatility.

According to Equation (2.7), a positive Ω corresponds to a risk-averse manager. Hence, as opposed to a in Equation (2.4), Ω has an intuitive interpretation. However, this model also has its shortcomings. First of all, it does not take into account the well-documented positive relation between performance and inflow of fund investments (Gruber 1996). Consequently, the slope of Fee with respect to R_p is probably underestimated. This affects both terms on the right-hand side of Equation (2.7), making it difficult to tell whether the actual β^* is higher or lower than that of Equation (2.9).

Second, as Giambona and Golec (2009) point out, this definition of Fee assumes that funds get paid exclusively in the form of fixed fees. For funds with various incentive fee structures, earned fees are not simply a linear function of absolute returns. To compensate for this, they suggest adding a general incentive fee term to the Fee definition:

$$Fee = k_b A(1 + R^e_p + R^f) + k_i A(1 + R^e_p)(R^e_p - R^{mkt}), \tag{2.10}$$

where k_i is the incentive fee as a percentage of assets under management. Here, fees earned also depend on fund returns in excess of market returns. When inserted into Equation (2.7), this yields no closed-form expression for β^*. In addition, the incentive fee term is somewhat arbitrary; incentive fees are not necessarily earned once fund returns exceed those of the benchmark. They are often contingent upon other performance measures, such as returns in excess of some fixed hurdle rate or fund net asset value (NAV) being above a high-water mark.

Nevertheless, the authors assume Equation (2.9) to be a reasonable estimate of optimal beta, and proceed by differentiating with respect to market volatility:

$$\frac{\partial \beta^*}{\partial \sigma^2_{mkt}} = \frac{\sigma^2_{mkt} \partial E[R^{mkt}]/\partial \sigma^2_{mkt} - E[R^{mkt}]}{2\lambda A k_b^2 (\sigma^2_{mkt})^2}. \tag{2.11}$$

As long as the expression above is negative, i.e. as long as

$$\frac{\partial E[R^{mkt}]}{\partial \sigma^2_{mkt}} < \frac{E[R^{mkt}]}{\sigma^2_{mkt}}, \tag{2.12}$$

fund managers would benefit from acting as countercyclical volatility timers. This result is exactly the same as that of Busse (1999), although the assumptions going into each method are different, indicating that the result is somewhat robust. Once again, the findings of Cai and Jian (2008) indicate that $\partial E[R_{mkt}]/\partial \sigma^2_{mkt} < 0$, hence that countercyclical volatility timing is always optimal, given that $E_t[R_{jt+1}] > 0$.

2.2 Empirical Model

As the basis of a regression model that can measure volatility timing, we use two different asset pricing models. The first one is the regular CAPM specification, given by

$$R_{pt} - R^f_t = \alpha_p + \beta^m_p(R^m_t - R^f_t), \tag{2.13}$$

where R_{pt} is the return of fund portfolio p at time t, R^m_t is the market return at time t, α_p is the risk-adjusted return of portfolio p, β^m_p is the market beta coefficient of portfolio p, and R^f_t is the risk-free rate at time t. Since bond markets are highly diverse and heterogeneous, with various risk classifications, payout structures, and maturities, we have refrained from benchmarking all fund categories against a single market index. Instead, funds are assigned an appropriate benchmark based on Morningstar's fund categorization system. This method leaves us with a total of eleven different customized marked indexes, against which the funds in our sample are benchmarked. As a result, R^m_t denotes the the benchmark index return that most accurately reflects the market that the given fund is operating in.

The second basic specification is proposed by Bai, Bali, and Wen (2019). They introduce three novel bond risk factors; illiquidity risk, credit risk and downside risk, and find that a four-factor model consisting of these three, along with the market factor, outperforms all other corporate bond pricing models considered in previous literature. In mathematical terms, the model is expressed as

$$R_{pt} - R_t^f = \alpha_p + \beta_p^m(R_t^m - R_t^f) + \beta_p^{ILQ} ILQ_{pt} \\ + \beta_p^{CDS} CDS_{pt} + \beta_p^{DWS} DWS_{pt}, \tag{2.14}$$

where ILQ_{pt} is the illiquidity risk factor of portfolio p at time t, CDS_{pt} is the credit risk factor of portfolio p at time t, DWS_{pt} is the downside risk factor of portfolio p at time t, with corresponding regression coefficients, and all other parameters are defined as above. In the following sections, we will explain what constitutes each factor and how the factors are calculated.

2.2.1 Illiquidity Risk

There is an extensive literature documenting the relationship between bond illiquidity and bond returns. Chen, Lesmond, and Wei (2007), Bao, Pan, and Wang (2011) and Dick-Nielsen, Feldhütter, and Lando (2012) find that higher liquidity in corporate bonds is associated with lower yield spreads. We follow the approach of Bao, Pan, and Wang (2011) and Bai, Bali, and Wen (2019) in constructing a liquidity measure based on bond-level data using bond transaction data from the Trade Reporting and Compliance Engine (TRACE) database. The benefit of this measure, relative to others, is that it captures a larger part of liquidity than what is visible through bid-ask spreads. Moreover, it does so without relying on specific pricing models for bonds. On bond-level, the illiquidity factor is defined as

$$ILQ = -Cov(\Delta p_{bt}, \Delta p_{bt+1}), \tag{2.15}$$

where $\Delta p_{bt} = ln(p_{bt}/p_{bt-1})$, is the log price change of bond b from time $t-1$ to t. We use this measure to create a proxy for the liquidity risk premium in the manner of Fama and French (1992). One ILQ value is calculated for every bond each month and used for portfolio sorting.

We remove the 5% most liquid and 5% least liquid bonds. The most liquid bonds are removed due to non-sensible ILQ values. These bonds have the attributes of "fallen angels"; high liquidity for a short period when they are downgraded and sold off by funds that are only allowed to hold investment grade (IG) bonds. These bonds would be wrongly categorized as the most liquid bonds and are therefore removed. We remove the 5% least liquid bonds since a large part of their price dynamic is censored due to excessive illiquidity.

At this point, a couple of possible error sources must be addressed. First of all, the TRACE database only includes US corporate bond transactions. It is clearly a simplification to use US bond data exclusively to calculate what is supposed to be a universal bond liquidity risk premium. In our view, this simplification is justifiable, considering the following: The US bond market accounted for 40.2% of the global bond market in 2018, measured in terms of total outstanding value (Securities Industry and Financial Markets Association 2019), and this share has been relatively stable throughout our period of study. Second, as financial markets are gradually becoming more integrated across national and continental borders, we expect global macroeconomic trends to be important drivers of corporate bond market liquidity. To our knowledge, there is currently no reliable literature on the co-movements of international corporate bond markets, but observations of extreme events support our hypothesis. For instance, during the 2008 financial crisis, corporate bond markets dried up across the world, more or less simultaneously (Aussenegg, Goetz, and Jelic 2015). Lastly, to our knowledge, no comparable data set exists for corporate bonds outside of the US.

2.2.2 Credit Risk

The credit risk of a bond can be loosely defined as the hazard introduced by the possibility that the issuer could default on its debt. This is the only risk factor an investor who intends to hold a bond until maturity needs to concern himself with; bond liquidity and market price fluctuations are irrelevant, as long as the underlying creditworthiness of the issuer is intact.

Recent literature suggests several different ways of quantifying the credit risk of a bond. The most widely used metric appears to be the credit ratings issued by rating agencies like Standard & Poor's (S&P), Moody's, and Fitch. These ratings are supposed to synthesize all public information about the issuer's ability to service his debt, including balance sheet strength, operating cash flow, and bond specific features, like seniority and coupon rates. Hence, a credit rating sounds like an appealing proxy for the actual credit risk of a given bond. Unfortunately, the direct application of ratings in an empirical model introduces a multitude of complications. First of all, ratings are typically discrete (AA, A, BBB, etc.), and there is no generally accepted standard for what a given rating means in numerical terms. What default rate should be expected among bonds with a CCC rating? How much riskier is a BB-rated bond than an A-rated bond? Questions like these are conveniently left unanswered by the rating agencies, who prefer to give qualitative comments like "obligations rated B are considered speculative and are subject to high credit risk" (Moody's 2020).

Second, as pointed out by Flannery, Houston, and Partnay (2010), rating agencies have gradually shifted from selling valuable information to selling "regulatory licenses". In other words, their business model has shifted from providing investors with insight to providing bond issuers with access to capital markets. As an example, consider an investment bank that approaches S&P in order to obtain a rating on a bond that it is marketing on behalf of a client. Naturally, the bank wants as high a rating as possible, because a higher rating will give investors an impression of a better risk/reward-profile, as long as the yield is held constant. S&P takes a fee for assigning the rating, regardless of whether or not their analysis accurately reflects the bond's credit risk. As a result, not only has S&P no real incentive to conduct careful analyses, they may also be inclined to assign unduly good ratings, in order to get more business from the investment banks. Thus, ratings may be highly biased, which has been empirically documented by Poon (2003). In spite of the abovementioned weaknesses, credit ratings are used in empirical analyses by Silva, Cortéz, and Armada (2003), Eom, Helwege, and Huang (2004), Bai, Bali, and Wen (2019) and many others.

Another, presumably more accurate, credit risk metric is the spread on credit default swaps (CDS). A CDS is essentially an insurance against payment default in an underlying bond or other financial instruments. Analogously to a regular insurance contract holder, the holder of a CDS pays a periodic premium and receives a larger payment in the event of a default. CDS prices are usually quoted in terms of the size of the premium, called the CDS spread. Consequently, the quoted spread reflects the current market opinion on the probability of a default in the underlying bond.

Given that the CDS spread is a continuous variable, determined by the market and not by a single institution, we find this to be a more practical and appropriate credit risk measure than credit ratings. Hence, we follow in the footsteps of Longstaff, Helwege, and Neis (2005), in basing our credit risk proxy on the market price of CDS premiums.

Flannery, Houston, and Partnay (2010) note that a common objection to using CDS spreads in empirical models is the lack of liquidity and coverage of the CDS market. This is still a valid point; according to International Swaps and Derivatives Association (2019), 542 unique underlying instruments accounted for 90% of the total single-name CDS market activity between mid-2015 and mid-2019. As a result, we cannot use CDS spreads to calculate the bond-level credit risk of every fund's underlying portfolio. Instead, we use an aggregate CDS index as a market-wide, systematic credit risk factor. Specifically, we use three CDS indexes; iTraxx Europe Crossover, CDX.NA.HY, and iTraxx Asia ex-Japan, covering the European, North-American and Asian corporate bond markets, respectively. If a fund primarily invests in European bonds, the credit risk factor is set equal to the European CDS index and so forth. For global funds, we use the American CDS index, as this one covers the largest share of the global market.

2.2.3 Downside Risk

In the previous section, we mention that credit risk is the only relevant risk factor for an investor who intends to hold a bond until maturity. This is clearly an overly stylized depiction of a bond investor. In reality, most asset managers are susceptible to permanent loss if the market value of their portfolios falls below some given threshold, even for only a short period. There are several reasons for this. First, many investors operate with some degree of leverage, meaning that a drop in portfolio value can trigger a margin call. Second, there is a plethora of research indicating that basic human psychology makes it difficult to hold on to a portfolio with decreasing market price, even for an investor who is certain of the underlying value. Akerlof and Shiller (2009) explore this phenomenon in their critically acclaimed book *Animal Spirits*. Third, and most relevant in the context of our study, investors who manage open-ended funds may have to sell assets to meet shareholder redemptions. When the market value of a fund portfolio declines, redemptions typically increase, forcing the fund manager to sell off assets at an unfavorable price, in a so-called "fire sale".

In light of the above discussion, it seems natural to add to our model a factor covering downside risk (DWS), which is the risk associated with a sudden, short-term drop in the market value of a bond. Here, the Value-at-Risk (VaR) measure is commonly used. We follow Bai, Bali, and Wen (2019) in constructing a proxy for 5% VaR by taking the second-lowest return over the past 40 trading days. We reuse the TRACE sample and find one VaR value for each bond each month. Similar sources of errors as those pointed out in Section 2.2.1 will also apply to this procedure. Nevertheless, we consider this approach the best way to capture the downside risk based on the data available.

2.2.4 Orthogonalization Procedure

It would be rather naive to expect all of our risk factors to be perfectly uncorrelated. Fama and French (1993) illustrate that, in an equity context, with several risk factors driving stock returns, all risk factors are baked into the market return factor. As a result, each risk factor must be somewhat correlated with both the market return and with every other risk factor. Given this correlation, it is necessary to orthogonalize the factor time series in order for our regression betas to reflect the associated risk factor premia accurately. However, since our core objective is to study volatility timing and not risk factor exposure, we do not find it necessary to include the CDS factor in this process. This inclusion would lead to a more involved process because we would have to first regress fund returns on the CDS factor to obtain a measure of CDS exposure on which sorting could be based.

We follow the orthogonalization procedure suggested by Fama and French (2015), but with a 3x3 sort, instead of their 5x5 sort, in order to get large enough sub-portfolios for sufficient diversification. Each month, bonds gathered from the TRACE database are sorted based on their exposure to the various risk factors. This yields two lists, one ILQ-sorted and one DWS-sorted. Each list is divided into three groups, resulting in two groups of bonds with a high factor exposure, two groups with a medium factor exposure, and two groups with a low factor exposure. The intersections ($\cap$) of every combination of these groups of bonds constitute nine portfolios with either a low, medium, or high exposure to each risk factor. Each portfolio is value-weighted, based on bond issuance size. The orthogonalized illiquidity factor, ILQ_{pt}, is set equal to the average return of the three value-weighted portfolios with a high liquidity risk exposure minus the average return of the three value-weighted portfolios with a low liquidity risk exposure. An analogous procedure is followed in the construction of DWS_{pt}.

2.2.5 The Volatility Timing Term

We use the approach of Busse (1999) as a starting point for developing a model that can capture volatility timing. The crux of his model is a simplified Taylor expansion of the market beta, given by

$$\beta_{pt}^{m} = \beta_{p0}^{m} + \gamma_p(\sigma_t^m - \overline{\sigma}^m), \tag{2.16}$$

where β_{pt}^{m} is the market beta of fund p at time t, β_{p0}^{m} is the average market beta of fund p, $(\sigma_t^m - \overline{\sigma}^m)$ is the de-meaned market volatility and γ_p is a volatility timing coefficient for fund p. In effect, the market beta is split up into a constant mean and a variable component, fluctuating between positive and negative values. Equation (2.16) is then substituted into the risk pricing models, which in our case are given by Equations (2.13) and (2.14). This yields our final models, based on CAPM and the four-factor model suggested by Bai, Bali, and Wen (2019), respectively:

$$R_{pt} - R^f_t = \alpha_p + \beta^m_{p0}(R^m_t - R^f_t) + \gamma_p(\sigma^m_t - \overline{\sigma}^m)(R^m_t - R^f_t) \tag{2.17}$$

and

$$\begin{aligned} R_{pt} - R^f_t = \alpha_p + \beta^m_{p0}(R^m_t - R^f_t) + \gamma_p(\sigma^m_t - \overline{\sigma}^m)(R^m_t - R^f_t) \\ +\beta^{ILQ}_p ILQ_{pt} + \beta^{CDS}_p CDS_{pt} + \beta^{DWS}_p DWS_{pt}. \end{aligned} \tag{2.18}$$

One could imagine expanding other regression coefficients in the manner of Equation (2.16) as well. Foran and O'Sullivan (2017) actually use this approach to study whether equity fund managers time market liquidity. In this thesis, we are mainly interested in market volatility timing, but we suggest timing of liquidity, and other risk factors for that matter, in the fixed income universe as a compelling area for future research.

2.2.6 Monthly Volatility and ARMA Modelling

For every market index, we estimate realized market volatility σ^r_t, in month t, with the following formula:

$$\sigma^r_t = \left(\sum_{n=1}^{N_t} (R^m_n - \bar{R}^m_n) \right)^{\frac{1}{2}} \tag{2.19}$$

where there are N_t daily returns, R^m_n, in month t.

To model monthly conditional volatility σ^{cm}_t at time t, we use an ARMA(1,1) model with a constant term and t-distributed errors terms:

$$\sigma^{cm}_t = c + \phi\sigma^{cm}_{t-1} + \theta\hat{\epsilon}_{t-1} + \hat{\epsilon}_t$$

$$\hat{\epsilon}_t | \hat{\epsilon}_{t-1}, \hat{\epsilon}_{t-2} ... \sim t(0, \hat{\sigma}_t) \tag{2.20}$$

where σ^{cm}_t is the conditional monthly volatility at time t, c is a constant term, ϕ is the autoregressive (AR) coefficient and θ is the moving average (MA) coefficient. $\hat{\epsilon}_t$ is the t-distributed residuals, and $\hat{\sigma}_t$ is the volatility of residuals.

This specification had the lowest Akaike information criterion (AIC) and Bayesian information criterion (BIC) for all indexes, compared to models with one and two AR and MA terms, with and without a constant term, and with Gaussian and t-distributed error terms.

2.2.7 Daily Volatility and GARCH Modelling

To model the daily conditional volatility, we evaluate various generalized autoregressive conditional heteroskedasticity (GARCH) models. The GARCH models are selected by estimating different models over the sample period for every index. We try specifications with one and two MA, AR and leverage terms, Gaussian, and t-distributed innovations and with and without a drift term. In addition to a regular GARCH specification, we also test an exponential GARCH (EGARCH), and the Glosten-Jagannathan-Runkle GARCH.

We choose the model with the lowest AIC and BIC. For ten out of eleven indexes, an EGARCH(1,1,1) with a drift term with t-distributed error terms was selected:

$$
\begin{aligned}
R_t^m - R_t^f &= c + \hat{\epsilon}_t \\
\hat{\epsilon}_t | \hat{\epsilon}_{t-1}, \hat{\epsilon}_{t-2} ... &\sim t(0, \hat{\sigma}_t) \\
ln(\sigma_t^{cd}) = \omega + \alpha \left(\frac{\hat{\epsilon}_{t-1}}{\sigma_{t-1}^{cd}} - E\left[\frac{\hat{\epsilon}_{t-1}}{\sigma_{t-1}^{cd}} \right] \right) &+ \beta ln(\sigma_{t-1}^{cd}) + \gamma \frac{\hat{\epsilon}_{t-1}}{\sigma_{t-1}^{cd}}
\end{aligned}
\tag{2.21}
$$

where c is the drift term, σ_t^{cd} is the daily conditional volatility, at time t, ω, α, β, are the coefficients of the EGARCH model and γ is the leverage term. $E\left[\frac{\hat{\epsilon}_{t-1}}{\sigma_{t-1}^{cd}}\right]$ with two or more degrees of freedom is defined as

$$
E\left[\frac{\hat{\epsilon_{t-1}}}{\sigma_{t-1}^{cd}} \right] = \sqrt{\frac{\nu - 2}{\pi}} \frac{\Gamma(\frac{\nu-1}{2})}{\Gamma(\frac{\nu}{2})}
\tag{2.22}
$$

where ν is the number of degrees of freedom and $\Gamma(\cdot)$ is the gamma function.

For the last index, the most suiting model, according to our criteria, was a GARCH(1,1) model with t-distributed error terms and a drift term:

$$
\begin{aligned}
R_t^m - R_t^f &= c + \hat{\epsilon}_t \\
\hat{\epsilon}_t | \hat{\epsilon_{t-1}}, \hat{\epsilon_{t-2}} ... &\sim t(0, \hat{\sigma}_t) \\
\sigma_t^{cd} &= \omega + \alpha \hat{\epsilon}_t + \beta \sigma_{t-1}^{cd}.
\end{aligned}
\tag{2.23}
$$

2.2.8 Synthetic Portfolios

Pro- or countercyclical volatility timing can occur either actively or passively. When fund managers make the conscious decision to reduce market exposure in response expectations of higher market volatility, we call it active countercyclical timing. From here on out, we will use the phrases "active timing" and simply "timing" interchangeably. Since CAPM beta can be expressed as

$$\beta_{pt} = \rho_{pt} \frac{\sigma_{pt}}{\sigma_t^m}, \tag{2.24}$$

beta can also decrease automatically if market volatility increases, without a corresponding increase in portfolio volatility σ_{pt} or correlation ρ_{pt}. We denote this phenomenon passive timing. Since the average CAPM beta for all assets in the market must always be equal to one, passive timing can only occur in certain sub-sections of the market. Nevertheless, since we are primarily interested in active timing, passive timing effects could distort our results. To mitigate this problem, we construct a synthetic portfolio for every real portfolio and repeat the regressions on the synthetic portfolios. Active volatility timing coefficients are then derived by subtracting the coefficients of synthetic portfolio regressions from the real volatility coefficients, thereby isolating the volatility timing effect attributable to active fund management.

In order for the artificial portfolios to be comparable to their real counterparts, they must be equally exposed to various risk factors. One way of achieving this is by following the characteristic-based approach of Daniel et al. (1997). That would entail forming one portfolio each period of time for every underlying fund asset based on the given asset's exposure to ILQ, CDS, DWS, and the market. The artificial portfolio return would then be constructed as the sum of the differences in returns between each underlying asset and its associated benchmark portfolio, weighted by the funds' share of total allocation placed in the given asset.

Since we do not have access to underlying fund assets, this procedure becomes impossible. Instead, like Busse (1999), we follow Sharpe (1992) in determining appropriate risk factor exposures for the artificial portfolios by means of *style analysis*. This involves solving a quadratic programming problem that minimizes the variance of the return difference between the real fund portfolios and their associated synthetic portfolios:

$$\min_{\beta_p^1,\ldots,\beta_p^n} \left[Var\left(R_{pt} - \sum_{i=1}^{n} \beta_p^i R_t^i \right) \right] \tag{2.25}$$

$$\sum_{i=1}^{n} \beta_p^i = 1,$$

where R_t^i is the return of factor i in period t, and β_p^i is the exposure of portfolio p to factor i. When adapted to our case, the objective function becomes

$$\min_{\beta_p^m, \beta_p^{ILQ}, \beta_p^{CDS}, \beta_p^{DWS}} \Big[Var\Big(R_{pt} - \big(\beta_p^m R_t^m + \beta_p^{ILQ} ILQ_{pt} + \beta_p^{CDS} CDS_{pt} + \beta_p^{DWS} DWS_{pt} \big) \Big) \Big] \tag{2.26}$$

or

$$\min_{\beta_p^1, \ldots, \beta_p^{11}} \left[Var\left(R_{pt} - \sum_{i=1}^{11} \beta_p^i R_t^i \right) \right], \tag{2.27}$$

depending on whether we want to determine fund style with respect to risk factor exposures or to asset class exposures. We choose a similar approach as Sharpe, and calculate the synthetic portfolios using Equation (2.27).

After solving this optimization problem, synthetic portfolio returns are set equal to the sum of resulting factor exposures multiplied by the associated factor returns. Evidently, it is not necessary to form actual bond-level portfolios. Indeed, for our purposes, it is sufficient to determine the *style* of each fund.

2.2.9 Persistence in Volatility Timing

Evidence of volatility timing in past fund performance does not necessarily indicate that the fund manager is persistently applying a volatility timing strategy. To investigate whether volatility timing is persistent over longer time periods, we adopt a similar method as Carhart (1997) and Foran and O'Sullivan (2017). The process is applied separately for daily and monthly return data. Two different time windows are used to evaluate persistence in volatility timing. On daily return data, windows of one and four year returns are used, respectively, to estimate two separate models. On monthly returns, only a four year time period is estimated due to the low number of monthly observations in a one year window. We set an inclusion-threshold of at least 128 daily observations for funds in the one year window model, and 256 daily or 12 monthly observations for the four year window model.

Starting in 2010, the four-factor volatility timing model previously defined in Equation (2.18),

$$R_{pt} - R_t^f = \alpha_p + \beta_{p0}^m(R_t^m - R_t^f) + \gamma_p(\sigma_t^m - \overline{\sigma}^m)(R_t^m - R_t^f) \\ +\beta_p^{ILQ} ILQ_{pt} + \beta_p^{CDS} CDS_{pt} + \beta_p^{DWS} DWS_{pt}, \tag{2.18}$$

is estimated for each fund over a one or four year time period, respectively. After this period, the funds are sorted based on their volatility timing coefficient t-statistic, where the lowest values represent the most countercyclical timers, and the highest values represent the most procyclical timers. We then divide the sorted funds into five equally weighted quintile portfolios, which are held for one year. If a fund disappears during this year, the return weights are redistributed equally between the remaining funds. Finally, we form an equally weighted portfolio that is long in the first quintile of most countercyclical timers, and short in the fifth quintile of most procyclical timers. The whole process is repeated by shifting the one- or four-year return window one year forward and applying the same regression as before. This yields a portfolio of weighted returns for each year until 2020.

The portfolio returns are regressed on the simplified volatility timing model given by Equation (2.28),

$$R_{pt} - R_t^f = \alpha_p + \hat{\gamma}_p(\sigma_t^m - \overline{\sigma}^m)(R_t^m - R_t^f), \tag{2.28}$$

where $R_{pt} - R_t^f$ is the weighted time series of fund returns. The resulting $\hat{\gamma}_p$ coefficient can be interpreted as a measure of persistence in volatility timing. We set the null hypothesis to $H0 : \hat{\gamma}_p = 0$, indicating that funds do not time persistently over time. Since the portfolio is long-short, the alternative hypothesis is one-sided, and is therefore, $H1 : \hat{\gamma}_p < 0$, meaning that persistence in volatility timing ability exists.

2.2.10 Statistical Testing

We employ a selection of different test statistics to assess the statistical significance of various model results. In this section, we discuss the nature of these tests.

As will be discussed in more depth later on, there is a substantial degree of both autocorrelation and heteroscedasticity present in our data set. Consequently, coefficient estimates based on ordinary least squares (OLS) will be unbiased but inefficient. To alleviate this problem, we follow Foran and O'Sullivan

(2017) in using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with two lags.

To find the statistical significance of active timing coefficients in Section 4.2 and 4.3, and differences between performance measures in Section 4.5, we use Welch's t-tests from Welch (1947) and randomized permutation tests. Welch's t-test is more robust to type I errors, than regular t-tests, when conducting tests on samples with different variances and sizes (Delacre, Lakens, and Leys 2017).

Randomized permutation tests, on the other hand, have no underlying assumption of distribution or homoscedasticity, allowing for further relaxations of assumptions when conducting hypothesis testing (Pesarin and Salmaso 2010). Using an exact permutation test will yield unbiased p-values, but this is computationally heavy and has therefore not been done. Hence, some p-values from permutation testing may differ from their true value. The results in Tables C.7 through C.10 in Appendix C show that the permutation tests in general estimate higher p-values than the Welch tests. The most plausible explanation, based on the distribution of the data, is that the residuals from the regressions are not normally distributed. Outliers occur too often, and the data show signs of leptokurtosis, which is common in financial data (Cuthbertson, Nitzsche, and O'Sullivan 2012; Kosowski et al. 2006; Levy 2010). Nevertheless, the p-values usually only differ significantly when the p-values in question are large. Highly significant values tend to stay significant at the 5% or 10 % level.

To test for independence between observed and expected values in Section 4.4, we use Pearson's chi-squared test. This test is recommended when the sample size is larger than 20, and the expected values of cells are larger than 5, in addition to being straightforward compared to other Fischer's exact test when the contingency table is larger than 2x2 (Pett 2015).

3 Data

This chapter outlines the retrieval and processing of input data for the models described in Section 2.2.

3.1 Data Sources

First, we present our data sources and discuss some key properties of the derived data. The following sections do so for fund returns, benchmark index returns, and individual bond returns.

3.1.1 Fund Sample

The scope of this paper is limited to studying funds that mainly invest in bonds issued by corporations. To obtain a fund sample that satisfies this criterion, we use the Fund Screener tool on Morningstar's Norwegian web site. This does not entail that the majority of our funds are Norwegian, only that they are registered for sale in Norway. Morningstar operates with an extensive fund categorization system, including 249 different mutual fund categories. The category names usually indicate what type of securities the included funds invest in, and which currency the investment is denominated in. This allows us to screen funds by only including funds that belong to a corporate bond fund category. We identify eleven corporate bond categories, comprising a total of 1617 funds. Appendix A contains an overview of the fund categories, along with summary statistics of fund return time series.

We study returns over the ten-year interval stretching from 1 January 2010 to 1 January 2020. Naturally, some return time series will be shorter than ten years, as a result of funds being launched at some point between these two dates.

Monthly fund returns are retrieved from Datastream. Here, monthly total returns, wherein dividend payouts are assumed to be automatically reinvested, are readily available. The Datastream database does not include corresponding daily time series. Instead, we extract daily net asset value (NAV) figures, along with dividend payouts. Daily total returns are then calculated as

$$R_{pt} = \frac{NAV_{pt} + DIV_{pt}}{NAV_{pt-1}} - 1, \tag{3.1}$$

where NAV_{pt} is the net asset value of fund p on day t and DIV_{pt} is the dividend payout of fund p on day t.

Our sample contains survivorship bias, as neither dissolved nor merged funds are included. Because funds are usually dissolved in response to poor performance, the sample exhibits a general skew towards superior performance. However, survivorship bias is less influential when studying bond funds rather than equity funds, since bond fund performance is less variable, and consequently fewer funds dissolve or merge (Blake, Elton, and Gruber 1993). Busse (1999) studied the link between volatility timing and survival of funds, and found that non-surviving funds tend to not time volatility. Based on the relation between performance and survival of funds, the non-timing funds in our sample may have a larger bias towards positive performance than that of the timing funds. Hence, non-timing funds could appear to perform unduly well, relative to timing funds.

Incubation bias is, in all likelihood, present in our sample. Fund incubation is a technique used by asset managers in the initiation phase (Evans 2010) of a fund. A set of funds is started privately and evaluated after a time period. Some of the best performing funds are then opened up to the public. Because the incubation period is included in the performance history, we get an oversampling of successful funds. To the authors' knowledge, the impact of this bias has not yet been studied in regard to volatility timing, and we assume this bias to affect the timing and non-timing funds equally. Removal of this bias would lead to a substantial reduction in the number of data points and funds. Thus, we have chosen not to adjust for this bias. Nevertheless, both incubation and survivorship bias should be taken into consideration when interpreting performance results.

3.1.2 Benchmark Indexes

The Morningstar website is used for assigning a benchmark index to each fund in our sample. Specifically, Morningstar suggests an appropriate benchmark for each fund category, which is applied to every fund of the given class. An overview of the categorization and associated benchmark indexes of our sample is presented in Table A.1 in the Appendix. All benchmark return time series are extracted from Morningstar.

As an alternative approach, we could have applied the funds' self-designated benchmarks. We have refrained from doing so because fund managers are incentivized to suggest benchmarks that are easily outperformed. This argument is supported by Sensoy (2009), who finds that outperformance of a self-designated benchmark positively affects subsequent cash inflows, regardless of whether or not the benchmark is suitable.

3.1.3 Currency Considerations

As evident in Table A.1, all funds in our sample are denominated in either USD, EUR, or GBP. In order to eliminate the impact of exchange rate fluctuations, all fund and benchmark returns are retrieved in their default currencies. For example, return data for the benchmark index BBgBarc US Corporate High Yield TR USD is retrieved in USD terms. If this time series had instead been Euro-denominated, a compounded 29% additional benchmark return would have been observed in the sample period, because of USD appreciation relative to EUR in our period of study. In addition, exchange rate fluctuations may distort coefficient estimates. Clearly, the return time series of a USD-denominated fund could still be affected by variable exchange rates if, for instance, the fund invests in Euro-denominated assets. Returns of the non-hedged part of currency-hedged funds will also be affected by currency fluctuations.

Risk-free interest rates are also retrieved from Datastream. We use the ask yields of three-month US Treasury bills, UK government bonds, and German government bonds as proxies for risk-free rates in USD, GBP, and EUR, respectively.

3.1.4 Bond Sample

Following the recommendation from Bessembinder, Maxwell, and Venkataraman (2006), the bond data used to construct the liquidity and downside risk factors is gathered from TRACE. This database includes transaction data covering more than 25.000 US corporate bonds, making up 99.9% of the total market. We extract prices, bond identifiers (CUSIPs), and timestamps for all transactions from November 2009 through December 2019. The data sample begins two months before the beginning of our period of study in order to make the calculation of downside risk factors in January and February 2010 possible. To construct value-weighted sub-portfolios in the risk factor process, we extract the issuance size of all bonds from Datastream.

3.2 Data Processing

In the following sections, we will outline how the raw data from the above-mentioned sources was processed, and what removal criteria were applied.

3.2.1 Fund Data

Fund returns are based on NAVs, which could lead to some inaccuracies. First, several funds in the sample report equal NAVs on consecutive days. This could be caused by low returns and rounding errors. However, such an explanation is unlikely to be the case over longer time periods. A more likely explanation for these observations is that the funds have not reported updated NAVs. To avoid an overrepresentation of zero returns, NAV values that are equal over three or more consecutive days are therefore removed from the sample. Second, some funds report large jumps in NAVs between two consecutive observations, likely caused by events like share class restructurings. Fund share structure is not relevant for our research, but the large jumps in NAV could cause erroneously large returns to be calculated if left unaddressed. NAVs that change by more than 10% on two consecutive observations are therefore removed from the sample. After calculating fund returns based on NAVs and dividend payouts, funds with less than 252 (12) data points on a daily (monthly) basis are finally excluded from the data sample.

3.2.2 Bond Data

Data points with erroneous or missing data from TRACE are removed. Specifically, bonds without issuance size from Datastream are taken out of the sample. All transactions without CUSIPs or with prices equal to or below zero are removed. Transactions on non-trading days (Saturdays, Sundays or bank holidays) are also removed.

A return data point is only included if the bond has at least one registered transaction at the previous trading day to ensure a consistent measure of returns. Bonds with less than four returns in any given month are omitted as this is the minimum requirement to construct the illiquidity measure, ILQ. These procedures introduce a bias where the most illiquid bonds are removed. Nevertheless, we would not be able to capture the underlying changes of the bonds' value without historical bid-ask prices or other estimates of their value on days without transactions.

4 Empirical Results

In this chapter, empirical model results will be presented and discussed. We begin with coefficient estimates from the basic four-factor model in Section 4.1, then continue with the models capturing prevalence, persistence and consistency in volatility timing, in Sections 4.2 through 4.4. Finally, in Section 4.5, we discuss the impact of volatility timing on fund performance.

4.1 Basic Model

Before diving into the volatility timing models, we find it helpful to present the results from the four-factor regression model in Equation (2.14) based on daily and monthly returns. Results from the CAPM regression model in Equation (2.13) and complementary synthetic portfolio regressions are provided in Appendix B. All regressions are estimated using the OLS method.

4.1.1 Daily Regressions

Mean values of coefficient estimates from the daily four-factor regressions are presented in Table 4.1. Funds are grouped by their associated Morningstar category and benchmark index. An overview of categories and benchmark indexes is presented in Table A.1 in the Appendix.

As evident in the second column, all market betas are statistically significant and positive, ranging from 0.41 to 0.84. This is important because, without a certain level of market exposure among the funds in our sample, it would be meaningless to study market volatility timing in the first place. The ILQ-, CDS- and DWS-factors are statistically significant for some categories and insignificant for others. Caution must be taken when considering the absolute value of β_p^{CDS} because CDS spreads are far more volatile than fund returns. Consequently, these beta values will naturally be lower than those of the other risk factors.

Table 4.1: Four-Factor Regression Coefficients With Daily Data
This table reports the coefficients from regressing daily fund returns on the four-factor model in Equation (2.14). All coefficients are provided as the mean value of individual fund regressions in the corresponding category.

	$\alpha(\%)$	β^m	β^{ILQ}	β^{CDS}	β^{DWS}	R^2
All	0.506**	0.663**	0.006	0.001	0.040**	0.515
High Yield						
Asian HY	−0.054	0.843**	0.038*	0.000	0.030	0.497
European HY	−0.441**	0.779**	0.009*	0.001**	0.025**	0.578
Global HY	1.731**	0.425**	0.066**	0.000	0.129**	0.384
Global HY HEUR	−0.192	0.758**	−0.052**	0.002**	−0.038**	0.433
Global HY HGBP	0.022	0.773**	−0.064**	0.003*	−0.054**	0.399
US HY	0.579**	0.754**	−0.018**	0.002	−0.005	0.588
Investment Grade						
European IG	0.263**	0.769**	0.013**	−0.002**	0.025**	0.598
Global IG	0.631	0.411**	0.074	0.001	0.168**	0.476
Global IG HEUR	0.548**	0.513**	0.001	−0.001*	0.090**	0.469
Global IG HUSD	1.280**	0.542**	−0.006	0.000	0.081**	0.478
US IG	0.491**	0.679**	0.019	0.001	0.047**	0.706

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

We note that mean alphas are statistically significant for several categories of funds. The values are, however, economically small. In conjunction with the relatively high R^2-values, this implies that our model has a high degree of explanatory power. Nonetheless, these R^2-values are not much higher than those of Table B.1 in the Appendix, obtained by running a simple CAPM regression. This could be an indication that some of the bond-level risk factor exposure identified by Bai, Bali, and Wen (2019) gets diversified away at the portfolio level.

Another reason why the market factor appears to soak up the majority of explanatory power could be that the market indexes are overly "customized". When researching equity markets, one conventionally employs a single market index believed to represent the entire regional equity market, such as the S&P 500, whereas we rely on indexes representing a particular sub-section of the market. Consequently, if the subsection that a given index represents is, for instance, more exposed to credit risk than the rest of the market, then some explanatory power will be transferred from the credit risk factor to the market factor.

It must be noted that there is significant intercorrelation between the various risk factors in our model, meaning that it suffers from multicollinearity. As a result, coefficient estimates will be inefficient but remain unbiased. Thus, we may sometimes fail to reject the null hypothesis that a coefficient is equal to zero, even though the underlying variation suggests it should be rejected.

4.1.2 Monthly Regressions

Figures equivalent to those in Table 4.1, but based on monthly regressions, are presented in Table 4.2. It comes as no surprise that market betas estimated on monthly returns are higher than those estimated on daily returns, as this observation is well-documented in the literature (Handa, Kothrani, and Wasley 1989; Hawawini 1983). Beyond this, it is notable that the ILQ-, CDS- and DWS-factor exposures switch signs for several categories of funds when moving from daily to monthly regressions. This can possibly be attributed to the previously mentioned multicollinearity, which leads to instability in coefficient estimates.

Table 4.2: Four-Factor Regression Coefficients With Monthly Data
This table reports the coefficients from regressing monthly fund returns on the four-factor model in Equation (2.14). All coefficients are provided as the mean value of individual fund regressions in the corresponding category.

	$\alpha(\%)$	β^m	β^{ILQ}	β^{CDS}	β^{DWS}	R^2
All	-0.168^{**}	0.805^{**}	0.154^{**}	-0.007^{**}	0.040^{**}	0.877
High Yield						
Asian HY	-0.875^{**}	0.992^{**}	0.364^{**}	0.002	−0.062	0.781
European HY	-0.427^{**}	0.803^{**}	0.065^{**}	-0.008^{**}	0.039^{**}	0.904
Global HY	0.974^{**}	0.509^{**}	0.443^{**}	-0.023^{**}	0.162^{**}	0.838
Global HY HEUR	-0.939^{**}	0.901^{**}	0.058^{*}	-0.009^{**}	-0.071^{**}	0.889
Global HY HGBP	-0.603^{**}	0.929^{**}	0.067^{*}	−0.004	-0.080^{**}	0.903
US HY	-0.562^{**}	0.895^{**}	0.157^{**}	0.003	-0.058^{**}	0.859
Investment Grade						
European IG	0.073	0.902^{**}	0.035^{*}	-0.008^{**}	0.066^{**}	0.907
Global IG	−0.252	0.618^{**}	0.338^{**}	0.015^{*}	0.196^{**}	0.702
Global IG HEUR	-0.255^{**}	0.806^{**}	0.071^{**}	-0.009^{**}	0.110^{**}	0.898
Global IG HUSD	−0.105	0.876^{**}	0.094^{**}	-0.005^{**}	0.084^{**}	0.906
US IG	−0.132	0.812^{**}	0.158^{**}	0.001	0.024	0.896

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

The R^2-values are also considerably higher in the monthly than in the daily setting. This should be expected, as idiosyncratic noise that hampers model fit on a daily basis gets smoothed out when using monthly return series. However, once again, R^2-values are only marginally higher than those of equivalent CAPM regressions. The first column of Table 4.2 reveals that actively managed bond funds generally struggle to obtain positive risk-adjusted returns, whereas, in the daily setting, we observed less negative alpha values. This is likely due to the beta values being higher in the monthly than in the daily setting. The poor performance is particularly evident in the HY segment, where five out of six fund categories underperform significantly. HY fund underperformance has previously been documented by Blake, Elton, and Gruber (1993) and Trainor (2010).

4.2 Daily Volatility Timing

In Table 4.3, the volatility timing coefficients resulting from daily OLS estimation of Equations (2.17) and (2.18) are presented. When discussing volatility timing coefficients, our main focus will be on $\gamma_{adjusted}$, which we consider a more reliable estimate than simply γ, for reasons previously discussed.

A quick glance at Table 4.3 reveals that volatility timing coefficients are not particularly sensitive to model specification. This is probably due to market indexes having superior explanatory power compared to the other risk factors. There is, however, substantial variation across funds associated with different benchmark indexes. With the exception of European IG funds, the majority of IG funds appear to be timing volatility countercyclically. This behavior is similar to that observed by researchers in equity markets. On the other hand, most managers exhibit an inclination towards timing volatility procyclically when considering HY funds. This contradicts what one would expect based on both the theoretical models in Section 2.1 and literature on equity markets. What is more, Busse (1999) finds the tendency to time volatility countercyclically to be more prevalent among growth funds than among income funds, suggesting that countercyclical timing is primarily an attribute of "aggressive" funds. Giambona and Golec (2009) arrives at a similar conclusion. With this in mind, one might have expected to see more countercyclical timing among HY funds, which are perceived as more aggressive than IG funds.

To investigate these peculiar results further, we consider the market return autocorrelation and the correlation between returns and conditional volatility. As evident in the first and fourth columns of results in Table 4.4, there

Table 4.3: Timing Coefficients of Daily Conditional Volatility
The table reports the average timing coefficients of daily conditional volatility in each fund category, obtained from regressions of the CAPM model in Equation (2.17) and four-factor model in Equation (2.18), with daily return data. γ is the average timing coefficient from the regressions, with t-statistics based on two-sided t-tests. $\gamma_{adjusted}$ is the timing coefficient adjusted for passive timing, with t-statistics from Welch's t-test.

	CAPM		Four-Factor	
	$\gamma_{adjusted}$	γ	$\gamma_{adjusted}$	γ
High Yield				
Asian HY	4.95**	4.11**	5.94**	5.32**
European HY	0.74**	0.60**	1.05**	0.77**
Global HY	1.42**	5.40**	2.26**	6.20**
Global HY HEUR	1.01**	1.44**	0.98**	1.26**
Global HY HGBP	2.61**	2.96**	2.92*	3.20**
US HY	0.89**	0.54**	1.12**	0.46
Investment Grade				
European IG	2.53**	3.52**	4.32**	4.75**
Global IG	−2.30	−2.78	−3.39	−3.83*
Global IG HEUR	−1.25	−1.96*	−2.27	−2.95*
Global IG HUSD	−1.39	−1.87*	−2.06	−2.44*
US IG	−1.45*	−1.87**	−2.04*	−2.85**

* Significant at the 5% level.
** Significant at the 1% level.

Table 4.4: Autocorrelation, and Correlation of Returns and Conditional Volatility
This table presents the daily and monthly autocorrelations ($\rho_{t,t-1}$) of the benchmark indexes associated with the different fund categories, and the daily and monthly correlation between returns and conditional volatility ($\rho_{\sigma r}$). The last column is the R^2 value obtained by regressing monthly conditional volatility on realized volatility.

	$\rho_{t,t-1_{daily}}$	$\rho_{t,t-1_{monthly}}$	$\rho_{\sigma r_{daily}}$	$\rho_{\sigma r_{monthly}}$	R^2
High Yield					
Asian HY	0.32	−0.05	0.00	0.19	0.23
European HY	0.40	0.02	−0.06	0.24	0.33
Global HY	0.34	−0.04	−0.04	0.21	0.21
Global HY HEUR	0.42	0.00	−0.09	0.17	0.22
Global HY HGBP	0.41	0.01	−0.09	0.18	0.22
US HY	0.39	−0.02	−0.05	0.16	0.25
Investment Grade					
European IG	0.08	0.01	−0.02	0.07	0.33
Global IG	−0.02	−0.01	−0.02	0.02	0.44
Global IG HEUR	−0.04	0.04	−0.02	0.00	0.28
Global IG HUSD	−0.03	0.03	−0.02	−0.03	0.28
US IG	−0.10	0.01	−0.01	0.03	0.35

is an apparent connection between these two properties. If returns are autocorrelated, then there will also be some correlation between conditional volatility and contemporaneous returns.

The $\rho_{\sigma r_{monthly}}$ column of Table 4.4 suggests a viable explanation for the surprisingly positive timing coefficients of HY funds; the correlation between returns and conditional volatility is consistently higher here than in investment grade markets. A positive correlation encourages fund managers to time procyclically, because carrying a high market exposure in an increasingly volatile environment will be rewarded with higher returns. Conversely, in times of volatility compression, market returns will be lower on average, motivating managers to reduce market exposure. It might seem dubious that we are emphasizing monthly, rather than daily correlations when discussing daily gamma values. We do this because ARMA-modelled conditional volatility simply leads to a better forecast of realized volatility than GARCH-modelled conditional volatility. Goyal (2020) finds that regressing daily GARCH-modelled forecasts on realized volatility yielded an R^2 of merely 8%. Since we do not have access to intraday data, we cannot test this relation in the daily setting ourselves. However, we note that regressing ARMA-based conditional volatility on realized volatility results in R^2-values way above those of Goyal (2020). Hence, we view the monthly ARMA-based correlation between conditional volatility and returns as the best representation of the actual correlation between expected volatility and realized returns.

With reference to the theoretical models developed in Section 2.1, recall that they suggested countercyclical timing to be optimal when $E_t[R_{jt+1}] > 0$, as long as $\partial E[R_m]/\partial\sigma_m^2 \leq 0$, i.e. as long as the correlation between market returns and conditional volatility is small or negative. As it turns out, this condition is not fulfilled in our data set, meaning that our empirical results do not necessarily contradict theoretical expectations.

At this point, the reader may ask himself: why would market return time series be autocorrelated? In the book *Yield Curve Dynamics: State of the Art Techniques for Modelling, Trading and Hedging*, Ronald J. Ryan states that bond index returns generally exhibit substantially more (positive) autocorrelation than stock index returns. This stems from the accrual of interest constituting a significant component of bond returns over a given period. Since accrual of interest is somewhat predictable, so is a portion of bond index returns. We emphasize that this argument holds for dirty prices, which are the relevant ones in our case, and not for clean prices.

Table 4.5 presents the percentages of funds for which the volatility timing coefficients are significantly positive, significantly negative, or insignificant,

Table 4.5: Percentage of Funds Timing Daily Conditional Volatility
The table reports the percentage of funds timing daily conditional volatility procyclically (Pro), countercyclically (Counter), or not timing (Neutral), grouped by category. In Panel A, funds are classified as timers if the volatility timing coefficient from regressions of the CAPM model in Equation (2.17) or four-factor model in Equation (2.18) is significant at the 5% level, based on two-sided t-tests with Newey-West standard errors. In Panel B, volatility timing coefficients are adjusted for passive timing, and statistical significance based on two-sided Welch's t-tests with Newey-West standard errors.

	CAPM			Four-Factor		
	Pro (%)	Neutral (%)	Counter (%)	Pro (%)	Neutral (%)	Counter (%)
Panel A: γ						
All	35.1	48.7	16.1	33.5	50.4	16.1
High Yield	41.1	42.6	16.3	38.5	45.8	15.7
Investment Grade	25.1	59.0	15.9	25.1	58.2	16.7
High Yield						
Asian HY	45.0	50.0	5.0	45.0	50.0	5.0
European HY	45.0	35.3	19.7	44.0	38.1	17.9
Global HY	59.0	36.2	4.9	54.0	42.0	4.0
Global HY HEUR	32.6	51.4	16.0	26.4	56.6	17.0
Global HY HGBP	41.5	39.6	18.9	37.7	39.7	22.6
US HY	25.0	48.4	26.2	27.0	48.4	24.6
Investment Grade						
European IG	35.5	51.7	12.8	32.9	53.9	13.2
Global IG	23.3	46.5	30.2	20.9	46.5	32.6
Global IG HEUR	17.0	67.0	16.0	23.0	62.0	15.0
Global IG HUSD	18.2	71.4	10.3	20.6	67.5	11.9
US IG	18.6	57.8	23.5	16.7	57.8	25.5
Panel B: $\gamma_{adjusted}$						
All	20.1	67.2	12.7	20.2	67.0	12.9
High Yield	26.5	57.4	16.1	26.0	59.2	14.8
Investment Grade	9.4	83.6	6.9	10.4	80.0	9.6
High Yield						
Asian HY	45.0	50.0	5.0	45.0	50.0	5.0
European HY	34.9	50.0	15.1	34.9	51.4	13.8
Global HY	17.7	63.8	18.5	17.7	66.8	15.5
Global HY HEUR	20.8	63.7	15.6	13.2	72.2	14.6
Global HY HGBP	39.6	41.5	18.9	37.7	41.5	20.8
US HY	29.1	55.7	15.2	34.0	51.2	14.8
Investment Grade						
European IG	14.5	78.6	6.8	15.0	77.8	7.3
Global IG	11.6	74.4	14.0	11.6	65.1	23.3
Global IG HEUR	4.0	90.0	6.0	6.0	85.0	9.0
Global IG HUSD	4.0	90.5	5.6	7.1	84.1	8.7
US IG	8.8	84.3	6.9	7.8	81.4	10.8

respectively. Regardless of model specification, there are approximately twice as many procyclical timers as countercyclical timers among HY fund managers, which is in line with the conclusions drawn regarding Tables 4.3 and 4.4. Among IG fund managers, however, the distribution of procyclical and countercyclical timers is virtually even. This is mainly due to European IG funds timing procyclically, as opposed to their American counterparts, which time countercyclically. In general, the number of IG funds with insignificant timing coefficients is substantially higher than that of HY funds, which is in line with the relatively low number of significant gamma values for IG funds in Table 4.3. With this in mind, we probably should not put too much emphasis on the signs of the timing coefficients of IG funds.

4.3 Monthly Volatility Timing

In this section, we discuss monthly volatility timing results based on conditional and realized volatility. Volatility time series are based on the methodology outlined in Section 2.2.6.

4.3.1 Conditional Volatility

Tables 4.6 and 4.7 present the results obtained by running analyses equivalent to those in Section 4.2, but with a monthly instead of a daily frequency. Note that, although the methodology is equivalent to that of the previous section, monthly and daily volatility timing are different concepts. While the latter requires daily adjustments, the former can be done with more gradual, long-term adjustments.

In general, monthly regressions yield substantially fewer significant volatility timing coefficients. As evident in Table 4.6, the total share of funds with statistically insignificant gammas ranges from 69% to 81%, depending on model specification, whereas the corresponding daily figures lay between 49% and 67%. When comparing Table 4.6 to Table 4.3, we also notice that these results are more sensitive to model specification than the previous ones.

According to Table 4.6, the only funds that exhibit statistically significant volatility timing behavior across all models are Asian HY funds. These appear to be timing procyclically, as they did in the daily context.

At first glance, Table 4.7 may give the impression that monthly volatility timing is virtually non-existent in bond markets. The percentages of funds with statistically significant timing coefficients are, however, surprisingly similar to those found by Foran and O'Sullivan (2017) in equity markets.

Table 4.6: Timing Coefficients of Monthly Conditional Volatility
The table reports the average timing coefficients of monthly conditional volatility in each fund category, obtained from regressions of the CAPM model in Equation (2.17) and four-factor model in Equation (2.18), with monthly return data. γ is the average timing coefficient from the regressions, with t-statistics based on two-sided t-tests. $\gamma_{adjusted}$ is the timing coefficient adjusted for passive timing, with t-statistics from Welch's t-test.

	CAPM		Four-Factor	
	$\gamma_{adjusted}$	γ	$\gamma_{adjusted}$	γ
High Yield				
Asian HY	9.08	14.14*	11.26	11.31
European HY	0.34	2.69**	1.89*	2.96**
Global HY	−0.68	7.37**	1.20	10.46**
Global HY HEUR	−2.19	−3.23**	−1.07	−0.68
Global HY HGBP	−3.11	−2.02	−2.53	−1.15
US HY	−0.82	−1.38	−2.71**	−3.43**
Investment Grade				
European IG	7.45	−1.48	5.30	2.66
Global IG	−11.11	−14.44*	−12.86	−16.74*
Global IG HEUR	0.21	6.60*	−1.66	5.92
Global IG HUSD	−5.57**	1.87	−6.42**	−0.99
US IG	0.30	4.90*	−3.00	−0.63

* Significant at the 5% level.
** Significant at the 1% level.

Table 4.7: Percentage of Funds Timing Monthly Conditional Volatility
The table reports the percentage of funds timing monthly conditional volatility procyclically (Pro), countercyclically (Counter), or not timing (Neutral), grouped by category. In Panel A, funds are classified as timers if the volatility timing coefficient from regressions of the CAPM model in Equation (2.17) or four-factor model in Equation (2.18) is significant at the 5% level, based on two-sided t-tests with Newey-West standard errors. In Panel B, volatility timing coefficients are adjusted for passive timing, and statistical significance based on two-sided Welch's t-tests with Newey-West standard errors.

	CAPM			Four-Factor		
	Pro (%)	Neutral (%)	Counter (%)	Pro (%)	Neutral (%)	Counter (%)
Panel A: γ						
All	13.8	71.5	14.7	17.6	68.8	13.7
High Yield	13.5	72.6	13.9	18.6	69.9	11.6
Investment Grade	14.3	69.7	16.0	15.8	67.0	17.2
High Yield						
Asian HY	35.0	65.0	0	35.0	65.0	0
European HY	19.0	75.8	4.7	26.0	71.1	3.3
Global HY	18.0	78.4	3.2	30.0	69.6	0.8
Global HY HEUR	8.7	71.4	20.0	9.7	77.7	13.0
Global HY HGBP	6.1	73.5	20.4	8.2	77.5	14.3
US HY	7.0	64.8	28.3	9.0	60.9	30.0
Investment Grade						
European IG	18.7	57.8	23.5	23.9	52.6	23.5
Global IG	12.2	61.0	26.8	17.1	56.1	26.8
Global IG HEUR	7.0	81.4	11.0	10.0	76.3	13.0
Global IG HUSD	8.3	79.3	12.4	6.6	76.9	16.5
US IG	19.8	77.1	3.1	13.5	83.3	3.1
Panel B: $\gamma_{adjusted}$						
All	5.2	80.9	13.9	8.0	77.7	14.3
High Yield	6.0	82.1	11.9	8.2	81.8	10.0
Investment Grade	3.7	79.1	17.2	7.8	70.8	21.4
High Yield						
Asian HY	10.0	90.0	0	30.0	70.0	0
European HY	14.7	83.4	1.9	22.3	75.8	1.9
Global HY	0.4	94.8	4.8	1.2	96.8	2.0
Global HY HEUR	4.4	82.0	13.6	4.4	81.1	14.6
Global HY HGBP	4.1	79.6	16.3	6.1	79.6	14.3
US HY	6.0	67.0	27.0	5.2	73.0	21.9
Investment Grade						
European IG	7.0	70.9	22.2	15.2	56.1	28.7
Global IG	4.9	87.8	7.3	12.2	80.5	7.3
Global IG HEUR	2.1	82.5	15.5	5.2	75.3	19.6
Global IG HUSD	0.8	82.6	16.5	0	77.7	22.3
US IG	1.0	86.5	12.5	1.0	87.5	11.5

They estimate 11% of equity funds to be procyclical timers and 21% to be countercyclical timers.

4.3.2 Realized Volatility

Tables 4.8 and 4.9 present results from monthly regressions based on realized volatility, rather than ARMA-based conditional volatility. Comparing the results of Table 4.6 to Table 4.8 suggests that timing based on realized volatility and timing based on conditional volatility are very different concepts. For starters, the realized market volatility during a given month is not known to a fund manager until the end of that month. Hence, we would expect the share of funds with insignificant timing coefficients to be higher when employing the realized volatility, rather than the conditional. Table 4.9 confirms this hypothesis. The total percentage of insignificant volatility timers ranges from 76% to 87%, depending on model specification, versus 72% to 81% in the case of conditional volatility. A few categories of funds also appear to be timing conditional volatility one way, and realized volatility the other. This phenomenon is only statistically significant for European IG funds in the CAPM setting, and US HY funds in the four-factor setting. The former time conditional volatility procyclically and realized volatility countercyclically, while the latter time conditional volatility countercyclically and realized volatility procyclically.

Does it make sense to time realized and conditional volatility in opposite directions? Admittedly, the figures in Table 4.8 do not necessarily imply that individual funds follow such a strategy, only that a group of funds as a whole does. Still, the fact that this behavior is recorded for groups of relatively homogeneous funds is rather striking. In the case of European IG funds, the discrepancy could be explained by the fact that the correlation between conditional market volatility and market returns is 7.3%, whereas the correlation between realized volatility and returns is -32.3%. However, equivalent figures for the US HY funds are 15.7% and -28.1%, respectively. Hence, following the same rationale, we would expect these funds to also time conditional volatility procyclically and realized volatility countercyclically. Instead, we observe the opposite.

Another pressing question is how timing realized volatility differs from timing conditional volatility in practice. Given that we model monthly conditional volatility by an ARMA(1,1) specification, all information that is relevant for estimating the conditional volatility of a given month is available at the outset of the month. Realized volatility, on the other hand, is unknown at the beginning of the month, but the fund manager gradually receives information about what the realized volatility will be throughout the month. Consequently, we would imagine that a fund manager whose sole focus is on the realized volatility adjusts his portfolio in a more gradual fashion. The ARMA specification is meant to model the manager's timing of realized volatility, but our results indicate that this is not a perfect representation of the strategy he follows. Hence, a possible reason for the disparities between gammas based on conditional and realized volatility could be that fund managers adjust their portfolios in response to information received, say, halfway through a given month.

Table 4.8: Timing Coefficients of Monthly Realized Volatility
The table reports the average timing coefficients of monthly realized volatility in each fund category, obtained from regressions of the CAPM model in Equation (2.17) and four-factor model in Equation (2.18), with monthly return data. γ is the average timing coefficient from the regressions, with t-statistics based on two-sided t-tests. $\gamma_{adjusted}$ is the timing coefficient adjusted for passive timing, with t-statistics from Welch's t-test.

	CAPM		Four-Factor	
	$\gamma_{adjusted}$	γ	$\gamma_{adjusted}$	γ
High Yield				
Asian HY	1.66	1.63	2.78	2.35
European HY	0.55	1.21*	1.10*	1.34**
Global HY	−0.47	2.22**	0.30	2.35**
Global HY HEUR	−0.93	−1.40**	0.04	−0.52
Global HY HGBP	−0.86	−0.72	−0.25	−0.41
US HY	1.13**	0.67*	1.39**	0.70
Investment Grade				
European IG	−4.48**	2.54*	−3.51**	−0.89
Global IG	1.27	1.21	2.38	1.80
Global IG HEUR	0.86	3.55**	0.70	3.00**
Global IG HUSD	0.12	2.81**	0.41	0.52
US IG	1.90*	1.63	−0.13	−0.26

* Significant at the 5% level.
** Significant at the 1% level.

Table 4.9: Percentage of Funds Timing Monthly Realized Volatility
The table reports the percentage of funds timing monthly realized volatility procyclically (Pro), countercyclically (Counter), or not timing (Neutral), grouped by category. In Panel A, funds are classified as timers if the volatility timing coefficient from regressions of the CAPM model in Equation (2.17) or four-factor model in Equation (2.18) is significant at the 5% level, based on two-sided t-tests with Newey-West standard errors. In Panel B, volatility timing coefficients are adjusted for passive timing, and statistical significance based on two-sided Welch's t-tests with Newey-West standard errors.

	CAPM			Four-Factor		
	Pro (%)	Neutral (%)	Counter (%)	Pro (%)	Neutral (%)	Counter (%)
Panel A: γ						
All	13.6	79.7	6.7	15.4	76.4	8.2
High Yield	13.4	78.4	8.2	16.7	75.9	7.4
Investment Grade	14.0	81.7	4.3	13.2	77.4	9.4
High Yield						
Asian HY	35.0	65.0	0	35.0	65.0	0
European HY	15.2	80.1	4.7	22.7	73.0	4.3
Global HY	20.0	76.4	3.6	24.4	72.0	3.6
Global HY HEUR	6.3	83.0	10.7	8.3	80.6	11.2
Global HY HGBP	8.2	71.4	20.4	6.1	83.7	10.2
US HY	10.3	77.7	12.0	11.2	77.7	11.2
Investment Grade						
European IG	19.6	75.2	5.2	13.5	72.2	14.3
Global IG	7.3	90.2	2.4	7.3	87.8	4.9
Global IG HEUR	12.4	85.6	2.1	20.6	78.4	1.0
Global IG HUSD	10.7	86.0	3.3	10.7	81.8	7.4
US IG	9.4	84.4	6.2	10.4	79.2	10.4
Panel B: $\gamma_{adjusted}$						
All	6.2	87.4	6.4	7.4	85.3	7.3
High Yield	8.6	83.9	7.5	9.1	84.8	6.1
Investment Grade	2.4	93.2	4.4	4.6	86.2	9.2
High Yield						
Asian HY	25.0	75.0	0	25.0	75.0	0
European HY	17.5	79.1	3.3	17.1	80.6	2.4
Global HY	3.6	90.8	5.6	5.2	91.2	3.6
Global HY HEUR	1.9	88.8	9.2	3.4	88.8	7.8
Global HY HGBP	6.1	83.7	10.2	2.0	89.8	8.2
US HY	10.7	77.3	12.0	11.2	78.1	10.7
Investment Grade						
European IG	0.9	88.7	10.4	3.9	75.2	20.9
Global IG	7.3	90.2	2.4	9.8	87.8	2.4
Global IG HEUR	1.0	97.9	1.0	3.1	94.8	2.1
Global IG HUSD	1.7	98.3	0	4.1	95.0	0.8
US IG	6.2	93.8	0	6.2	91.7	2.1

4.4 Consistency and Persistence

In this section, we examine whether funds that time volatility do so persistently over time, and whether there is consistency between daily and monthly timing ability.

4.4.1 Consistency in Volatility Timing

The results presented in previous sections indicate that, both in the monthly and in the daily setting, there are funds timing volatility both countercyclically and procyclically. Based on these results, it seems natural to ask whether the funds that time countercyclically in the daily setting are the same as those timing countercyclically in the monthly setting and vice versa.

There are several rather intuitive reasons for expecting to see some degree of consistency between daily and monthly timing coefficients. First of all, if every daily reaction to a changing volatility outlook is of the same proportion, then, for purely mathematical reasons, there will be a connection between daily and monthly timing coefficients. This can be illustrated by a stylized example: consider a situation in which market volatility increases steadily every day for two months. In such an environment, a countercyclical timer with a daily timing horizon would decrease market exposure gradually throughout the period, ending up with a lower market beta in the second month than in the first. The monthly regression would record this as a countercyclical reaction to the increasing volatility, consistent with the daily timing behavior of the fund manager in question.

Secondly, a fund manager who is both conceptually aware of the benefits of volatility timing and capable of adjusting his portfolio to exploit these benefits probably has a somewhat similar attitude towards volatility in the short run as in the long run. For example, a manager who times volatility countercyclically because he knows that this will lead to greater risk-adjusted returns (as long as market volatility and market returns are uncorrelated) can be expected to strive for a negative volatility timing coefficient both in the daily and in the monthly setting. It should be noted that this argument does not necessarily hold for managers who time volatility based on an assumed correlation between market volatility and market returns. If, for instance, volatility and market returns are positively correlated in the short run, but negatively correlated in the long run, then a manager trying to exploit this will strive for a negative timing coefficient in the short run, and a positive one in the long run.

To test for consistency between daily and monthly volatility timing coefficients, we run the simple linear regression of Equation (4.1):

$$t_{\gamma_{monthly}} = \alpha + \beta t_{\gamma_{daily}}, \tag{4.1}$$

where $t_{\gamma_{monthly}}$ and $t_{\gamma_{daily}}$ are t-statistics from the regression of Equation (2.18) with daily and monthly conditional volatility, adjusted for passive timing. This regression is estimated for the entire fund sample, as well as for the sample of funds with negative $t_{\gamma_{monthly}}$ and positive $t_{\gamma_{monthly}}$ separately, in order to examine whether consistency in volatility timing is driven by procyclical or countercyclical timers. The results are presented in Table 4.10.

According to Panel A of Table 4.10, there is a positive relation between volatility timing in the monthly and daily settings. The β-values of Equation (4.1) are positive for every category of funds and mainly statistically significant. However, the R^2-values are quite low, indicating that, while there are some common drivers of daily and monthly volatility timing, there are also substantial individual drivers. The low R^2-values could also signify that a linear model is not a particularly good approximation of the relation between daily and monthly volatility timing coefficients.

Panels B and C of Table 4.10 present the results obtained when applying Equation (4.1) on all funds with a positive monthly gamma and all funds with a negative monthly gamma, respectively. When comparing the two, it becomes clear that the positive overall relation between daily and monthly timing coefficients is mainly driven by consistency among countercyclical timers. With reference to the discussion above, it makes sense for the negative timing coefficients to be more consistent than the positive ones. After all, fund managers motivated by the opportunity to increase risk-adjusted returns should, in theory, always time countercyclically. Managers motivated by a supposed correlation between returns and volatility, on the other hand, should time volatility in the same direction as the correlation, the sign of which is not necessarily the same in the monthly and the daily setting.

The analysis above takes every fund into account, regardless of whether the fund's associated volatility timing coefficient is statistically significant. This approach is scientifically questionable, since we are, in effect, treating statistically insignificant results as meaningful. To verify our results, we therefore find it necessary to perform a complementary analysis based solely on the statistically significant volatility timers. We do this by comparing the number of funds that are significant volatility timers at the 5% level, both in the monthly and in the daily context, to the expected number under

Table 4.10: Consistency Regression Coefficients
The table shows the slope coefficients obtained from regressing monthly volatility timing coefficients on daily timing coefficients, according to Equation (4.1). Results in Panel A, B, and C, are obtained by regressing all, only positive, and only negative monthly four-factor timing coefficients on their associated daily timing coefficients, respectively.

	Panel A: All funds			**Panel B: $\gamma_{adjusted} > 0$**			**Panel C: $\gamma_{adjusted} < 0$**		
	# Funds	β	R^2	# Funds	β	R^2	# Funds	β	R^2
All	1554	0.32^{**}	0.10	700	0.01	0.00	854	0.26^{**}	0.14
High Yield									
Asian HY	20	0.36	0.15	18	0.26	0.19	2	-	-
European HY	211	0.22^{**}	0.06	137	0.11	0.02	74	0.11	0.13
Global HY	250	0.22^{**}	0.10	109	0.05	0.03	141	0.11	0.04
Global HY HEUR	206	0.43^{**}	0.21	94	−0.06	0.01	112	0.26^{**}	0.19
Global HY HGBP	49	0.77^{**}	0.28	34	0.23	0.07	15	0.65	0.34
US HY	233	0.19^{**}	0.05	84	−0.09	0.05	149	0.26^{**}	0.18
Investment Grade									
European IG	230	0.50^{**}	0.15	105	0.03	0.00	125	0.26^{*}	0.13
Global IG	41	0.20	0.06	13	−0.13	0.08	28	0.04	0.01
Global IG HEUR	97	0.22^{*}	0.04	27	−0.35	0.24	70	0.36^{**}	0.24
Global IG HUSD	121	0.34^{**}	0.13	37	0.02	0.01	84	0.34^{**}	0.19
US IG	96	0.32	0.03	42	0.26	0.07	54	0.54^{*}	0.29

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Table 4.11: Observed and Expected Number of Funds Timing Consistently
The table shows the observed and expected number of funds exhibiting active procyclical (Pro) or countercyclical (Counter) volatility timing in equal and opposite directions, on a monthly and daily basis, respectively. Funds are classified as timers if the volatility timing coefficient from a regression of the four-factor volatility timing model in Equation (2.18), adjusted for passive timing, is significant at a 5% level based on Welch's t-test with Newey-West standard errors. χ^2 test statistics are based on Pearson's chi-squared test.

Observed Number of Funds (Monthly - Daily):			
Pro - Pro	Counter - Counter	Pro - Counter	Counter - Pro
34	45	4	3
Expected Number of Funds based on No Relation (Monthly - Daily):			
Pro - Pro	Counter - Counter	Pro - Counter	Counter - Pro
29	20	8	38
χ^2 test statistic:			
31.4^{**}		34.1^{**}	

* Significant at the 5% level.
** Significant at the 1% level.

the assumption that daily and monthly timing are completely independent phenomena. The latter are calculated as the product of the percentage of funds that are significant timers in the monthly setting, the percentage of funds that are significant timers in the daily setting, and the total number of funds. Once again, we base our analysis on the t-statistics of the difference between actual and synthetic gamma values obtained by applying the regression in Equation (2.18), as we view this as our most sophisticated model. The figures are presented in Table 4.11.

Evidently, both the number of consistently positive timers and the number of consistently negative timers are greater than the number one would expect if there was no relation between daily and monthly timing. There is also a far greater discrepancy between the observed and the expected number of consistently countercyclical timers than for consistently procyclical timers, which is in line with results from the previous analysis. Moreover, the observed number of funds that time volatility with significant inconsistency is less than the expected number, lending further support to the hypothesis that daily and monthly timing are related. The discrepancy is particularly large for funds that time volatility countercyclically in the monthly setting and procyclically in the daily setting. The results are tested using Person's chi-squared test. The χ^2-statistics reported in the table, show a strong rejection of the null hypothesis of no relation between daily and monthly timing, verifying that there is consistency in volatility timing. In conclusion, both analyses presented in this section indicate that funds that time volatility one way in the daily setting are more likely to time volatility the same way in the monthly setting.

4.4.2 Persistence in Volatility Timing

Previous analyses indicate that the number of funds that exhibit volatility timing behavior is quite small. With this in mind, it seems reasonable to ask whether these few funds do so persistently over time, or if their significant volatility timing coefficients are driven by a few outlying data points.

Results based on the methodology described in Section 2.2.9, with a daily sampling frequency and a rolling window of four years, are presented in the second result column of Table 4.12. We put little emphasis on Asian HY funds, as there are very few data points available in this category. Interestingly, except for these funds, all HY fund categories appear to exhibit persistence in volatility timing, while persistence appears non-existent for all IG categories. Recall that in Section 4.2, we found daily volatility timing to be predominantly procyclical among HY funds, and predominantly countercyclical among IG funds. We also hypothesized that the reason for this difference could be the positive correlation between conditional market volatility and market returns in HY markets. In conjunction with the figures presented in Table 4.12, this could imply that volatility timers that are motivated by a supposed correlation between volatility and returns generally time persistently.

Results equivalent to those above, but based on monthly conditional volatility regressions are presented in the third column of Table 4.12. Given that the monthly volatility coefficients discussed in Section 4.3.1 were largely insignificant, it comes as no surprise that the persistence of said coefficients is also insignificant. This result is in line with that of Foran and O'Sullivan (2017), who find no evidence of persistence in volatility timing based on monthly regressions.

Results from persistence analysis based on daily data, but with a time interval of one year, rather than four, are presented in the first column of Table 4.12. These figures can be interpreted as representing the short-term persistence in volatility timing, whereas the remaining result columns represent the medium- to long-term persistence. With a one-year interval, the number of data points becomes too small for analysis based on monthly data. Hence, no such analysis is presented.

In the first result column, the narrative that HY funds time persistently, while

Table 4.12: Persistence of Volatility Timing Coefficients
The table shows the persistence coefficients obtained from estimating the simplified volatility timing model in Equation (2.28), with a portfolio that has a long position in countercyclical timers and a short position in procyclical timers. Each column represents regressions based on daily or monthly data, with a one- or four-year rolling window. C or R in superscript represents conditional or realized volatility, respectively.

	$\hat{\gamma}^{C}_{daily}$ (1 year)	$\hat{\gamma}^{C}_{daily}$ (4 year)	$\hat{\gamma}^{C}_{monthly}$ (4 year)	$\hat{\gamma}^{R}_{monthly}$ (4 year)
High Yield				
Asian HY	1.75	−1.01	41.48	37.11
European HY	−0.72	−3.27**	−1.07	2.40
Global HY	−3.69**	−8.23**	0.97	0.95
Global HY HEUR	−3.87**	−7.56**	10.69	0.53
Global HY HGBP	−3.74**	−11.39**	7.94	1.77
US HY	−0.31	−2.46**	5.18	2.57
Investment Grade				
European IG	5.53	−3.62	8.22	4.84
Global IG	−16.90**	4.20	10.01	7.22
Global IG HEUR	3.96	−0.71	−6.05	6.69
Global IG HUSD	2.17	−1.08	−10.20	−6.14
US IG	−15.80**	1.84	−2.13	−8.48

Significance is based on one-sided t-tests with Newey-West standard errors.
* Significant at the 5% level.
** Significant at the 1% level.

IG funds do not, is less obvious. There appears to be persistence in timing for three out of six HY fund categories, and two out of five IG categories. It may sound strange that, for three HY fund categories, we register statistically significant long-term persistence, but no significant short-term persistence. This could be the result of the analysis based on one-year intervals being more sensitive to outliers than that based on four-year intervals. For example, a fund that exhibits substantial timing ability over a very short period of time has a better chance of making it into the outermost quintiles of timers in the one-year analysis, than in the four-year analysis. If the fund in question cannot sustain this ability in the subsequent period, then the short-term persistence registered by the model will be reduced. Moreover, Carhart (1997) argues that with a one-year horizon, the data becomes too noisy for persistence testing.

Finally, results equivalent to those in the third column, but with realized, instead of conditional, monthly volatility are presented in the fourth column. As expected, these are all insignificant. Anything else would have been strange, given the absence of significant values in Table 4.8.

4.5 Volatility Timing and Performance

In this section, we examine the relationship between volatility timing and fund performance. We have previously theorized how volatility timing can increase performance. To the authors' knowledge, the effect of volatility timing on performance of mutual bond funds has not yet been studied. However, some studies have been done in the equity universe, where volatility timing has been found to increase Sharpe ratios (Admati and Ross 1985; Busse 1999). Furthermore, Giambona and Golec (2009) find that procyclical timing increases alphas. On the other hand, Foran and O'Sullivan (2017) find that volatility timing decreases alphas. Lastly, Kim and In (2012) find that procyclically timing funds performed the best in-sample, whereas countercyclical timers performed best out-of-sample. Hence, previous research has been inconclusive. Using the same performance measures, namely Jensen's alpha and Sharpe ratio, we examine if volatility timing leads to superior fund performance.

4.5.1 Jensen's Alpha

Jensen's alpha is one of the most common measures of performance (Murthi, Choi, and Desai 1997), and measures unexplained excess returns of a portfolio. To study if volatility timing funds perform better, we estimate alphas using Equations (2.13) and (2.14). Tables 4.13 through 4.15 present the mean four-factor alphas of funds timing daily conditional, monthly conditional and monthly realized volatility. In Panel A, the criterion for being considered a timer is that a given fund must have a volatility timing coefficient that is significant at the 5% level, while the corresponding criterion is set to 10% in Panel B. Results for the CAPM model, as well as Welch and permutation tests for performance differences, are provided in Appendix C.

Table 4.13 shows that IG funds who time volatility countercyclically have achieved the highest alphas. This outperformance is mainly driven by the impressive performance of the countercyclically timing hedged global IG funds. Nevertheless, only one out of five categories of IG funds have had negative alpha, yielding a high average. Welch and permutation testing show that the outperformance is statistically significant at the 5% level when compared to funds timing procyclically. However, only 10% of IG funds have timed daily volatility procyclically. The second-best strategy for both IG and HY funds has been to not engage in volatility timing, something a clear majority of the funds have done. The results are similar when using the CAPM model. It is somewhat surprising based on the results from Table 4.13 that 10% (15%)

Table 4.13: α for Four-Factor Based Daily Conditional Volatility
The table displays the mean alphas from regressions of the four-factor model in Equation (2.14) with funds timing daily conditional volatility procyclically (Pro), countercyclically (Counter) or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the four-factor volatility timing model in Equation (2.18), adjusted for passive timing, is significant at a 5% (5% α) or 10% (10% α) level, based on t-statistics from Welch's t-test with Newey-West standard errors.

	Panel A: 5% α			**Panel B: 10% α**		
	Pro (%)	Counter (%)	Neutral (%)	Pro (%)	Counter (%)	Neutral (%)
All	0.57**	0.50**	0.49**	0.58**	0.63**	0.46**
High Yield	0.68**	0.02	0.43**	0.71**	0.38	0.38**
Investment Grade	0.31**	0.83**	0.60**	0.28**	0.82**	0.61**
High Yield						
Asian HY	−0.14	−0.35**	−0.02	−0.58	−0.35**	0.21
European HY	−0.91**	0.51	−0.23*	−0.85**	0.70	−0.30*
Global HY	4.14**	−1.60	1.37**	3.87**	1.32	1.35**
Global HY HEUR	−0.09	−0.97*	−0.14	−0.33	−0.88*	−0.10
Global HY HGBP	0.58	−0.68	−0.01	0.25	−0.68	0.08
US HY	0.68*	1.15**	0.47	1.15**	1.05**	0.16
Investment Grade						
European IG	0.44**	0.01	0.25*	0.32*	−0.08	0.30*
Global IG	0.23	−0.16	1.04	0.45	0.49	0.80
Global IG HEUR	−0.42*	2.15**	0.55**	−0.11	1.68**	0.46**
Global IG HUSD	0.20	3.05**	1.24**	0.20	2.79**	1.24**
US IG	0.66	0.45	0.47*	0.45	0.31	0.59*

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

of IG (HY) funds timed volatility procyclically (countercyclically) when this strategy has lead to the lowest alpha.

For HY funds, the procyclical timing has lead to the highest alphas. However, while the difference between procyclical and countercyclical timers is statistically significant at the 5% level using a Welch test, the difference between procyclical timers and non-timers is insignificant. Tables 4.3 and 4.12 show that the majority of the HY funds timing volatility daily, do so both procyclically and persistently. Hence, the greater number of timing HY funds seem to follow the strategy that increases alpha, as one would expect. The performance of the procyclically timing unhedged global HY funds is substantial, with a yearly alpha above 4%. This average is based on 40 alpha values, hence a too small sample size is unlikely to be the explanation. The performance of the hedged global HY funds is decent, but not as exceptional. Possible explanations might be currency gains when timing the market procyclically or a high level of idiosyncratic risk among these funds. Besides, unconditional alpha estimates are biased, either upwards or downwards, depending on strategy and past returns, when funds time the market volatility (Admati and Ross 1985; Dybvig and Ross 1985), which obviously is the case for the timing funds.

Table 4.14: α for Four-Factor Based Monthly Conditional Volatility
The table displays the mean alphas from regressions of the four-factor model in Equation (2.14) with funds timing monthly conditional volatility procyclically (Pro), countercyclically (Counter) or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the four-factor volatility timing model in Equation (2.18), adjusted for passive timing, is significant at a 5% (5% α) or 10% (10% α) level, based on t-statistics from Welch's t-test with Newey-West standard errors. Missing values indicate that no funds of the given category follow the given timing strategy.

	Panel A: 5% α			**Panel B: 10% α**		
	Pro (%)	Counter (%)	Neutral (%)	Pro (%)	Counter (%)	Neutral (%)
All	-0.53^{**}	-0.11	-0.14^{**}	-0.41^{**}	-0.11	-0.15^{**}
High Yield	-0.63^{**}	-0.14	-0.19^{**}	-0.46^{**}	-0.05	-0.22^{**}
Investment Grade	-0.35^{**}	-0.10	-0.04	-0.31^{**}	-0.16^{*}	0.00
High Yield						
Asian HY	-1.56^{*}	-	-0.58	-1.56^{*}	-	-0.58
European HY	-0.56^{**}	-0.56	-0.38^{**}	-0.47^{**}	-0.56	-0.41^{**}
Global HY	0.46^{**}	0.89	0.98^{**}	1.25^{*}	0.70^{*}	0.98^{**}
Global HY HEUR	-1.40^{**}	-0.30	-1.03^{**}	-1.21^{**}	-0.29	-1.06^{**}
Global HY HGBP	0.52	-0.38	-0.73^{**}	0.52	-0.38	-0.78^{**}
US HY	-0.41	-0.07	-0.72^{**}	-0.60^{*}	-0.04	-0.80^{**}
Investment Grade						
European IG	-0.35^{**}	0.06	0.19	-0.33^{**}	0.00	0.26^{*}
Global IG	-0.49	-1.00	-0.15	-0.64	-1.19	0.22
Global IG HEUR	-0.53	-0.43^{**}	-0.19^{**}	-0.29	-0.44^{**}	-0.18^{*}
Global IG HUSD	-	-0.24^{*}	-0.07	-	-0.17	-0.08
US IG	1.15^{**}	0.16	-0.19	0.36	0.14	-0.21

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

When considering monthly timing of conditional volatility in Table 4.14, timing countercyclically or not timing at all has yielded the best results for HY funds. The performance is, however, nowhere close to the performance seen at a daily level. Specifically, procyclical HY timers perform subpar.

Table 4.15: α for Four-Factor Based Monthly Realized Volatility
The table displays the mean alphas from regressions of the four-factor model in Equation (2.14) with funds timing monthly realized volatility procyclically (Pro), countercyclically (Counter) or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the four-factor volatility timing model in Equation (2.18), adjusted for passive timing, is significant at a 5% (5% α) or 10% (10% α) level, based on t-statistics from Welch's t-test with Newey-West standard errors. Missing values indicate that no funds of the given category follow the given timing strategy.

	Panel A: 5% α			**Panel B: 10% α**		
	Pro (%)	Counter (%)	Neutral (%)	Pro (%)	Counter (%)	Neutral (%)
All	-0.40^{**}	-0.32^{*}	-0.11^{*}	-0.31^{**}	-0.22^{*}	-0.12^{*}
High Yield	-0.28	-0.42^{*}	-0.20^{**}	-0.21	-0.36^{*}	-0.21^{**}
Investment Grade	-0.32	0.08	-0.08	-0.20	0.11	-0.10^{*}
High Yield						
Asian HY	-0.29	-	-0.15	-0.29	-	-0.14
European HY	-1.24^{**}	0.00	-0.56^{**}	-0.98^{**}	0.26	-0.61^{**}
Global HY	1.55^{*}	0.99^{*}	0.67^{**}	0.97^{*}	1.11^{**}	0.67^{**}
Global HY HEUR	-0.18	-0.28	-0.98^{**}	-0.42	-0.65^{**}	-0.97^{**}
Global HY HGBP	-1.13^{**}	0.24	-0.40^{**}	-0.13	0.24	-0.46^{**}
US HY	-0.54^{**}	-1.80^{**}	0.25	-0.39^{*}	-1.74^{**}	0.28
Investment Grade						
European IG	-0.34	0.08	-0.14^{*}	-0.43^{**}	0.09	-0.16^{*}
Global IG	0.77	1.85^{**}	0.15	0.54	1.99	0.05
Global IG HEUR	-0.99	-0.55	-0.26^{**}	-0.60	-0.25	-0.27^{**}
Global IG HUSD	-0.12	-1.12^{**}	-0.20^{*}	-0.06	-0.45^{*}	-0.21^{*}
US IG	0.07	-0.10	0.13	0.06	-0.30	0.15

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

These results are in line with our previous findings, which show a lack of persistence and prevalence of monthly timing among HY funds, especially for procyclical timers.

IG funds timing countercyclically have performed in line with those not timing at all. Both strategies outperformed procyclical timing at a 5% significance level. There are twice as many IG funds timing conditional monthly volatility countercyclically as procyclically, which is in line with previous findings.

Table 4.15 shows that HY funds not engaging in the timing of realized volatility have delivered the best performance. Funds timing procyclically have had a slightly lower alpha, while countercyclical timers have performed the worst.

Hence, timing realized volatility has not been favourable, giving a possible explanation for the low persistence and it being the most uncommon volatility timing strategy among HY funds.

In Table 4.15 countercyclical IG timers have achieved the best results. However, only 9% of managers time realized volatility countercyclically. Given that 21% of IG funds time monthly conditional volatility countercyclically, but only 9% do so with realized volatility, a lack of ability or success in timing the volatility shocks may explain the reduction. Still, the alphas of IG funds are insignificant, and one should be cautious about putting too much emphasis on these figures.

It is important to note that Jensen's alpha is sensitive to the choice of benchmark and risk-pricing model (Murthi, Choi, and Desai 1997). However, the Morningstar benchmarks should be fair, as Morningstar is an independent and respected institution. Our results are also fairly consistent when using the CAPM model instead of the four-factor model, showing robustness regarding the choice of risk-pricing model. The alphas are net of fees, causing a negative skew, and the numbers reflect the performance an investor receives, rather than the actual performance of the funds' positions. By studying alphas gross of fees, new relationships might be inferred. Specifically, such analyses could possibly reveal that the poor performance of several of the timing funds is due to high fees to cover trading costs.

In conclusion, HY fund managers engaging in volatility timing seem to employ strategies that increase their alphas. The optimal timing strategies are highly dependent on what kind of timing that is in question. For IG funds, timing countercyclically has, in general, yielded the best performance. The strategies of IG fund managers also seem to be reasonably aligned with our results, where the majority of timing IG funds follow the strategy that has yielded the highest performance.

4.5.2 Sharpe Ratio

By using Sharpe ratios to evaluate performance, one overcomes some of the challenges associated with Jensen's alpha, namely, the choice of benchmark and risk-pricing model. We estimate the Sharpe ratio of each fund with daily returns using Equation (1.1), and annualize by multiplying with the square root of 252 or 12 depending on whether we use daily or monthly data. Annualizing in such a manner is only valid under special circumstances (Lo 2002), not necessarily fulfilled by our data, and comparisons of daily and monthly results should be made with caution. Nevertheless, results will be

Table 4.16: Sharpe Ratios for Four-Factor Based Daily Conditional Volatility The table displays the annualized mean Sharpe ratios of funds timing daily conditional volatility procyclically (Pro), countercyclically (Counter), or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the four-factor volatility timing model in Equation (2.18) is significant at a 5% (5% λ) or 10% (10% λ) level, based on two-sided t-tests with Newey-West standard errors.

	Panel A: 5% λ			**Panel B: 10% λ**		
	Pro	Counter	Neutral	Pro	Counter	Neutral
All	1.16	1.01	1.02	1.13	1.00	1.02
High Yield	1.21	1.09	1.09	1.19	1.16	1.08
Investment Grade	1.04	0.95	0.91	1.00	0.87	0.92
High Yield						
Asian HY	1.18	1.70	1.33	1.37	1.70	1.28
European HY	1.12	1.49	1.08	1.10	1.39	1.08
Global HY	1.22	0.34	1.32	1.22	1.26	1.31
Global HY HEUR	0.91	0.78	0.70	0.91	0.79	0.69
Global HY HGBP	1.51	0.91	0.84	1.34	0.91	0.87
US HY	1.32	1.37	1.24	1.32	1.31	1.24
Investment Grade						
European IG	1.09	1.06	0.94	1.01	1.02	0.95
Global IG	0.59	0.49	0.52	0.60	0.57	0.46
Global IG HEUR	0.59	0.88	0.58	0.68	0.47	0.60
Global IG HUSD	1.25	1.42	1.19	1.25	1.34	1.19
US IG	1.20	0.80	0.99	1.14	0.79	1.02

comparable within each table, and we report annualized values for ease of interpretation.

We group the timing funds in the same manner as in the previous section. Results for the daily four-factor model and the monthly four-factor model with conditional and realized volatility are presented in Tables 4.16, 4.17 and 4.18. Results for the other models, as well as Welch's t-tests and permutation tests for differences, are in Appendix C.

For the daily four-factor specification, we obtain similar results for HY funds to those reported when using Jensen's alpha, namely that HY funds timing procyclically have had superior performance. The difference in Sharpe ratios is statistically significant at the 5% level compared to countercyclical timers. However, in Panel B, there is only a marginally higher Sharpe ratio for procyclical timers compared to countercyclical timers. The global HY funds hedged in GBP have the highest Sharpe ratio, except for the single countercyclically timing Asian HY fund with a Sharpe ratio of 1.7. Almost 40%

of the global HY funds hedged in GBP exhibit procyclical volatility timing, showing that fund managers adopt the best strategy. For European HY funds, on the other hand, there are twice as many funds timing volatility procyclically, compared to those timing countercyclically, despite procyclical timing leading to lower Sharpe ratios and alphas. Hence, there are discrepancies, but the results for HY funds as a whole follow an expected pattern.

IG funds timing daily volatility procyclically have outperformed countercyclical and non-timing funds. This result is contrary to the result for Jensen's alpha, where the countercyclical timers performed the best. These contradicting results could be the explanation of why equal amounts of IG funds time counter- and procyclically, namely due to different preferred performance measures. The Sharpe ratio for IG funds timing the daily volatility procyclically is consistently larger across all categories, compared to the non-timing funds in Table 4.16. This result also holds for the CAPM model tabulated in Appendix C. Thus, investors should choose IG funds that engage in daily volatility timing either, pro- or countercyclically, depending on their preferred performance measure.

For monthly conditional volatility, HY funds that time countercyclically and non-timers have achieved the highest Sharpe ratio, which is in line with the results for Jensen's alpha. However, in Panel B, one can observe that procyclical timers perform virtually as well as countercyclical timers, and non-timers perform the worst. These differences are caused by diverging results across different HY categories. Therefore, one should be cautious about making inferences about HY funds as a whole. Looking at Panel B, procyclically timing unhedged global HY have delivered an impressive Sharpe ratio of almost 2, and at least 0.5 higher than the Sharpe ratios of all other timing strategies, whereas procyclical global HY funds hedged in EUR have had a Sharpe ratio of 0.31 and at least 0.4 less than all other timing strategies.

IG funds that have engaged in countercyclical timing have a significantly larger Sharpe ratio than non-timers and procyclical timers. The outperformance gives a further explanation for why the most common timing strategy for IG funds is timing monthly conditional volatility countercyclically. The results are similar but slightly weaker in Panel B and for the CAPM model in Appendix C.

Table 4.18 reports the Sharpe ratios of timers and non-timers of monthly realized volatility. Countercyclical timers have achieved the greatest risk-adjusted returns. However, the differences in performance across all timing strategies are largely insignificant when using Welch's or permutation tests. For HY funds, the Sharpe ratio results are also inconsistent when comparing

Table 4.17: Sharpe Ratios for Four-Factor Based Monthly Conditional Volatility

The table displays the annualized mean Sharpe ratios of funds timing monthly conditional volatility procyclically (Pro), countercyclically (Counter), or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the four-factor volatility timing model in Equation (2.18) is significant at a 5% (5% λ) or 10% (10% λ) level, based on two-sided t-tests with Newey-West standard errors. Missing values indicate that no funds of the given category follow the given timing strategy.

	Panel A: 5% λ			**Panel B: 10% λ**		
	Pro	Counter	Neutral	Pro	Counter	Neutral
All	0.96	1.20	1.10	1.02	1.18	1.10
High Yield	1.01	1.10	1.09	1.12	1.13	1.07
Investment Grade	0.87	1.28	1.13	0.84	1.23	1.16
High Yield						
Asian HY	1.24	-	1.02	1.24	-	1.02
European HY	1.05	1.05	1.02	1.10	1.05	1.00
Global HY	1.32	1.29	1.29	1.94	1.40	1.25
Global HY HEUR	0.19	0.98	0.71	0.31	0.96	0.71
Global HY HGBP	1.30	1.22	1.13	1.30	1.13	1.15
US HY	1.18	1.13	1.23	1.20	1.15	1.23
Investment Grade						
European IG	0.88	1.26	1.00	0.85	1.23	1.01
Global IG	0.87	0.47	0.73	0.75	0.46	0.82
Global IG HEUR	0.62	1.00	0.82	0.59	0.89	0.86
Global IG HUSD	-	1.50	1.59	-	1.53	1.59
US IG	1.81	1.56	1.27	1.51	1.52	1.26

Table 4.18: Sharpe Ratios for Four-Factor Based Monthly Realized Volatility The table displays the annualized mean Sharpe ratios of funds timing monthly realized volatility procyclically (Pro), countercyclically (Counter), or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the four-factor volatility timing model in Equation (2.18) is significant at a 5% (5% λ) or 10% (10% λ) level, based on two-sided t-tests with Newey-West standard errors. Missing values indicate that no funds of the given category follow the given timing strategy.

	Panel A: 5% λ			**Panel B: 10% λ**		
	Pro	Counter	Neutral	Pro	Counter	Neutral
All	1.04	1.16	1.11	1.13	1.16	1.09
High Yield	1.06	1.11	1.08	1.14	1.12	1.07
Investment Grade	0.99	1.21	1.15	1.08	1.20	1.14
High Yield						
Asian HY	0.97	-	1.12	0.91	-	1.16
European HY	0.97	1.42	1.03	1.07	1.29	1.00
Global HY	1.26	1.55	1.28	1.40	1.59	1.25
Global HY HEUR	0.64	1.08	0.70	0.68	0.98	0.69
Global HY HGBP	1.23	1.21	1.15	1.29	1.21	1.13
US HY	1.21	0.89	1.25	1.22	0.90	1.25
Investment Grade						
European IG	0.54	1.22	1.04	0.75	1.14	1.05
Global IG	0.70	0.76	0.73	0.78	0.92	0.70
Global IG HEUR	0.31	0.86	0.86	0.38	1.04	0.86
Global IG HUSD	1.64	1.60	1.56	1.55	1.88	1.55
US IG	1.65	1.27	1.28	1.60	1.34	1.28

Panel A to Panel B. We therefore refrain from drawing any conclusions for HY funds in general.

For IG funds, the results are more aligned with previous findings. Countercyclical timers have the highest Sharpe ratios and alphas, and this is consistent across panels. As previously discussed, the challenge of timing the volatility shocks may explain why only 9% of IG funds do this.

In conclusion, the results based on Sharpe ratios are reasonably aligned with those based on alphas. There is also a clear correspondence between the number of funds following a strategy, and the strategy's past performance. The results are fully aligned for HY funds when considering timing of conditional volatility. For realized volatility, on the other hand, there is no clear relation between timing and performance, casting doubt on whether timing of realized volatility increases the performance of HY funds. For IG funds, timing of daily volatility has been a trade-off between maximizing alpha or Sharpe ratio. The timing of monthly volatility is, to a much larger extent, aligned. The overall finding of inconsistency in optimal timing strategies is similar to the results of previous research on equity funds, wherein conflicting conclusions have been drawn (Busse 1999; Foran and O'Sullivan 2017; Giambona and Golec 2009; Kim and In 2012).

5 Conclusion

Although a handful of researchers have explored the concept of volatility timing among equity funds, there has been a dearth of such studies concerning bond funds. This paper serves to close the resulting research gap between equity markets and bond markets.

Contrary to the conclusions drawn about equity funds, we do not find conclusive evidence of countercyclical volatility timing among corporate bond funds. Our results paint a more nuanced picture, in which fund manager behavior varies considerably across different asset classes. Daily regressions indicate that HY funds on average time volatility procyclically, whereas IG funds on average time countercyclically, although the latter tendency is less pronounced than the former. This discrepancy appears to be driven by a more positive correlation between market returns and conditional volatility in HY markets than in IG markets. Corresponding monthly regressions yield considerably less significant results, wherein the aforementioned disparity is largely evened out.

Across all asset classes, there appears to be a significant relation between daily and monthly timing. This relation is mainly driven by a strong, positive correlation between daily and monthly timing coefficients for countercyclical timers. In other words, a fund manager who times volatility countercyclically on a daily basis is more likely to also do so on a monthly basis. However, the timing ability of procyclical timers appears to be more persistent over time than that of countercyclical timers.

Finally, our performance analysis yields somewhat ambiguous results. Nevertheless, there is one fairly consistent pattern; the volatility timing strategy followed by most fund managers and the volatility timing strategy followed by those that obtain the highest risk-adjusted returns are usually the same. For instance, when funds that time countercyclically outperform other funds, there are usually more countercyclical timers than procyclical timers. Although it is difficult to tell whether or not there is causality, this could imply that fund managers consciously time volatility in the direction that yields the highest risk-adjusted returns.

We have several suggestions on how our analyses could be improved on in future research. First of all, our results generally indicate that daily frequency data is paramount to the study of volatility timing. While we have been fortunate enough to have access to plenty of daily return data, our models are hampered by a lack of daily volatility time series. With intraday data, such time series could be constructed and used in the calculation of daily ARMA-based conditional volatility time series, which could more accurately reflect the conditional volatility of a given day. Second, the risk-pricing models we have used are by no means perfect. As the literature on common risk factors in corporate bond markets is still in rapid development, we expect the model of Bai, Bali, and Wen (2019) to be improved upon in the near future. With a more sophisticated risk-pricing model, our results would be more trustworthy. Third, we consider timing of other bond market risk factors to be an interesting area of future research. For instance, Foran and O'Sullivan (2017) find some evidence of liquidity timing in equity markets, and one could argue that liquidity should affect bond pricing more heavily than equity pricing. One could also imagine fund managers timing credit risk. Such strategies could be studied by constructing models very similar to those we have used, and could reveal new information about the nature of asset management.

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Appendices

Appendix A

Data Sample Overview

This appendix contains a mapping of Morningstar Category names to benchmark indexes (Table A.1) and descriptive statistics of daily fund return time series (Table A.2).

Table A.1: Overview of Fund Categories with Corresponding Morningstar Categories and Benchmark Indexes

Short Form	Morningstar Category	Benchmark Index
Asian HY	Asia High Yield Bond	JPM ACI Non Investment Grade TR USD
European IG	EUR Corporate Bond	BBgBarc Euro Agg Corps TR EUR
European HY	EUR High Yield Bond	BBgBarc Pan Euro HY Euro TR EUR
Global IG	Global Corporate Bond	BBgBarc Gbl Agg Corp TR USD
Global IG HEUR	Global Corporate Bond - EUR Hedged	BBgBarc Gbl Agg Corp 0901 TR Hdg EUR
Global IG HUSD	Global Corporate Bond - USD Hedged	BBgBarc Gbl Agg Corp 0901 TR Hdg USD
Global HY	Global High Yield Bond	ICE BofAML Gbl HY Constnd TR USD
Global HY HEUR	Global High Yield Bond - EUR Hedged	ICE BofAML Gbl HY Constnd TR HEUR
Global HY HGBP	Global High Yield Bond - GBP Hedged	ICE BofAML Gbl HY Constnd TR HGBP
US IG	USD Corporate Bond	BBgBarc US Corp Bond TR USD
US HY	USD High Yield Bond	BBgBarc US Corporate High Yield TR USD

Table A.2: Summary of Daily Fund Return Statistics Averaged by Fund Category

Fund Category	Number of funds	Number of observations	Return (%)	Std. Dev. (%)	Skewness	Kurtosis
All	1617	2 318 393	0.018	0.225	−0.59	17.40
Asian HY	20	20 339	0.023	0.256	−0.38	9.64
European HY	218	326 798	0.019	0.215	−0.57	13.24
Global HY	265	351 399	0.022	0.251	−0.56	12.10
Global HY HEUR	212	285 256	0.015	0.234	−0.53	15.58
Global HY HGBP	53	64 175	0.018	0.255	−1.09	33.63
US HY	244	345 087	0.023	0.260	−0.79	24.37
European IG	234	398 396	0.013	0.170	−0.70	34.72
Global IG	43	64 187	0.013	0.283	−0.29	2.68
Global IG HEUR	100	149 654	0.011	0.188	−0.40	3.84
Global IG HUSD	126	180 169	0.018	0.191	−0.31	1.97
US IG	102	132 933	0.018	0.229	−0.49	19.09

Appendix B

Factor Model Regressions

This appendix contains coefficient estimates associated with regression models without the volatility timing term. Coefficients of both actual fund regressions and synthetic portfolio regressions are presented.

Table B.1: CAPM Regression Coefficients With Daily Data
This table reports the coefficients from regressing daily fund returns on the CAPM model in Equation (2.13). All coefficients are provided as the mean value of individual fund regressions in the corresponding category.

	$\alpha(\%)$	β^m	R^2
All	0.581**	0.677**	0.495
High Yield			
Asian HY	0.067	0.890**	0.489
European HY	−0.284**	0.783**	0.569
Global HY	1.787**	0.513**	0.350
Global HY HEUR	−0.183	0.701**	0.421
Global HY HGBP	0.082	0.698**	0.389
US HY	0.603**	0.739**	0.577
Investment Grade			
European IG	0.386**	0.786**	0.574
Global IG	0.852*	0.477**	0.423
Global IG HEUR	0.634**	0.556**	0.434
Global IG HUSD	1.317**	0.584**	0.454
US IG	0.561**	0.700**	0.689

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Table B.2: CAPM Regression Coefficients With Monthly Data
This table reports the coefficients from regressing monthly fund returns on the CAPM model in Equation (2.13). All coefficients are provided as the mean value of individual fund regressions in the corresponding category.

	$\alpha(\%)$	β^m	R^2
All	-0.149^{**}	0.890^{**}	0.844
High Yield			
Asian HY	-0.184	0.978^{**}	0.762
European HY	-0.665^{**}	0.890^{**}	0.894
Global HY	0.728^{**}	0.766^{**}	0.795
Global HY HEUR	-0.898^{**}	0.908^{**}	0.866
Global HY HGBP	-0.366^{*}	0.898^{**}	0.891
US HY	-0.055	0.853^{**}	0.839
Investment Grade			
European IG	-0.102	1.019^{**}	0.856
Global IG	0.250	0.741^{**}	0.652
Global IG HEUR	-0.286^{**}	0.941^{**}	0.840
Global IG HUSD	-0.208^{*}	0.977^{**}	0.862
US IG	0.121	0.842^{**}	0.859

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Table B.3: CAPM Regression Coefficients With Synthetic Daily Data
This table reports the coefficients from regressing synthetic daily fund returns on the CAPM model in Equation (2.13). All coefficients are provided as the mean value of individual fund regressions in the corresponding category.

	$\alpha(\%)$	β^m	R^2
All	0.742**	0.812**	0.865
High Yield			
Asian HY	0.263*	0.837**	0.865
European HY	0.412**	0.834**	0.886
Global HY	1.066**	0.696**	0.762
Global HY HEUR	1.263**	0.854**	0.882
Global HY HGBP	0.645**	0.849**	0.913
US HY	0.503**	0.756**	0.839
Investment Grade			
European IG	0.699**	0.921**	0.902
Global IG	0.934**	0.738**	0.805
Global IG HEUR	1.266**	0.809**	0.881
Global IG HUSD	0.125	0.867**	0.933
US IG	0.506**	0.797**	0.928

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Table B.4: CAPM Regression Coefficients With Synthetic Monthly Data
This table reports the coefficients from regressing synthetic monthly fund returns on the CAPM model in Equation (2.13). All coefficients are provided as the mean value of individual fund regressions in the corresponding category.

	$\alpha(\%)$	β^m	R^2
All	0.464**	0.883**	0.924
High Yield			
Asian HY	0.055	0.888**	0.945
European HY	0.264**	0.876**	0.948
Global HY	0.700**	0.758**	0.889
Global HY HEUR	1.102**	0.884**	0.946
Global HY HGBP	0.371**	0.887**	0.961
US HY	0.219**	0.821**	0.910
Investment Grade			
European IG	0.349**	1.039**	0.934
Global IG	0.659**	0.819**	0.858
Global IG HEUR	1.076**	0.939**	0.899
Global IG HUSD	−0.249**	0.959**	0.933
US IG	0.128*	0.874**	0.942

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Table B.5: Four-Factor Regression Coefficients With Synthetic Daily Data
This table reports the coefficients from regressing synthetic daily fund returns on the four-factor model in Equation (2.14). All coefficients are provided as the mean value of individual fund regressions in the corresponding category.

	$\alpha(\%)$	β^m	β^{ILQ}	β^{CDS}	β^{DWS}	R^2
All	0.581**	0.748**	0.075**	−0.001**	0.091**	0.897
High Yield						
Asian HY	0.040	0.777**	0.081**	−0.001*	0.095**	0.901
European HY	0.284**	0.773**	0.077**	0.001**	0.103**	0.919
Global HY	0.964**	0.556**	0.130**	−0.004**	0.166**	0.811
Global HY HEUR	1.195**	0.809**	0.043**	0.000	0.051**	0.898
Global HY HGBP	0.601**	0.807**	0.044**	0.000	0.051**	0.923
US HY	0.346**	0.691**	0.094**	0.003**	0.104**	0.876
Investment Grade						
European IG	0.453**	0.876**	0.057**	−0.003**	0.063**	0.941
Global IG	0.616**	0.684**	0.100**	0.004**	0.117**	0.840
Global IG HEUR	0.978**	0.772**	0.060**	−0.003**	0.075**	0.919
Global IG HUSD	−0.103	0.834**	0.052**	−0.002**	0.063**	0.954
US IG	0.335**	0.777**	0.038**	−0.001**	0.051**	0.936

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Table B.6: Four-Factor Regression Coefficients With Synthetic Monthly Data
This table reports the coefficients from regressing synthetic monthly fund returns on the four-factor model in Equation (2.14). All coefficients are provided as the mean value of individual fund regressions in the corresponding category.

	$\alpha(\%)$	β^m	β^{ILQ}	β^{CDS}	β^{DWS}	R^2
All	0.612**	0.743**	0.133**	−0.006**	0.140**	0.954
High Yield						
Asian HY	0.059	0.797**	0.163**	0.000	0.117**	0.963
European HY	0.455**	0.779**	0.079**	0.001*	0.143**	0.964
Global HY	0.909**	0.506**	0.358**	−0.013**	0.242**	0.923
Global HY HEUR	1.094**	0.755**	0.139**	−0.005**	0.123**	0.960
Global HY HGBP	0.431**	0.791**	0.151**	−0.002	0.093**	0.969
US HY	0.520**	0.693**	0.127**	−0.001**	0.151**	0.932
Investment Grade						
European IG	0.474**	0.889**	0.048**	−0.007**	0.109**	0.982
Global IG	0.550**	0.716**	0.143**	0.002	0.135**	0.890
Global IG HEUR	1.182**	0.795**	0.021*	−0.011**	0.128**	0.964
Global IG HUSD	−0.052	0.853**	0.058**	−0.009**	0.081**	0.975
US IG	0.207**	0.812**	0.051**	−0.007**	0.063**	0.962

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Appendix C

Performance Statistics

This appendix contains results complementing those related to our performance analysis in Section 4.5. Tables C.1 through C.3 are related to alpha values, while Tables C.4 through C.6 are related to Sharpe Ratios. Tables C.7 through C.10 report p-values of differences in alphas and Sharpe ratios between funds employing different timing strategies. p-values based on both Welch's t-test and permutation tests are presented.

Table C.1: CAPM α for Daily Conditional Volatility Timing
The table displays the mean alphas from regressions of the CAPM model in Equation (2.13) with funds timing daily conditional volatility procyclically (Pro), countercyclically (Counter) or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the CAPM volatility timing model in Equation (2.17), adjusted for passive timing, is significant at a 5% (5% α) or 10% (10% α) level, based on t-statistics from Welch's t-test with Newey-West standard errors.

	Panel A: 5% α			**Panel B: 10% α**		
	Pro (%)	Counter (%)	Neutral (%)	Pro (%)	Counter (%)	Neutral (%)
All	0.75**	0.63**	0.54**	0.62**	0.72**	0.55**
High Yield	0.89**	−0.03	0.46**	0.69**	0.34	0.48**
Investment Grade	0.45**	1.20**	0.66**	0.45**	1.15**	0.65**
High Yield						
Asian HY	−0.70	−0.01**	0.63*	−0.68	−0.01**	0.75**
European HY	−0.78**	0.75	−0.09	−0.75**	0.56*	−0.08
Global HY	4.76**	0.45	1.38**	4.45**	1.44**	1.36**
Global HY HEUR	0.14	−1.18*	−0.13	−0.26	−1.19**	−0.05
Global HY HGBP	0.42	−0.96	0.18	0.36	−0.96	0.19
US HY	1.03**	0.87*	0.41	0.95**	0.82**	0.38
Investment Grade						
European IG	0.49**	0.12	0.39**	0.44**	0.07	0.42**
Global IG	0.76	2.74	0.35	0.82	1.67	0.40
Global IG HEUR	−0.13	2.00**	0.62**	0.08	1.91**	0.60**
Global IG HUSD	0.36	3.04**	1.30**	0.43	2.70**	1.28**
US IG	0.65	0.36	0.59**	0.52	0.81*	0.47*

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Table C.2: CAPM α for Monthly Conditional Volatility Timing
The table displays the mean alphas from regressions of the CAPM model in Equation (2.13) with funds timing monthly conditional volatility procyclically (Pro), countercyclically (Counter) or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the CAPM volatility timing model in Equation (2.17), adjusted for passive timing, is significant at a 5% (5% α) or 10% (10% α) level, based on t-statistics from Welch's t-test with Newey-West standard errors. Missing values indicate that no funds of the given category follow the given timing strategy.

	Panel A: 5% α			**Panel B: 10% α**		
	Pro (%)	Counter (%)	Neutral (%)	Pro (%)	Counter (%)	Neutral (%)
All	-0.40^{**}	-0.32^{*}	-0.11^{*}	-0.31^{**}	-0.22^{*}	-0.12^{*}
High Yield	-0.48^{**}	-0.67^{**}	-0.12	-0.36^{**}	-0.51^{**}	-0.12
Investment Grade	-0.12	0.06	-0.11^{*}	-0.14	0.07	-0.12^{*}
High Yield						
Asian HY	-0.29	-	-0.15	-0.29	-	-0.14
European HY	-1.24^{**}	0.00	-0.56^{**}	-0.98^{**}	0.26	-0.61^{**}
Global HY	1.55^{*}	0.99^{*}	0.67^{**}	0.97^{*}	1.11^{**}	0.67^{**}
Global HY HEUR	-0.18	-0.28	-0.98^{**}	-0.42	-0.65^{**}	-0.97^{**}
Global HY HGBP	-1.13^{**}	0.24	-0.40^{**}	-0.13	0.24	-0.46^{**}
US HY	-0.54^{**}	-1.80^{**}	0.25	-0.39^{*}	-1.74^{**}	0.28
Investment Grade						
European IG	-0.34	0.08	-0.14^{*}	-0.43^{**}	0.09	-0.16^{*}
Global IG	0.77	1.85^{**}	0.15	0.54	1.99	0.05
Global IG HEUR	-0.99	-0.55	-0.26^{**}	-0.60	-0.25	-0.27^{**}
Global IG HUSD	-0.12	-1.12^{**}	-0.20^{*}	-0.06	-0.45^{*}	-0.21^{*}
US IG	0.07	-0.10	0.13	0.06	-0.30	0.15

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Table C.3: CAPM α for Monthly Realized Volatility Timing
The table displays the mean alphas from regressions of the CAPM model in Equation (2.13) with funds timing monthly realized volatility procyclically (Pro), countercyclically (Counter) or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the CAPM volatility timing model in Equation (2.17), adjusted for passive timing, is significant at a 5% (5% α) or 10% (10% α) level, based on t-statistics from Welch's t-test with Newey-West standard errors. Missing values indicate that no funds of the given category follow the given timing strategy.

	Panel A: 5% α			**Panel B: 10% α**		
	Pro (%)	Counter (%)	Neutral (%)	Pro (%)	Counter (%)	Neutral (%)
All	-0.31^{*}	-0.16	-0.14^{**}	-0.31^{*}	-0.20	-0.13^{**}
High Yield	-0.34	-0.40^{*}	-0.15^{*}	-0.40^{**}	-0.41^{**}	-0.12
Investment Grade	-0.15	0.51	-0.12^{*}	0.09	0.28	-0.13^{**}
High Yield						
Asian HY	-0.29	-	-0.15	-0.29	-	-0.14
European HY	-0.98^{**}	0.15	-0.63^{**}	-0.87^{**}	-0.10	-0.63^{**}
Global HY	2.08^{*}	1.42^{**}	0.63^{**}	1.06	0.73^{*}	0.71^{**}
Global HY HEUR	-1.02^{*}	-0.25	-0.96^{**}	-0.68^{*}	-0.36	-0.98^{**}
Global HY HGBP	-1.60^{*}	0.15	-0.34^{*}	-1.03	0.14	-0.38^{*}
US HY	-0.02	-1.66^{**}	0.19	-0.13	-1.60^{**}	0.22
Investment Grade						
European IG	-0.34	0.49	-0.17^{**}	-0.28	0.28	-0.17^{**}
Global IG	-0.34	1.85^{**}	0.25	-0.34	1.85^{**}	0.25
Global IG HEUR	-0.51^{**}	-0.39^{**}	-0.28^{**}	0.02	-0.55	-0.29^{**}
Global IG HUSD	-0.15	-	-0.21^{*}	-0.28	-	-0.21^{*}
US IG	0.07	-	0.12	0.70	-	0.06

Statistical significance is based on two-sided t-tests.
* Significant at the 5% level.
** Significant at the 1% level.

Table C.4: Sharpe ratios for CAPM Based Daily Conditional Volatility Timing The table displays the annualized mean Sharpe ratios of funds timing daily conditional volatility procyclically (Pro), countercyclically (Counter), or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the CAPM volatility timing model in Equation (2.17) is significant at a 5% (5% λ) or 10% (10% λ) level, based on two-sided t-tests with Newey-West standard errors.

	Panel A: 5% λ			**Panel B: 10% λ**		
	Pro	Counter	Neutral	Pro	Counter	Neutral
All	1.16	1.07	1.02	1.13	1.10	1.01
High Yield	1.21	1.13	1.09	1.19	1.20	1.08
Investment Grade	1.03	1.01	0.90	1.00	0.98	0.90
High Yield						
Asian HY	1.16	1.70	1.42	1.20	1.70	1.41
European HY	1.14	1.49	1.08	1.10	1.47	1.07
Global HY	1.14	1.05	1.32	1.20	1.39	1.30
Global HY HEUR	1.14	0.76	0.69	1.00	0.67	0.68
Global HY HGBP	1.45	0.91	0.85	1.33	0.91	0.86
US HY	1.31	1.38	1.25	1.31	1.38	1.23
Investment Grade						
European IG	1.07	1.22	0.92	1.04	1.10	0.94
Global IG	0.65	0.63	0.47	0.60	0.58	0.45
Global IG HEUR	0.57	0.88	0.58	0.63	0.87	0.57
Global IG HUSD	1.20	1.45	1.20	1.22	1.36	1.19
US IG	1.20	0.78	0.99	1.16	0.90	0.97

Table C.5: Sharpe Ratios for CAPM Based Monthly Conditional Volatility Timing

The table displays the annualized mean Sharpe ratios of funds timing monthly conditional volatility procyclically (Pro), countercyclically (Counter), or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the CAPM volatility timing model in Equation (2.17) is significant at a 5% (5% λ) or 10% (10% λ) level, based on two-sided t-tests with Newey-West standard errors. Missing values indicate that no funds of the given category follow the given timing strategy.

	Panel A: 5% λ			**Panel B: 10% λ**		
	Pro	Counter	Neutral	Pro	Counter	Neutral
All	0.92	1.18	1.10	0.94	1.18	1.11
High Yield	0.96	1.13	1.08	0.97	1.17	1.07
Investment Grade	0.83	1.23	1.14	0.88	1.18	1.16
High Yield						
Asian HY	1.00	-	1.10	1.01	-	1.10
European HY	1.04	1.05	1.02	1.07	1.29	1.00
Global HY	1.25	1.51	1.28	1.15	1.50	1.27
Global HY HEUR	0.01	0.97	0.73	0.06	1.00	0.71
Global HY HGBP	1.36	1.12	1.15	1.06	1.17	1.16
US HY	1.31	1.15	1.22	1.27	1.16	1.22
Investment Grade						
European IG	0.70	1.24	1.04	0.83	1.20	1.04
Global IG	0.96	0.35	0.74	0.87	0.39	0.81
Global IG HEUR	0.87	0.83	0.85	0.48	0.88	0.85
Global IG HUSD	2.16	1.42	1.59	2.16	1.45	1.59
US IG	1.28	1.57	1.27	1.25	1.52	1.27

Table C.6: Sharpe Ratios for CAPM Based Monthly Realized Volatility Timing

The table displays the annualized mean Sharpe ratios of funds timing monthly realized volatility procyclically (Pro), countercyclically (Counter), or not timing (Neutral), grouped by fund category. Funds are classified as timers if the volatility timing coefficient from a regression of the CAPM volatility timing model in Equation (2.17) is significant at a 5% (5% λ) or 10% (10% λ) level, based on two-sided t-tests with Newey-West standard errors. Missing values indicate that no funds of the given category follow the given timing strategy.

	Panel A: 5% λ			**Panel B: 10% λ**		
	Pro	Counter	Neutral	Pro	Counter	Neutral
All	1.12	1.14	1.10	1.11	1.16	1.10
High Yield	1.09	1.14	1.07	1.07	1.16	1.07
Investment Grade	1.29	1.15	1.14	1.25	1.16	1.14
High Yield						
Asian HY	0.97	-	1.12	0.91	-	1.16
European HY	1.08	1.40	1.00	1.03	1.31	1.00
Global HY	1.27	1.67	1.26	1.17	1.59	1.26
Global HY HEUR	0.24	0.97	0.71	0.57	0.94	0.70
Global HY HGBP	0.98	1.21	1.16	1.11	1.27	1.14
US HY	1.23	0.92	1.25	1.20	0.93	1.25
Investment Grade						
European IG	0.48	1.17	1.05	1.04	1.18	1.03
Global IG	0.68	0.76	0.73	0.68	0.76	0.73
Global IG HEUR	1.18	0.96	0.84	0.87	0.86	0.84
Global IG HUSD	1.96	-	1.56	1.70	-	1.56
US IG	1.65	-	1.28	1.61	-	1.27

Table C.7: *p*-values of Difference in α With Four-Factor Timing Coefficients
The table shows the *p*-values of the differences in alphas obtained from regressions of the four-factor model in Equation (2.14), grouped by daily timing coefficients from the four-factor volatility timing model in Equation (2.18) with a 5% significance level cut-off point. The *p*-values represent the difference in alphas of the strategy indicated by the column, less the strategy indicated by the row. Numbers 1-3 represent procyclical (Pro), countercyclical (Counter), and neutral (Neutral) timing, respectively. *p*-values in the left group are based on Welch's t-tests with Newey-West standard errors. *p*-values in the right group are based on permutation testing with 10000 permutations.

		Welch (%)			Permutation (%)		
		1.	2.	3.	1.	2.	3.
Panel A: IG Funds - Daily Conditional Volatility							
1.	Pro	0.0	3.0	3.5	0.0	2.2	13.6
2.	Counter	3.0	0.0	30.7	2.1	0.0	30.0
3.	Neutral	3.5	30.7	0.0	13.9	30.6	0.0
Panel B: HY Funds - Daily Conditional Volatility							
1.	Pro	0.0	5.0	21.2	0.0	10.5	15.0
2.	Counter	5.0	0.0	15.8	10.7	0.0	19.3
3.	Neutral	21.2	15.8	0.0	14.7	18.4	0.0
Panel C: IG Funds - Monthly Conditional Volatility							
1.	Pro	0.0	3.4	0.5	0.0	4.0	5.9
2.	Counter	3.4	0.0	49.6	4.3	0.0	57.5
3.	Neutral	0.5	49.6	0.0	5.5	56.9	0.0
Panel D: HY Funds - Monthly Conditional Volatility							
1.	Pro	0.0	13.5	0.0	0.0	18.4	5.2
2.	Counter	13.5	0.0	85.3	17.4	0.0	79.8
3.	Neutral	0.0	85.3	0.0	4.9	78.9	0.0
Panel E: IG Funds - Realized Monthly Volatility							
1.	Pro	0.0	8.6	16.6	0.0	10.8	21.0
2.	Counter	8.6	0.0	33.4	10.7	0.0	28.0
3.	Neutral	16.6	33.4	0.0	20.8	28.1	0.0
Panel F: HY Funds - Realized Monthly Volatility							
1.	Pro	0.0	64.8	71.6	0.0	66.8	73.0
2.	Counter	64.8	0.0	32.5	67.0	0.0	43.6
3.	Neutral	71.6	32.5	0.0	73.7	43.3	0.0

Table C.8: p-values of Difference in α With CAPM Timing Coefficients
The table shows the p-values of the differences in alphas obtained from regressions of the CAPM model in Equation (2.13), grouped by daily timing coefficients from the CAPM volatility timing model in Equation (2.17) with a 5% significance level cut-off point. The p-values represent the difference in alphas of the strategy indicated by the column, less the strategy indicated by the row. Numbers 1-3 represent procyclical (Pro), countercyclical (Counter), and neutral (Neutral) timing, respectively. p-values in the left group are based on Welch's t-tests with Newey-West standard errors. p-values in the right group are based on permutation testing with 10000 permutations.

		Welch (%)			Permutation (%)		
		1.	2.	3.	1.	2.	3.
Panel A: IG Funds - Daily Conditional Volatility							
1.	Pro	0.0	0.9	9.6	0.0	0.2	23.2
2.	Counter	0.9	0.0	5.0	0.3	0.0	1.8
3.	Neutral	9.6	5.0	0.0	22.8	1.8	0.0
Panel B: HY Funds - Daily Conditional Volatility							
1.	Pro	0.0	0.7	5.0	0.0	2.9	1.8
2.	Counter	0.7	0.0	7.9	3.0	0.0	10.6
3.	Neutral	5.0	7.9	0.0	2.0	10.7	0.0
Panel C: IG Funds - Monthly Conditional Volatility							
1.	Pro	0.0	87.5	5.2	0.0	90.0	31.6
2.	Counter	87.5	0.0	2.5	90.5	0.0	6.3
3.	Neutral	5.2	2.5	0.0	30.8	6.5	0.0
Panel D: HY Funds - Monthly Conditional Volatility							
1.	Pro	0.0	13.9	1.3	0.0	24.2	8.4
2.	Counter	13.9	0.0	94.0	25.4	0.0	92.0
3.	Neutral	1.3	94.0	0.0	8.4	92.6	0.0
Panel E: IG Funds - Monthly Realized Volatility							
1.	Pro	0.0	6.6	79.3	0.0	15.4	91.5
2.	Counter	6.6	0.0	6.1	15.2	0.0	1.1
3.	Neutral	79.3	6.1	0.0	91.8	0.9	0.0
Panel F: HY Funds - Monthly Realized Volatility							
1.	Pro	0.0	81.0	30.8	0.0	81.7	37.8
2.	Counter	81.0	0.0	18.8	80.6	0.0	27.1
3.	Neutral	30.8	18.8	0.0	37.9	26.5	0.0

Table C.9: *p*-values of Difference in Sharpe Ratio With Four-Factor Timing Coefficients

The table shows the *p*-values of the differences in Sharpe ratios, grouped by daily timing coefficients from the four-factor volatility timing model in Equation (2.18) with a 5% significance level cut-off point. The *p*-values represent the difference in Sharpe ratio of the strategy indicated by the column, less the strategy indicated by the row. Numbers 1-3 represent procyclical (Pro), countercyclical (Counter), and neutral (Neutral) timing, respectively. *p*-values in the left group are based on Welch's t-tests with Newey-West standard errors. *p*-values in the right group are based on permutation testing with 10000 permutations.

		Welch (%)			Permutation (%)		
		1.	2.	3.	1.	2.	3.
Panel A: IG Funds - Conditional Daily Volatility							
1.	Pro	0.0	23.0	1.3	0.0	22.2	4.5
2.	Counter	23.0	0.0	50.5	22.6	0.0	55.0
3.	Neutral	1.3	50.5	0.0	4.6	55.5	0.0
Panel B: HY Funds - Conditional Daily Volatility							
1.	Pro	0.0	21.3	1.8	0.0	26.1	1.2
2.	Counter	21.3	0.0	96.9	25.5	0.0	97.0
3.	Neutral	1.8	96.9	0.0	1.5	97.3	0.0
Panel C: IG Funds - Conditional Monthly Volatility							
1.	Pro	0.0	0.0	0.4	0.0	0.0	1.3
2.	Counter	0.0	0.0	0.3	0.0	0.0	2.2
3.	Neutral	0.4	0.3	0.0	1.2	2.2	0.0
Panel D: HY - Conditional Monthly Volatility							
1.	Pro	0.0	21.2	16.7	0.0	20.7	18.7
2.	Counter	21.2	0.0	84.0	20.8	0.0	85.0
3.	Neutral	16.7	84.0	0.0	17.8	85.2	0.0
Panel A: IG Funds - Realized Monthly Volatility							
1.	Pro	0.0	13.2	24.3	0.0	8.4	21.1
2.	Counter	13.2	0.0	34.9	8.9	0.0	47.1
3.	Neutral	24.3	34.9	0.0	21.0	48.0	0.0
Panel B: HY Funds - Realized Monthly Volatility							
1.	Pro	0.0	49.0	64.4	0.0	48.8	71.3
2.	Counter	49.0	0.0	64.5	48.9	0.0	69.5
3.	Neutral	64.4	64.5	0.0	72.2	70.3	0.0

Table C.10: p-values of Difference in Sharpe Ratio With CAPM Timing Coefficients

The table shows the p-values of the differences in Sharpe ratios, grouped by daily timing coefficients from the CAPM volatility timing model in Equation (2.17) with a 5% significance level cut-off point. The p-values represent the difference in Sharpe ratio of the strategy indicated by the column, less the strategy indicated by the row. Numbers 1-3 represent procyclical (Pro), countercyclical (Counter), and neutral (Neutral) timing, respectively. p-values in the left group are based on Welch's t-tests with Newey-West standard errors. p-values in the right group are based on permutation testing with 10000 permutations.

		Welch (%)			Permutation (%)		
		1.	2.	3.	1.	2.	3.
Panel A: IG Funds - Conditional Daily Volatility							
1.	Pro	0.0	78.8	1.1	0.0	78.7	4.9
2.	Counter	78.8	0.0	9.0	77.4	0.0	15.9
3.	Neutral	1.1	9.0	0.0	4.9	15.7	0.0
Panel B: HY Funds - Conditional Daily Volatility							
1.	Pro	0.0	38.4	2.2	0.0	44.4	1.9
2.	Counter	38.4	0.0	59.9	44.2	0.0	63.8
3.	Neutral	2.2	59.9	0.0	1.8	63.5	0.0
Panel C: IG Funds - Conditional Monthly Volatility							
1.	Pro	0.0	1.5	5.0	0.0	0.1	3.2
2.	Counter	1.5	0.0	9.4	0.1	0.0	21.3
3.	Neutral	5.0	9.4	0.0	3.2	21.0	0.0
Panel D: HY Funds - Conditional Monthly Volatility							
1.	Pro	0.0	3.8	9.9	0.0	2.6	7.3
2.	Counter	3.8	0.0	25.7	2.7	0.0	29.9
3.	Neutral	9.9	25.7				
Panel E: IG Funds - Realized Monthly Volatility							
1.	Pro	0.0	52.9	42.7	0.0	52.2	37.8
2.	Counter	52.9	0.0	94.8	52.7	0.0	95.2
3.	Neutral	42.7	94.8	0.0	37.3	94.8	0.0
Panel F: HY Funds - Realized Monthly Volatility							
1.	Pro	0.0	48.5	63.2	0.0	47.8	73.7
2.	Counter	48.5	0.0	25.2	49.0	0.0	28.2
3.	Neutral	63.2	25.2	0.0	72.5	28.4	0.0

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