Essays on Financial Performance Measurement

D I S S E R T A T I O N
of the University of St. Gallen,
Graduate School of Business and Administration,
Economics, Law and Social Sciences (HSG)
to obtain the title of
Doctor of Philosophy in Management

submitted by

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from

Pleigne - Delémont (Jura)

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Dissertation no. 3859

epubli, Berlin, 2010

The University of St. Gallen, Graduate School of Business and Administration, Economics, Law and Social Sciences (HSG) hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St. Gallen, November 2, 2010

The President:

Prof. Ernst Mohr, PhD

Acknowledgments

The work for this dissertation was extensive and sometimes exhausting, but in the first place exciting and fun. Without the help and support of several people, I would not have been able to finish this work in this fashion.

I would like to express my gratitude to my supervisor, Prof. Dr. Hato Schmeiser. I appreciate all his contributions of time and ideas which substantially shaped and improved this thesis. Furthermore, I would like to thank my co-supervisor Prof. Dr. Manuel Ammann.

Very special thanks go out to my co-authors Prof. Dr. Martin Eling, Prof. Dr. Hato Schmeiser, and Alexandra Zemp. I enjoyed the collaborative work with them strongly. While writing this thesis, I have profited from suggestions and discussions with many colleagues for whom I have great regard. I would also like to thank all my colleagues at the Institute of Insurance Economics for an inspiring working atmosphere and excellent research conditions.

Lastly, I would like to thank my parents for the support they provided me throughout my entire life.

Roger Faust
St. Gallen, December 2010

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Summary

This thesis consists of three individual papers. In the first paper, entitled "The Performance of Hedge Funds and Mutual Funds in Emerging Markets" we analyze the performance of mutual funds and hedge funds active in emerging markets. Because the use of short selling and derivatives is limited in most emerging markets it is questionable whether hedge funds, especially compared to traditional mutual funds, which are active in these markets, are able to add value. We use five existing performance measurement models plus a new asset-style factor model to identify the return sources and the alpha generated by both hedge funds and mutual funds in emerging markets. Our results indicate that some hedge funds generate significant positive alpha, whereas most mutual funds do not outperform traditional benchmarks.

In the second paper, "A Performance Analysis of Participating Life Insurance Contracts" the performance of participating life insurance contracts is analyzed. Participating life insurance contracts are one of the most important products in the European life insurance market. Even though these contract forms are very common, only very little research has been conducted in respect to its performance. We decompose a participating life insurance contract in a term life insurance and a savings part and simulate the cash flow distribution of the investment part. The latter is compared with cash flows resulting from a benchmark investing into the same portfolio but without investment guarantees and bonus distribution scheme in order to measure the impact of these two product features.

In a contingent claims approach, equity is expressed as a call option on the assets of a company with debt being the strike. Depending on option type and parameters, a reduction in the volatility of assets could imply a value reduction. If corporate diversification leads to a reduction in the volatility of assets this reasoning might explain the diversification discount. This is the hypothesis which we test empirically in the third paper, entitled "Corporate Risk, Diversification, and Shareholder Value". Using a maximum likelihood estimation, we first estimate the volatility of a companies assets within a down-and-out call option framework. The firm's actual value compared to the sum of stand-alone values of its business segments is used as measure for excess value. The estimated parameters are then used in a second-step regression with excess value as dependent variable.

The Performance of Hedge Funds and Mutual Funds in Emerging Markets

Martin Eling and Roger Faust*

Use of short selling and derivatives is limited in most emerging markets because such instruments are not as readily available as they are in developed capital markets. These limitations raise questions about the value added provided by hedge funds, especially compared to traditional mutual funds active in these markets. We use five existing performance measurement models plus a new asset-style factor model to identify the return sources and the alpha generated by both types of funds. We analyze subperiods, different market environments, and structural breaks. Our results indicate that some hedge funds generate significant positive alpha, whereas most mutual funds do not outperform traditional benchmarks. We find that hedge funds are more active in shifting their asset allocation. The higher degree of freedom that hedge funds enjoy in their investment style might thus be one explanation for the differences in performance.

*This paper has been published in the Journal of Banking and Finance. Acknowledgements: We are grateful to Benjamin A. Abugri, Christian Biener, Alexander Braun, Sandip Dutta, Christian Kraus, Przemysław Rymaszewski, Hato Schmeiser, and the participants in the 8th German Operations Research Society Workshop on Finance and Financial Institutions (Hannover, April 2009) for their valuable comments and suggestions.

1 Introduction

Institutional investors and high-net-worth individuals have put significant amounts of money into hedge funds, seeking high returns as well as diversification benefits promised by hedge fund managers (see Fung et al. (2008)). Due to the absence of reliable data, academic literature on hedge funds in the 1990s was restricted to descriptive analysis and relatively simple performance metrics (e.g., Fung and Hsieh (1997); Fung (1999); Ackermann et al. (1999)). However, as more information and data have become available, more sophisticated techniques from quantitative finance have been used to analyze hedge funds. One important stream of this literature has developed multifactor performance measurement models (Fung and Hsieh, 2001; Agarwal and Naik, 2004) that identify the sources of hedge fund returns and separate the risk premiums from different investments (beta) and the alpha that hedge fund managers provide.

Recent literature shows that classical, linear performance measurement models often cannot capture the dynamic trading strategies in the different asset classes and markets that many hedge funds pursue (Agarwal and Naik, 2004; Capocci, 2004). Moreover, hedge funds employ a variety of trading strategies, so analyzing all hedge funds using only one performance measurement framework that does not consider the characteristics of the specific strategies is of limited value. Hedge-fund-style specific performance measurement models are needed so as to capture the differences in management style (Fung and Hsieh, 2001, 2004; Agarwal and Naik, 2004).

In this paper, we use recent innovations from performance measurement literature (Agarwal and Naik, 2004; Fung and Hsieh, 2004; Fung et al., 2008) to analyze the performance of emerging market hedge funds. We define emerging markets as those countries or areas of the globe that are in the process of rapid growth and industrialization, such as China, India, and Latin America, as well as many eastern European and southeastern Asian countries. These markets exhibit significant growth opportunities, but also high political and economic risks, making emerging markets more volatile than mature markets (De Santis, 1997). A main difference between emerging market hedge funds and other hedge funds is that use of short selling and derivatives was relatively limited in the previous two decades because such instruments were not as readily available as they are in developed capital markets.[1] These limitations raise questions about the value added provided by these funds, for example, compared to traditional long-only mutual funds.

Emerging market hedge funds have been analyzed as one among many strategies in hedge fund performance measurement literature such as Fung and Hsieh (1997), Fung and Hsieh (2001), Agarwal and Naik (2004), and Capocci (2004). However, all these authors do not analyze these funds in detail or try to extract the main differences between these funds and other hedge funds.[2] This is somewhat surprising, especially given the relative importance of emerging markets in the hedge fund industry.[3] Further the underlying factors, such as emerging market stock and bond indices, are-at least recently-more readily available than for other hedge fund strategies which involve more complex arbitrage strategies. Our analysis will show that appropriate factor models can be derived much more easily for emerging market hedge funds than for other hedge funds. Among the few authors who focus on emerging market hedge funds are Sancetta and Satchell (2005). However, they analyze only a small sample of 15 emerging market hedge funds over a relatively short period (60 months). Furthermore, their aim is to apply a new test statistic for market timing on a data sample. More recently, Strömqvist (2007) analyzes the skills of emerging market hedge fund managers. Her focus is on comparing emerging market hedge funds with other hedge fund strategies, while our focus is on comparing emerging market hedge funds with mutual funds active in this market. Abugri and Dutta (2009) analyze whether emerging market hedge funds

[1] There is some evidence that in recent years emerging market hedge funds have had a growing set of instruments for trading in emerging markets. For example, Abugri and Dutta (2009) note that emerging market hedge funds have begun to accommodate distressed, relative value arbitrage, quantitative directional and activist strategies. Chen (2010) notes that by June 2006, 62.7% of the emerging market hedge funds in the TASS database were already using derivatives. Although this is one of the lowest values compared to other hedge fund strategies, it shows that emerging market hedge funds now face more trading opportunities and might thus have changed their strategy. This hypothesis is supported by the empirical findings of Abugri and Dutta (2009). Following Abugri and Dutta (2009), we will also analyze whether hedge funds have changed their strategy. See also Frino et al. (2009) for an analysis of derivative use in investment management.

[2] Fung and Hsieh (1997), Fung and Hsieh (2001), Agarwal and Naik (2004), and Capocci (2004) all develop performance measurement models for the whole hedge fund and funds of hedge funds market, but they do not consider emerging markets in detail.

[3] Based on the number of funds, emerging market hedge funds are the second largest hedge fund strategy group after long/short equity (see, e.g., Capocci (2004); Eling (2009)).

follow a pattern similar to that reported for advanced market hedge funds after 2006. The focus of this paper also differs from this analysis, in that we compare hedge funds and mutual funds active in emerging markets, while these authors analyze whether emerging market hedge funds are comparable with hedge funds that are active in advanced markets. Furthermore, we analyze individual hedge fund data; Abugri and Dutta (2009) consider hedge fund indices.[4,5]

The aim of this paper is to fill a gap in literature by providing a broad evaluation of the performance of emerging market hedge funds and mutual funds. We build upon insights from both the hedge fund and mutual fund literature and analyze six factor models, some of which are representative of recent innovations in this growing field of research. For comparison purposes, we start with the classical single-factor (1) Capital Asset Pricing Model (CAPM) and then extend our analysis to more complex multifactor models, including (2) Fama (1993), (3) Carhart (1997), (4) Fung and Hsieh (1997), and (5) Fung and Hsieh (2004). All these models are useful in identifying the risks underlying hedge funds and mutual funds, but they cannot account for the specific characteristics of emerging market hedge funds. We thus employ emerging market risk factors to set up our sixth model: an emerging market asset class factor model (6). In our analysis we compare the performance of hedge funds not only with traditional benchmark indices, but also with traditional mutual funds that have an investment focus in emerging markets. Most studies only consider either hedge funds or mutual funds; we analyze both investment vehicles active in this growing market.[6]

[4] In an analysis of different subperiods, we also analyze the hypotheses developed by Abugri and Dutta (2009) that since 2006 emerging market hedge funds have behaved like regular hedge funds, while traditionally before 2007 they behaved like mutual funds. Our empirical analysis of different subperiods thus extends the findings by Abugri and Dutta (2009) in that we analyze individual hedge fund data instead of hedge fund indices.

[5] Another stream of literature analyzes mutual funds with a focus on emerging markets, i.e., funds that do not use leverage, derivatives, and short selling (even if such might be possible in some emerging markets). Abel and Fletcher (2004) analyzes U.K. unit trusts with a focus on emerging market equity using stochastic discount factors and finds no evidence of superior performance. Overall, the literature reports mixed findings with regard to the performance of emerging market mutual funds (see, e.g., Tkac (2001); Ahmed et al. (2001)). Aggarwal et al. (2007) analyze the investment allocation decision of emerging market mutual fund managers with regard to American Depositary Receipts (ADRs).

[6] Chen and Chen (2009) analyze conflicts of interest with concurrent management of mutual and hedge funds for funds active in developed markets.

Our analysis builds upon the Center for International Securities and Derivatives Markets (CISDM) database, which is one of the largest hedge fund databases ever analyzed for this purpose. It contains data on 566 hedge funds which have an emerging market focus. Additionally, we select 1,542 mutual funds active in emerging markets from the Thomson Financial Datastream database. The analysis covers the years 1995 through August 2008, which is advantageous for three reasons. First, the results will not suffer as much from the survivorship and backfilling biases that plague much of the older hedge fund research.[7] Second, this period contains bull as well as bear markets, allowing us to analyze the performance of emerging market hedge funds in different market environments; many other studies are limited to the analysis of bull markets.[8] Third, the analyzed time period contains some critical events for emerging market hedge funds, such as the Asian crises in 1998 and the technology bubble in 2000. We consider these events in detail in our analysis of structural breaks, subperiods, and market environments.

Our main findings can be summarized as follows. (1) Hedge fund returns and alphas are much higher than those of traditional mutual funds. (2) Some hedge funds outperform traditional benchmarks, whereas most mutual funds tend to underperform traditional benchmarks. (3) In bad or neutral market environments, hedge funds outperform mutual funds while generating the same returns in good environments. Overall, our analysis indicates that emerging market hedge funds perform better than their traditional competitors. We also discuss potential reasons for the performance differences, i.e., higher flexibility, liquidity risk, lower regulation, and technical problems such as return smoothing.

The remainder of the paper is organized as follows. Section 2 covers the methodology, i.e., the six performance measurement models we use in the empirical part. Section 3 presents our data and discusses how we deal

[7]Major hedge fund data vendors did not cover dissolved funds prior to 1994. Hedge fund data before 1994 are thus not very reliable. For this reason, Capocci (2004) decided to exclude the largest part of their hedge fund data from 1984 to 2000 in their study of hedge fund performance. For the same reason, Liang and Park (2007) start their analysis in 1995. The unreliability of data before 1994 is also discussed by Fung and Hsieh (2000), Liang (2000), and Li and Kazemi (2007).

[8]See, e.g., Amenc et al. (2003), Baquero et al. (2005), and Brown et al. (1999). Although many hedge funds do not use trend-following strategies, Capocci et al. (2005) found that the market phase may influence the results. It thus seems important to have bullish as well as bearish market phases in the study. Ding and Shawky (2007) emphasizes the importance of considering different market cycles when analyzing hedge fund performance.

with the several data biases inherent in hedge fund data. In Section 4 we present our empirical findings, and we conclude in Section 5.

2 Performance Measurement Models

2.1 Traditional Performance Measurement Models

For comparison purposes, we consider both classical and modern performance measurement models in our empirical analysis. The most basic performance measurement model is Jensen's alpha, based on an ex-post test of the classical CAPM:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it}, \tag{1}$$

where R_{it} is the return of fund i in month t (with $t = -1, -2, .., -T$), R_{ft} is the risk-free return, R_{mt} the return of the market portfolio, and ϵ_{it} an error term. The α_i stands for the intercept of the regression and is commonly called Jensen's alpha Jensen (1968) and used as a performance measure relative to the market portfolio (see, e.g., Patro (2001), for an application to mutual funds); the slope of the regression β_i is called the beta factor. As the market proxy is the only factor used as a benchmark, the CAPM is a single-factor model. This single-factor modeling has been extended in literature to a multifactor framework in order to improve the portion of variance explained by the regression. We consider the Fama and French (1993) three-factor model and the Carhart (1997) model as basic multifactor specifications because they are generally not dominated by any other model in the mutual funds performance literature (see Capocci (2004)). The Fama and French (1993) model has two additional factors, one for size (SMB, i.e., small minus big) and one for the ratio of book-to-market value (HML, i.e., high minus low book-to-price ratio):

$$R_{it}-R_{ft} = \alpha_i+\beta_{im}(R_{mt}-R_{ft})+\beta_{iSMB}SMB_t+\beta_{iHML}HML_t+\epsilon_{it}, \tag{2}$$

Carhart (1997) adds a momentum (MOM) factor to the Fama and French (1993) model, which accounts for trend-following strategies in stock markets, i.e., buying stocks that were past winners and selling past losers:

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + \beta_{im}(R_{mt} - R_{ft}) + \beta_{iSMB}SMB_t \\ + \beta_{iHML}HML_t + \beta_{iMOM}MOM_t + \epsilon_{it}. \end{aligned} \tag{3}$$

Many empirical implementations (e.g., Fama (1993)) use diversified portfolios of stocks as a proxy for the market portfolio. The first three models thus focus primarily on stock markets. However, hedge funds are flexible enough to select from among many asset classes and can employ dynamic trading strategies. Accordingly, these three models have been extended to capture alternative asset classes as well as to accommodate differences between the approach used by hedge fund managers as compared to the strategies engaged in by traditional mutual fund managers (see Fung and Hsieh (1997)). Fung and Hsieh (1997) define eight standard asset classes useful for analyzing fund performance-three equity indices (MSCI North American (MSUSAM), MSCI non-US (MSWXUS), IFC Emerging Markets (IFCOMP)), two bond indices (JP Morgan US Government Bonds (USMGUSRI), JP Morgan Non-US Government Bonds (USMGEXRI)), currencies (Federal Reserve Traded Weighted Index of the US Dollar (USD)), the one-month Eurodollar Deposit Return of the previous month (ECUSD1M), and gold (GOLDBLN; London morning fixing):

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i &+ \beta_{iMSUSAM} MSUSAM_t + \beta_{iMSWXUS} MSWXUS_t \\ &+ \beta_{iIFCOMP} IFCOMP_t + \beta_{iUSMGUSRI} USMGUSRI_t \\ &+ \beta_{iUSMGEXRI} USMGEXRI_t + \beta_{iUSD} USD_t \\ &+ \beta_{iECUSD1M} ECUSD1M_t \\ &+ \beta_{iGOLDBLN} GOLDBLN_{t-1} + \epsilon_{it}, \end{aligned} \tag{4}$$

The eight standard asset classes used in Fung and Hsieh (1997) can capture the different asset classes used by hedge funds and mutual funds, but option-like factors are needed to capture the dynamic trading strategies of hedge funds. The most prominent model of this type that has demonstrated considerable explanatory power for hedge fund returns is the factor model developed by Fung and Hsieh (2001), Fung and Hsieh (2004):[9]

[9]The most recent application of this model is presented in Fung et al. (2008). Agarwal and Naik (2004), as well as Capocci (2004), present competing factor models that include some of the same factors as the Fung and Hsieh model considered in this paper.

$$
\begin{aligned}
R_{it} - R_{ft} = \alpha_i &+ \beta_{iSNPMRF} SNPMRF_t \\
&+ \beta_{iSCMLC} SCMLC_t + \beta_{iBD10RET} BD10RET_t \\
&+ \beta_{iBAAMTSY} BAAMTSY_t + \beta_{iPTFSBD} PTFSBD_t \\
&+ \beta_{iPTFSFX} PTFSFX_t + \beta_{iPTFSCOM} PTFSCOM_t \\
&+ \beta_{iMSEMKF} MSEMKF_t + \epsilon_{it},
\end{aligned} \tag{5}
$$

Fung and Hsieh employ two equity-oriented risk factors: an equity market factor, the Standard & Poor's 500 index excess returns (SNPMRF), and a size spread factor, the Russell 2000 index minus the Standard & Poor's 500 (SCMLC)[10]. Furthermore, they consider two bond-oriented factors, and three trend-following factors[11]. Recently, Fung and Hsieh added an eighth factor to this model-the MSCI Emerging Market Index (MSEMKF)[12] which is especially relevant in our context and therefore included in our analysis.

2.2 An Asset Class Factor Model for Emerging Market Funds

None of the above-mentioned models captures the specific location or strategy component characteristics of investing in emerging markets. The CAPM, Fama and French (1993), and Carhart (1997) do not consider emerging market indices at all and Fung and Hsieh's models contain only one index each (the IFC emerging market index and the MSCI emerging market index). We extend these models and set up an asset class factor model for emerging market funds using various emerging market stock indices, provided by MSCI, and various emerging market bond indices, provided by JP Morgan. There are two ways to construct an asset

[10] The original seven-factor model presented in Fung and Hsieh (2001, 2004) contains Wilshire indices, which ceased publication in December 2006. On his webpage, David Hsieh recommends using the Russell 2000 index instead (see `http://faculty.fuqua.duke.edu/~dah7/8FAC.htm`).

[11] The two bond-oriented factors are the change in the 10-year treasury constant maturity yield as a bond market factor (BD10RET) and the spread of the change of the Moody's Baa yield over the change of the 10-year treasury constant maturity yield as a credit spread factor (BAAMTSY). The three trend-following factors are the Bond Trend-Following Factor (PTFSBD), the Currency Trend-Following Factor (PTFSFX), and the Commodity Trend-Following Factor (PTFSCOM); see Fung and Hsieh (2001) for a detailed description of how the trend-following factors are constructed.

[12] See `http://faculty.fuqua.duke.edu/~dah7/8FAC.htm`

class factor model. The first is to screen many variables through stepwise regression techniques (see, e.g., Liang (1999), Agarwal and Naik (2004), Vrontos et al. (2008), in a hedge fund context), which usually leads to a relatively high in-sample R^2, but to a relatively low out-of-sample R^2. The second option is to select a short list of variables that are assumed to be economically relevant. Many authors find that this approach leads to a lower in-sample R^2, but a higher out-of-sample R^2 (see, e.g., Amenc et al. (2003) in a hedge fund context). Choosing the right approach therefore involves a tradeoff between quality of fit (higher with stepwise regression, lower with economic reasoning) and robustness (lower with stepwise regression, higher with economic reasoning). In our analysis, we combine the advantages of both approaches, i.e., we present a simple-to-interpret and easy-to-use emerging market factor model and additionally discuss a stepwise regression that we implemented.

An asset class factor model should be able to explain where the hedge fund invests (the location component) and how it invests (the strategy component). To derive both of these components, we examined the fund description provided within the CISDM database for the sample of funds which we analyze. The main geographic areas in which funds are reported to be active are Asia/Pacific excluding Japan (13%), Latin America (14%), and Eastern Europe (15%). 25% report investing globally and 30% do not report their geographic focus. Regarding strategy 70% of the funds report investing in equities and 19% report investing in some kind of bonds. Only 5% report using options and 5% report using futures or forward contracts. All other instruments which are reported within the database are used more infrequently.[13] From this we infer that the most important strategies focus on equities and bonds. Regarding leverage, 22% report on average a gross leverage above 1. For those funds which reported their average gross leverage, the leverage is 1.6.

We thus designed an emerging market factor model which captures the two main investment styles of emerging market hedge funds: equities and bonds. We use three stock market indices and three bond indices to account for the different regional exposures of emerging market hedge funds.

[13] Note that our values for use of futures and options are lower than the 62.7% reported in Chen (2010) for the TASS database. However, since reporting is not mandatory, we assume that funds are often reluctant to report all supported information fields. For example in our sample, 19% report having leveraged positions through options which is inconsistent with the low number of funds using options. For the deficiencies of hedge fund reporting, see also Fung and Hsieh (2000).

Furthermore, we include these bond indices with a lag of one month to capture possible autocorrelation effects, especially for hedge fund returns. Getmansky et al. (2004) discuss possible reasons for autocorrelation in hedge fund returns and conclude that it is probably mostly attributable to illiquidity and return smoothing. We think that this effect might be more pronounced for fixed income instruments which are often not publicly listed and have no observable market price. Thus we include lagged bond indices but not lagged equity indices.

Finally, we add the credit spread factor from the Fung and Hsieh (2001, 2004) model. Fung and Hsieh (2001, 2004) argue that the credit spread is relevant with hedge funds investing in corporate bonds which are then affected by changing credit risk premiums (BAA Yield). Furthermore, they argue that hedge funds often finance their activities through lending (10-Year treasury). Given that 22% report an average gross leverage above 1, we think that this might also be the case for emerging market hedge funds. Both the direction of the bet and the financing are represented within the credit spread. Emerging market funds thus face credit risk through their investments in emerging market corporate bonds. Emerging market funds also face credit risk through their investments in emerging market governments bonds since in times of crisis there is a rush from advanced market corporate bonds and emerging market (corporate and government) bonds to safe advanced market government bonds. We thus believe that the credit spread is highly relevant for bond investors in emerging markets.[14] In summary, the model is given by:[15]

$$
\begin{aligned}
R_{it} - R_{ft} = \alpha_i &+ \beta_{iMSEMFA} MSEMFA_t \\
&+ \beta_{iMSEMEA} MSEMEA_t + \beta_{iMSEFLA} MSEFLA_t \\
&+ \beta_{iJPMPASI} JPMPASI_t + \beta_{iJPMPEUR} JPMPEUR_t \\
&+ \beta_{iJPMPLAT} JPMPLAT_t + \beta_{iJPMPASIL} JPMPASI_{t-1} \\
&+ \beta_{iJPMPEURL} JPMPEUR_{t-1} \\
&+ \beta_{iJPMPLATL} JPMPLAT_{t-1} \\
&+ \beta_{iBAAMTSY} BAAMTSY_t + \epsilon_{it}
\end{aligned}
\tag{6}
$$

Furthermore, we use a stepwise regression which improves the location component that we analyze on a more general level in Equation (6). We run a stepwise regression on the factors from Equation (6) and allow for a

[14] Due to lack of appropriate data for emerging markets, we include the Fung and Hsieh (2001, 2004) credit spread which is constructed for advanced markets. The underlying assumption is that the advanced market risk factor is sufficiently highly correlated with the true emerging markets risk factor that we want to proxy. Additional tests indicate only minor variations in credit spreads among countries. In these tests we compare emerging markets credit default swaps from 2004 with Moody's Baa yield less the 10-year treasury yield which are used to derive the advanced market credit spread factor in the Fung and Hsieh (2001), Fung and Hsieh (2004) model. We used data on 1,273 credit default swaps for 29 emerging market countries and found that in most cases the correlation between the CDS data and the Moodys BAA yield, less the 10-year treasury yield, is positive and highly significant. We find that 70% of all correlations are significant on a 5% level and 50% (60%) of all correlations are higher than 0.84 (0.73). The empirical connection between credit risk in advanced and emerging markets is both statistically and economically significant. The Fung and Hsieh (2001, 2004) credit spread measures credit quality differences between high-quality government bonds and low-quality corporate bonds. In times of crises there is a rush away from advanced market corporate bonds and emerging market (corporate and government) bonds to safe advanced market government bonds. Both credit risk in advanced and emerging markets thus highly depends on the state of the global economy. We thus statistically and economically see a connection between these two risk factors and believe that the advanced market credit spread factor is an appropriate proxy for credit risk in emerging markets.

[15] Note that our model (6) is comparable to the models presented by Abugri and Dutta (2009). The main difference is the inclusion of different bonds indices, lagged bond indices, and the use of the credit spread. Furthermore, we do not include the Eurodollar deposit index, the spot price of gold, and the trade weighted dollar index. For example, only three of the 243 funds analyzed mention investing in gold.

maximum of five regressors. In a second step, we improve the geographic asset allocation by replacing the remaining MSCI and JPM Morgan indices with country-level indices for the same geographic area. Again, we run a stepwise regression and allow for a maximum of five regressors.

3 Data

3.1 Data Selection

We use hedge fund data provided by the Center for International Securities and Derivatives Markets (CISDM), a database frequently employed in hedge fund research (for the properties of this database, see, e.g., Edwards and Caglayan (2001); Kouwenberg (2003); Capocci (2004); Ding and Shawky (2007); Chen and Chen (2009)). Depending on the strategy, the database can be broken down into 22 hedge fund strategies and 7 funds of funds strategies. From this database we selected the sample of those funds that are classified as emerging market hedge funds. Our initial sample consists of 566 funds with returns between January 1995 and August 2008, but our refinement of the data to minimize the biases inherent in hedge fund data, causes the loss of more than half of these funds (see below). The mutual fund data are taken from Thomson Financial Datastream. We extracted 1,542 mutual funds that focus on emerging markets. Even though data biases are not as problematic for mutual funds, we prepare these data using the same principles as applied for the hedge funds. All following data are monthly, discrete return numbers. Hedge funds and mutual funds are compared with passive benchmark indices. The data on the passive benchmark indices were collected from Thomson Financial Datastream, the US Federal Reserve, and the webpages of Kenneth R. French[16] and David A. Hsieh[17]. The equity market proxy (i.e., the market portfolio in the CAPM) is the value-weighted portfolio of all NYSE, Amex, and Nasdaq stocks used in Fama and French (1993) and Carhart (1997). The risk-free interest rate is the one-month U.S. treasury bill rate.

3.2 Data Biases

Like other hedge fund databases, the CISDM database suffers from several biases, including survivorship bias, backfilling bias, selection bias, and

[16] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`
[17] `http://faculty.fuqua.duke.edu/~dah7/8FAC.htm`

multiperiod sampling bias. Surviving funds are those still operating and reporting whereas defunct funds have stopped reporting (Fung and Hsieh, 2000). Why funds stop reporting is difficult to discern but, quite likely, poor performance is one of the main reasons. Thus, returns of surviving funds are upward-biased. We calculated survivorship bias as the difference in fund returns between all funds and the surviving funds. This bias is 0.217 percentage points per month-a value comparable to those found in the literature (see, e.g., Fung and Hsieh (2000); Fung (1999); Liang (2000)). For the mutual funds, survivorship bias is slightly higher at only 0.223 percentage points per month, a trend also well documented in literature (see Liang (2000)). However, as we include both surviving and defunct funds, survivorship bias should not be a problem in this study. When new hedge funds are added to a database, data vendors tend to backfill historical returns, which may cause another upward bias in performance, the so-called backfilling bias (also known as instant history bias). The underlying assumption is that funds have an incentive to backfill historical returns only if they have been successful in the past. Estimators for the backfilling bias can be calculated by stepwise deleting the first 12 or 24 months of returns (see Brown et al. (1999); Fung and Hsieh (2000); Capocci (2004)). In our sample, the monthly excess return of the portfolio that invests in all hedge funds is 0.96%. Eliminating the first 12 (24) months of returns reduces the return about 0.23% (0.23%). These values are a bit higher compared to literature (e.g., if the first 12 months are deleted Eling (2009) reports 0.18% per month and Fung and Hsieh (2000) 1.4% per year; note that for mutual funds there is no backfilling so that this bias is not relevant for this group). To adequately address the backfilling bias in our investigation, we follow Fung and Hsieh (2000) and Edwards and Caglayan (2001) and delete the first 12 monthly returns of all funds. Since reporting to a data vendor is voluntary for hedge funds, the data might contain a selection bias. The assumption is that a manager who decides to report has a better performance than one who does not. Quantifying the selection bias would require access to returns from hedge funds that decide not to report, which are not available and thus selection bias cannot be directly addressed in a performance study. However, Fung and Hsieh (1997) argue that this bias might be limited because there also is a substantial number of well-performing funds that do not report their data because they do not want to attract new investors. A minimum number of returns is necessary for a meaningful performance analysis, but requiring a minimum return history might create a multiperiod sampling bias (also called minimum history bias), i.e., a group of short-lived, unsuccessful funds might be eliminated. Following Fung and Hsieh (1997) and Liang (2000), we eliminate hedge funds with less than 36 monthly returns, including the 12 months deleted to address the backfilling bias. As mutual fund returns are not backfilled, we eliminate those mutual funds with less than 24 monthly returns. This reduces our sample to 243 hedge funds and 629 mutual funds. We find that our main results are not affected by the variation of the minimum number of returns and thus conclude that this bias has no substantial impact on our results.

4 Empirical Results

4.1 Summary Statistics

Table 1 contains descriptive statistics on the monthly return distributions of the 243 hedge funds, the 629 mutual funds, and the 26 benchmark indices; it shows the first four moments (mean, standard deviation, skewness, and kurtosis), the minimum and the maximum as well as three quantiles (25% quantile, median, 75% quantile). The last column of Table 1 provides information on autocorrelation in returns (with lag of one month). As the benchmark indices represent diversified portfolios in the various investments, we use an equally weighted average across all hedge funds and mutual funds to provide a fair basis for the comparison (as done, e.g., in Capocci (2004)). Hedge funds provide returns (0.96%) much higher than those of mutual funds (0.43%), but they also have a lower standard deviation (4.69% vs. 4.84%). The difference in returns also leads to much higher Sharpe ratios for the hedge funds. However, although some investors might be more concerned with central tendencies of the return distribution (mean value, standard deviation), others may care more about the distributions shape and extreme values, that is, skewness and kurtosis. We find that both hedge funds and mutual funds on average display a negative skewness with a positive kurtosis. The values are more extreme for the hedge funds, i.e., the skewness is lower and the kurtosis is much higher. This is an important finding because investors with a positive marginal utility, consistent risk aversion, and strict consistency of moment preference prefer higher values with the odd moments (mean, skewness) and lower values with the even moments (standard deviation, kurtosis) (Scott and Horvath, 1980). The negative skewness and positive kurtosis displayed by the hedge funds might thus be an unattractive combination for such investors that is not reflected by the classical Sharpe ratio or under the classical Markowitz framework (see, e.g., Moreno and Rodríguez (2009), for a broader analysis of skewness in performance evaluation). We also use a Jarque and Bera (1987) test to check whether the observed values of skewness and excess kurtosis are consistent with the normal distribution assumption. At a 5% significance level, the rejection rate for emerging market hedge funds is 53.91% and 40.70% for the mutual funds.

Figure 1 illustrates the risk return combinations of hedge funds, mutual funds, and most of the benchmark indices (the extreme option factors are not shown). Overall, there appears to be a positive relationship between risk and return (i.e., investments with a higher return generally have higher risk). EM hedge funds outperform most other investments. Only one of the benchmark indices (the JPM EM Asia) provides a higher Sharpe ratio than hedge funds, which again look very attractive from an investor's point of view, especially because hedge fund returns are net of all fees; passive indices, in contrast, do not include the costs of portfolio management.[18,19]

4.2 Correlation

In Table 2 we report correlation coefficients between hedge funds, mutual funds, and the passive benchmark indices. We show both the full investigation period (January 1996 to August 2008) as well as selected subperiods

[18]The Sharpe ratio is the most widely used and best known performance measure in the investment industry (see Eling (2008)), which is why we consider it here. The Sharpe ratio, however, is only one of many performance measures and it has several deficiencies that can be addressed by alternative performance measures. For example, the classical Sharpe ratio is difficult to interpret when the excess return term in the numerator is negative (see Abugri and Dutta (2009)). Furthermore, if returns do not display a normal distribution pattern, the Cornish-Fisher expansion can be used to include skewness and kurtosis in performance measurement (see Eling and Schuhmacher (2007)). We calculated other measures such as the modified Sharpe ratio developed by Israelsen (2003, 2005), the modified Sharpe ratio developed by Gregoriou and Gueyie (2003), the Sortino ratio (see Sortino and van der Meer (1991)), or the Calmar ratio (see Young (1991)). The performance comparison among these measures is presented in the Appendix. These tests show that the statement with regard to the performance of hedge funds is robust among these measures.

[19]The difference in Sharpe ratio between hedge funds and mutual funds is statistically significant at 1% level. See Jobson and Korkie (1981) and the Appendix 8 for the test results.

	Mean (%)	SD (%)	Skew.	Kurt.	Min. (%)	25% (%)	Median (%)	75% (%)	Max. (%)	Autocor. (lag 1)
243 Hedge Funds	0.96	4.69	-1.46	9.88	-26.52	-1.48	1.80	3.68	14.20	0.27
631 Mutual Funds	0.43	4.84	-1.03	5.72	-23.00	-1.94	1.07	3.57	9.96	0.14
Market Proxy	0.45	4.37	-0.69	3.69	-16.20	-2.31	0.96	3.50	8.18	0.05
SMB*	0.25	4.01	0.80	9.77	-16.79	-2.21	-0.02	2.61	21.96	-0.08
HML*	0.43	3.61	0.08	5.47	-12.40	-1.37	0.33	2.34	13.85	0.06
Momentum*	0.84	5.40	-0.56	7.07	-25.06	-1.20	0.87	3.21	18.39	-0.08
MSCI North Am.	0.42	4.27	-0.48	3.38	-14.33	-2.11	0.85	3.38	9.51	0.01
MSCI non-US	0.32	4.19	-0.55	3.40	-13.18	-2.22	0.50	3.24	10.12	0.11
IFC Emerg. Markets	0.63	6.21	-0.82	4.44	-25.85	-2.28	1.11	4.94	12.20	0.11
JPM US Gov. Bonds	0.20	1.33	-0.38	3.76	-4.75	-0.57	0.23	1.06	3.06	0.05
JPM Non-US	0.15	2.32	0.30	2.84	-4.71	-1.63	0.03	1.64	6.37	0.17
Eurodollar Deposit	-0.30	6.78	-0.89	8.35	-32.64	-1.25	0.00	2.06	23.19	0.32
Gold	0.29	4.28	0.63	3.85	-9.38	-2.71	-0.04	2.72	16.96	-0.01
US Dollar*	0.11	5.00	-0.20	3.51	-15.19	-3.03	0.15	3.07	12.17	0.00

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Table 1: Descriptive statistics for hedge funds, mutual funds, and passive benchmark indices. All indices are analyzed on basis of excess returns, unless indicated with an asterisk (*).

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	Mean (%)	SD (%)	Skew.	Kurt.	Min. (%)	25% (%)	Median (%)	75% (%)	Max. (%)	Autocor. (lag 1)
S&P 500	0.41	4.23	-0.53	3.55	-14.89	-2.07	0.84	3.43	9.31	0.01
Size*	0.10	3.77	0.25	7.43	-16.38	-2.49	0.12	2.50	18.41	-0.14
Bond*	-0.01	0.22	0.40	2.92	-0.53	-0.16	-0.04	0.15	0.65	0.18
Credit*	0.01	0.14	0.83	4.05	-0.25	-0.08	-0.01	0.06	0.48	0.39
TFBond*	-1.73	13.78	1.54	7.28	-25.36	-10.22	-4.15	3.37	68.86	0.06
TFCur*	0.71	17.77	0.98	4.08	-30.00	-11.67	-1.97	9.36	66.01	-0.01
TFCom*	0.62	14.03	1.31	5.82	-23.04	-8.22	-2.03	7.05	64.75	-0.15
MSCI EM Total	0.62	6.76	-0.86	4.70	-29.34	-2.81	0.98	5.60	13.23	0.08
MSCI EM Asia	0.21	7.52	-0.17	3.31	-19.98	-4.55	0.31	5.32	21.10	0.21
MSCI EM Europe	1.11	7.49	-0.71	4.91	-31.42	-3.26	2.17	6.18	20.55	-0.01
MSCI EM Latin Am.	1.39	8.13	-0.84	4.93	-35.12	-3.42	2.62	6.63	19.90	-0.02
JPM EM Asia	0.68	3.03	-2.37	24.65	-22.13	-0.46	0.69	1.95	12.94	-0.10
JPM EM Europe	1.18	6.36	-4.41	41.16	-54.77	-0.61	1.12	3.87	15.96	0.14
JPM EM Latin Am.	0.65	4.13	-1.64	11.74	-24.64	-0.97	1.13	2.85	11.97	-0.13

Table 1: Descriptive statistics for hedge funds, mutual funds, and passive benchmark indices. All indices are analyzed on basis of excess returns, unless indicated with an asterisk (*).

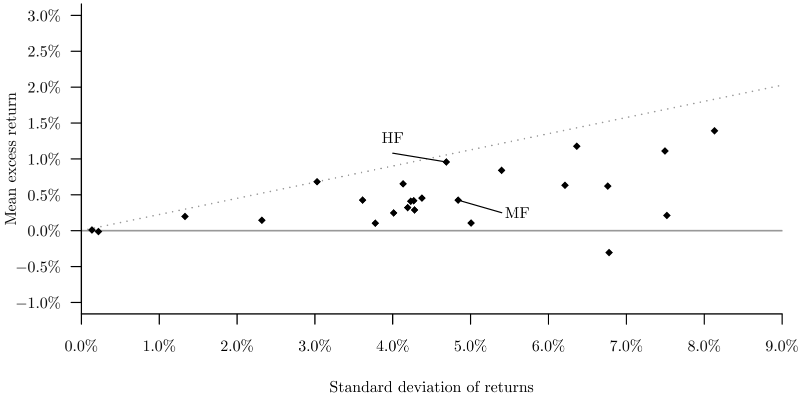

Figure 1: Risk and return combinations for hedge funds, mutual funds, and passive benchmark indices (monthly data, the three trend-following factors are not presented).

that we will analyze in the paper.[20]

With regard to the full investigation period (columns 2 and 3), the correlations between mutual funds and the stock and bond market indices are positive and significant. When considering the three emerging market stock indices and the three emerging market bond indices presented in the last six rows of Table 2, we only find significant and positive correlations. The same result is found when analyzing the correlations between hedge funds and the traditional stock and bond indices. A major argument for investing in hedge funds, however, is that the correlations with traditional investments such as stocks and bonds are somewhat lower, which

[20] The selection of subperiods follows Fung et al. (2008) and Abugri and Dutta (2009) and will be motivated below. The correlations among the passive investment strategies are available upon request. Here we have to be careful with those indices that we use in the performance measurement model, as extremely high correlations might raise multicollinearity concerns. The correlations between indices that we use in one model, however, are all below 0.79 (and higher than -0.63) and most of them are below 0.5 which is too low to raise multicollinearity concerns. Other correlations, of course, might be higher, e.g., the correlation between the market proxy and the S&P 500 (which is 0.97), as the market proxy represents a broadly diversified U.S. stock portfolio. An analysis of the variance inflation factors (available upon request) confirms that multicollinearity is not problematic.

	January 1996 to August 2008		January 1996 to September 1998		October 1998 to March 2000		April 2000 to December 2006		January 2007 to August 2008	
	MF	HF	MF	HF	MF	HF	MF	HF	MF	HF
HF	0.91	1.00	0.91	1.00	0.91	1.00	0.95	1.00	0.95	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MF	1.00	0.91	1.00	0.91	1.00	0.91	1.00	0.95	1.00	0.95
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Market Proxy	0.78	0.66	0.81	0.68	0.61	0.54	0.83	0.78	0.76	0.60
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
SMB	0.36	0.33	0.33	0.37	0.30	0.21	0.53	0.53	-0.26	-0.37
	(0.00)	(0.00)	(0.06)	(0.03)	(0.23)	(0.41)	(0.00)	(0.00)	(0.27)	(0.11)
HML	-0.44	-0.36	-0.50	-0.35	-0.38	-0.28	-0.45	-0.41	-0.45	-0.55
	(0.00)	(0.00)	(0.00)	(0.05)	(0.12)	(0.26)	(0.00)	(0.00)	(0.04)	(0.01)
Momentum	-0.15	-0.06	-0.15	-0.10	0.05	0.10	-0.31	-0.23	0.21	0.35
	(0.07)	(0.50)	(0.41)	(0.58)	(0.84)	(0.69)	(0.00)	(0.04)	(0.37)	(0.13)
MSCI North Am.	0.70	0.59	0.76	0.62	0.43	0.41	0.79	0.72	0.69	0.53
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.09)	(0.00)	(0.00)	(0.00)	(0.02)

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Table 2: Correlation between mutual funds (MF) and hedge funds (HF), and passive investment strategies (p-values are given in parentheses).

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	January 1996 to August 2008		January 1996 to September 1998		October 1998 to March 2000		April 2000 to December 2006		January 2007 to August 2008	
	MF	HF	MF	HF	MF	HF	MF	HF	MF	HF
MSCI non-US	0.77	0.66	0.74	0.60	0.56	0.48	0.80	0.77	0.93	0.87
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
JPM US Gov. Bonds	-0.27	-0.22	-0.32	-0.35	-0.04	0.00	-0.19	-0.11	-0.60	-0.56
	(0.00)	(0.01)	(0.07)	(0.04)	(0.88)	(0.99)	(0.09)	(0.33)	(0.00)	(0.01)
JPM Non-US	-0.14	-0.13	-0.32	-0.37	-0.25	-0.28	0.00	0.10	-0.30	-0.21
	(0.08)	(0.10)	(0.07)	(0.03)	(0.32)	(0.26)	(0.97)	(0.37)	(0.20)	(0.37)
Eurodollar Deposit	0.05	0.07	-0.18	-0.04	0.21	0.36	0.03	0.00	0.08	0.08
	(0.57)	(0.39)	(0.31)	(0.84)	(0.40)	(0.14)	(0.79)	(0.99)	(0.72)	(0.73)
Gold	0.14	0.12	0.27	0.15	-0.12	-0.20	0.20	0.27	0.05	0.16
	(0.08)	(0.13)	(0.14)	(0.41)	(0.65)	(0.43)	(0.08)	(0.02)	(0.84)	(0.51)
US Dollar	0.48	0.47	0.56	0.51	0.27	0.28	0.39	0.39	0.71	0.81
	(0.00)	(0.00)	(0.00)	(0.00)	(0.28)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)
S& P 500	0.70	0.59	0.77	0.63	0.42	0.39	0.79	0.72	0.68	0.51
	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.11)	(0.00)	(0.00)	(0.00)	(0.02)

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Table 2: Correlation between mutual funds (MF) and hedge funds (HF), and passive investment strategies (p-values are given in parentheses).

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	January 1996 to August 2008		January 1996 to September 1998		October 1998 to March 2000		April 2000 to December 2006		January 2007 to August 2008	
	MF	HF	MF	HF	MF	HF	MF	HF	MF	HF
Size	0.29	0.26	0.23	0.25	0.28	0.20	0.41	0.43	-0.13	-0.25
	(0.00)	(0.00)	(0.19)	(0.17)	(0.26)	(0.42)	(0.00)	(0.00)	(0.58)	(0.28)
Bond	0.19	0.21	0.16	0.25	0.12	0.24	0.11	0.06	0.44	0.49
	(0.02)	(0.01)	(0.37)	(0.16)	(0.63)	(0.33)	(0.33)	(0.59)	(0.05)	(0.03)
Credit	-0.36	-0.38	-0.16	-0.38	-0.26	-0.30	-0.45	-0.46	-0.46	-0.48
	(0.00)	(0.00)	(0.38)	(0.03)	(0.30)	(0.22)	(0.00)	(0.00)	(0.04)	(0.03)
TFBond	-0.22	-0.27	-0.53	-0.61	-0.22	-0.03	-0.02	-0.01	-0.32	-0.31
	(0.01)	(0.00)	(0.00)	(0.00)	(0.38)	(0.90)	(0.86)	(0.94)	(0.18)	(0.18)
TFCur	-0.15	-0.09	-0.16	-0.05	-0.26	-0.33	-0.12	-0.03	-0.24	-0.28
	(0.07)	(0.26)	(0.39)	(0.78)	(0.30)	(0.18)	(0.30)	(0.78)	(0.32)	(0.23)
TFCom	-0.09	-0.08	-0.16	-0.12	-0.48	-0.42	0.01	0.08	0.13	0.03
	(0.25)	(0.31)	(0.36)	(0.52)	(0.04)	(0.09)	(0.90)	(0.49)	(0.59)	(0.92)
MSCI EM Total	0.96	0.86	0.96	0.84	0.93	0.84	0.96	0.92	0.97	0.95
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

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Table 2: Correlation between mutual funds (MF) and hedge funds (HF), and passive investment strategies (p-values are given in parentheses).

Continued from last page

	January 1996 to August 2008		January 1996 to September 1998		October 1998 to March 2000		April 2000 to December 2006		January 2007 to August 2008	
	MF	HF	MF	HF	MF	HF	MF	HF	MF	HF
MSCI EM Asia	0.85	0.72	0.80	0.65	0.69	0.55	0.89	0.83	0.93	0.88
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
MSCI EM Europe	0.80	0.78	0.82	0.82	0.62	0.59	0.81	0.82	0.82	0.89
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
MSCI EM Latin Am.	0.88	0.82	0.92	0.83	0.83	0.82	0.87	0.86	0.91	0.91
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JPM EM Asia	0.54	0.48	0.76	0.61	0.31	0.03	0.43	0.49	0.26	0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.20)	(0.91)	(0.00)	(0.00)	(0.28)	(0.80)
JPM EM Europe	0.66	0.74	0.83	0.84	0.74	0.69	0.60	0.65	0.06	-0.11
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.80)	(0.64)
JPM EM Latin Am.	0.63	0.61	0.82	0.70	0.62	0.59	0.54	0.55	0.39	0.23
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.09)	(0.34)

Table 2: Correlation between mutual funds (MF) and hedge funds (HF), and passive investment strategies (p-values are given in parentheses).

makes hedge funds interesting for portfolio diversification. In fact, the correlations of the hedge fund returns with the traditional investments are generally lower than the corresponding correlation with the mutual funds. For example, the correlation between mutual funds and the S&P 500 is 0.70, but it is only 0.59 with the hedge funds. Nevertheless, both hedge funds and mutual funds are found to be highly correlated with the returns of traditional stock and bond indices, a finding which is also quite robust among the different subperiods analyzed in Table 2. An exception, however, are the bonds indices in the most recent period (January 2007 to August 2008), where we find much lower and insignificant correlations, especially with hedge funds. For example, with the hedge funds all three JPM EM bond indices are insignificant (see last three rows in the last column of Table 2). This finding is in line with Abugri and Dutta (2009) who find significant correlations with the benchmark assets in the pre-2007 period and overwhelmingly insignificant correlations in the post-2006 period.[21]

Both for hedge funds and mutual funds, the correlation with gold, Eurodollar deposit, and the trend following factors are insignificant in most cases, while the credit spread is mostly significant. The analysis of correlation thus confirms our model design that we have based on the funds strategy description: emerging market funds exhibit credit risk. The correlation between hedge fund and mutual fund returns is 0.91. This is an interesting finding, since it illustrates that although hedge funds and mutual funds produce highly correlated returns and they tend to invest in the same asset classes, hedge funds produce a significantly higher Sharpe ratio in the full investigation period. An investigation into the underlying sources of these returns is provided in the following performance analysis.

[21] The findings by Abugri and Dutta (2009) also hold especially for bonds, while they still have positive and significant correlations with stocks in many cases. We also analyzed correlation in the subperiods at the individual fund level and found that most of the individual hedge funds exhibit much lower and often insignificant correlations with the three JPM bond indices in the most recent period. For example, while in the full sample period 60.91% (61.73%, 51.85%) of the individual hedge funds were positively and significantly correlated at 5% level with the JPM Europe index (JPM Latin America, JPM Asia), in the fourth subperiod no funds (only 6.56%, only 3.28%) were so. The findings of Abugri and Dutta (2009) with regard to differences in the post 2006 period can thus also be confirmed at the individual hedge fund level. With the individual mutual funds we also find lower correlations with the JPM bond indices, but these are less extreme.

4.3 Performance Measurement Results for 1996 to August 2008

As expected, we find the lowest adjusted R^2 for the CAPM-based single-index model. Considering the equally weighted portfolio, the CAPM explains about 60.02% of the variation in the mutual funds returns and 43.41% of the variation in hedge fund returns. These values are comparable to other findings, e.g., Capocci (2004) report an adjusted R^2 of 38% in their analysis of hedge fund performance. The explanatory power is on average lower for the individual funds. For example, the median across all funds is only 38.14% for the mutual funds and 20.12% for the hedge funds. This is due to the fact that the equally weighted averages represent diversified portfolios (like the benchmark indices), whereas the individual funds are much more diverse. The adjusted R^2 of the equally weighted portfolio is better than the individual funds median for all six performance measurement models.[22]

The Fama (1993) and Carhart (1997) models increase the explanatory power by nearly 4% for both types of funds. Consistently, the adjusted R^2 for hedge funds is about 17% lower than that of mutual funds. The increase of approximately 4% is again in line with literature (see Capocci (2004)). Interestingly, for the equally weighted index the Carhart (1997) model does not increase adjusted R^2 compared to the Fama (1993) model, i.e. the increase in explanatory power delivered by the momentum factor is not large enough to outweigh the negative impact of adding another variable to the model. The more sophisticated multifactor models based on Fung and Hsieh (1997) and Fung and Hsieh (2004) increase the explanatory power by another 30%. The adjusted R^2 for the mutual funds is 93.10% and 93.52%, while hedge funds are again approximately 20% below that value (74.76% and 76.35%). The major reason for this increase in explanatory power is the use of an emerging market index.

This finding emphasizes the need for improved modeling of the location component with respect to different emerging stock and bond markets, which is the approach we use in our emerging market factor model. Our model is therefore able to reduce the difference in explanatory power between hedge funds and mutual funds and to capture most of the variation

[22] An alternative to the CAPM with the market proxy (i.e. the value-weighted portfolio of all NYSE, Amex, and Nasdaq stocks used in Fama (1993) and Carhart (1997)) is to use a broad emerging market index such as the IFC emerging market index, which results in much higher adjusted R^2.

	Equally weighted portfolio (%)	Individual funds quantiles (%)				
		Min.	25%	Median	75%	Max.
Panel A: Mutual Funds						
(1) CAPM	60.02	-3.40	21.98	38.14	50.25	88.43
(2) Fama/French	64.08	-9.37	23.65	40.31	52.54	92.19
(3) Carhart	63.86	-13.21	23.93	43.07	55.34	91.91
(4) Fung/Hsieh (1997)	93.10	-19.29	47.07	67.58	84.05	95.92
(5) Ext. Fung/Hsieh (2004)	93.52	-28.49	43.05	64.97	80.62	98.03
(6) EM Modell	94.57	-16.76	53.56	75.55	84.76	97.56
Panel B: Hedge Funds						
(1) CAPM	43.41	-4.48	7.99	20.12	31.49	59.79
(2) Fama/French	47.16	-7.11	11.05	23.38	34.67	78.00
(3) Carhart	47.15	-9.39	11.88	23.64	36.53	79.52
(4) Fung/Hsieh (1997)	74.76	-28.55	22.00	40.62	53.20	93.73
(5) Ext. Fung/Hsieh (2004)	76.35	-21.77	22.58	39.85	53.88	87.68
(6) EM Modell	89.75	-17.94	31.07	49.56	64.96	93.69

Table 3: Adjusted R^2 (%) of the performance measurement models.

in hedge fund returns. The adjusted R^2 for the equally weighted portfolio of hedge funds is 89.75%. This is a very high value compared to other asset class factor models developed for specific hedge fund styles. For example, Fung and Hsieh (2002) develop asset class factor models for fixed income hedge funds and find adjusted R^2 values of up to 79%. The reason for the higher explanatory power of our model might be that many hedge funds in emerging markets are long only and it thus might be easier to identify the return sources for these funds compared to fixed income funds that use complex arbitrage strategies. We also compared our results to the regression models presented by Abugri and Dutta (2009) and using our data we found an adjusted R^2 of 78.90% with their model for the composite EMHF category.[23,24]

In Table 4 we present the alpha values for the six performance measurement models.[25] In addition to the alpha values for the equally weighted portfolio (Columns 2 and 3) and the individual funds (Columns 4 to 8), we present the percentage of funds that exhibit a significant negative (sign. < 0) and positive alpha (sign. > 0), calculated at 95% confidence level. The mutual funds have negative alpha values in most cases, indicating that mutual fund managers on average underperform the benchmark indices. However, considering the equally weighted portfolio, none of the alpha values are significantly different from zero, except for the emerging market factor model (6). In this model, the equally weighted portfolio of the mutual funds on average underperforms the benchmark indices by 0.23%. The finding that mutual funds in emerging markets on average do not outperform traditional benchmark indices is in line with other findings in the literature (e.g., Abel and Fletcher (2004)).

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[23] We thank Benjamin A. Abugri and Sandip Dutta for helping us implement their approach. The other three models presented by Abugri and Dutta (2009) yield an adjusted R^2 of 71.12% (Asian model), 79.71% (European model), and 71.10% (Latin American model). If we use their Asian, European and Latin American index in one regression model, which would be most comparable with our model, the adjusted R^2 yields 84.98%.

[24] Using stepwise regression, we find an adjusted R^2 of 87.45% for the equally weighted portfolio of mutual funds and 91.02% for the hedge fund portfolio. Compared to model (6), the stepwise regression is thus worse for the mutual funds and slightly better for the hedge funds. On an individual-fund level, however, the stepwise regression performs much better as it better fits the specific geographic and tactical exposure of the individual funds. The median adjusted R^2 for mutual funds is 78.22% and 62.17% for hedge funds. For diversified portfolios, however, the more general model (6) provides a sufficiently good approximation that cannot be improved by stepwise regression.

[25] Results were determined using a heteroskedasticity and autocorrelation consistent covariance matrix (Newey and West (1987) and Andrews (1991)).

	Equally weighted portfolio		Individual funds						
			Alpha quantiles (%)					Alpha sign. (%)	
	Alpha (%)	t-stat	Min.	25%	Median	75%	Max.	< 0	> 0
Panel A: Mutual Funds									
(1) CAPM	0.04	0.12	-6.46	-0.15	0.34	0.75	8.27	3.97	14.15
(2) Fama/French	-0.07	-0.24	-7.86	-0.25	0.19	0.65	8.10	3.97	10.33
(3) Carhart	-0.05	-0.18	-7.28	-0.26	0.12	0.46	7.92	3.18	7.15
(4) Fung/Hsieh (1997)	-0.12	-1.08	-4.93	-0.44	-0.16	0.14	8.11	9.86	2.23
(5) Ext. Fung/Hsieh (2004)	0.01	0.06	-4.10	-0.30	-0.02	0.29	7.26	3.18	4.61
(6) EM Modell	-0.23^{***}	-2.37	-4.05	-0.55	-0.27	0.01	6.77	14.15	0.95
Panel B: Hedge Funds									
(1) CAPM	0.64^{*}	1.74	-5.47	0.06	0.48	1.15	3.58	1.65	30.45
(2) Fama/French	0.51	1.36	-5.78	-0.01	0.44	1.03	3.37	2.47	25.10
(3) Carhart	0.45	1.17	-5.38	-0.12	0.36	0.95	3.06	2.47	20.58
(4) Fung/Hsieh (1997)	0.49^{**}	2.01	-5.48	-0.18	0.30	0.80	10.55	2.88	17.70
(5) Ext. Fung/Hsieh (2004)	0.59^{**}	2.11	-5.20	-0.02	0.33	1.08	5.78	3.29	20.99
(6) EM Modell	0.15	1.03	-5.98	-0.35	0.05	0.57	3.87	5.35	11.52

Table 4: Alpha of the performance measurement models. Note: * (**, ***) indicates significance at 10% (5%, 1%) level.

This situation might be different for hedge funds, as the few fund managers who have beaten passive strategies tend to move to alternative investments and start their own hedge fund (see Agarwal and Naik (2000)). In contrast to the mutual funds, hedge funds have positive alpha values and two of them are statistically significant on a 5% level (with the Fung and Hsieh (1997) model and the ext. Fung and Hsieh (2004) model). For all models except model (5), the percentage of hedge funds exhibiting underperformance (sign. < 0) is lower than that of mutual funds and the percentage of hedge funds outperforming (sign. > 0) is higher for all models than for mutual funds, indicating that hedge fund managers on average perform better than mutual fund managers. Using the CAPM, 30.45% of all hedge funds outperform the benchmark, while with the EM factor model only 11.52% have a superior performance. With the EM factor model, only 0.95% of the mutual funds outperform the traditional benchmark indices, while 14.15% provide a significantly lower performance.[26]

In Table 5 we show regression results for the equally weighted portfolios of mutual funds and hedge funds. While for both mutual funds and hedge funds the equity factors are significant, this is not the case for the bond factors for Latin America and Asia. The intercept (i.e., alpha) is significant and negative for mutual funds while it is positive but insignificant for hedge funds. The credit spread is significant and negative for both hedge funds and mutual funds. The negative sign of the credit spread can be interpreted as follows: As the yield of low quality bonds rises faster than the yield of 10-year US treasuries (i.e. credit risk increases), returns of the funds are negatively affected because the low-quality bonds in which funds are invested lose value.

4.4 Performance Measurement Results for Different Subperiods

In Table 6 we present the results for different subperiods in an effort to test the robustness of our results over time. The selection of subperiods is motivated by two recent studies (Fung et al. (2008); Abugri and Dutta (2009)) which allows us to analyze the impact of two highly relevant events (Asian crisis, peak of the technology bubble; Fung et al. (2008)) as well as

[26] With the stepwise regression, the results are mostly more extreme, i.e., both the number of funds with a significant positive alpha and those with a significant negative alpha are higher than with model (6). For example, with model (6), 35.18% percent of all mutual funds have a negative alpha on a 5% significance level.

	Mutual Funds	Hedge Funds
Intercept	-0.230**	0.150
	(-2.375)	(1.034)
MSCI EM Asia	0.267***	0.126***
	(13.421)	(4.953)
MSCI EM Europe	0.145***	0.133***
	(7.456)	(4.138)
MSCI EM Latin Am.	0.164***	0.191***
	(6.782)	(5.692)
JPM EM Latin Am.	0.786	0.280
	(1.618)	(0.045)
JPM EM Asia	0.644	-0.519
	(1.179)	(-0.784)
JPM EM Europe	0.088***	0.252***
	(2.946)	(7.282)
JPM EM Latin Am.$_{t-1}$	0.397	0.439
	(1.201)	(1.062)
JPM EM Asia$_{t-1}$	-0.574	-0.603
	(-1.303)	(-1.009)
JPM EM Europe$_{t-1}$	0.408*	0.126***
	(1.750)	(3.787)
Credit Spread	-3.129***	-3.504***
	(-4.470)	(-3.799)

Table 5: Regression result for mutual funds and hedge funds with EM model (6). Note: * (**, ***) indicates significance at 10% (5%, 1%) level, t-stat is given in brackets.

to analyze whether a recent style shift in hedge fund behavior has occurred (Abugri and Dutta, 2009). We thus subdivide the sample period of 1996 to August 2008 into four subperiods. For the first three periods we follow Fung et al. (2008) in how we subdivide the sample: the Asian crises (January 1996 to September 1998), the time after the Asian crises until the peak of the technology bubble (October 1998 to March 2000), and the time after the peak of the technology bubble (April 2000 to December 2006). The selection of the last period is motivated by Abugri and Dutta (2009) and spans from January 2007 to August 2008. Abugri and Dutta (2009) find that emerging market hedge funds have followed a pattern similar to that reported for advanced market hedge funds only in the most recent period, from January 2007 to August 2008, while before that time they behaved like regular mutual funds.

Table 6 confirms the above finding that hedge funds on average have better performance than mutual funds. For both the equally weighted portfolio and the individual funds (Median, Sign. < 0, Sign. > 0), hedge funds perform better in nearly all subperiods and for all models. An interesting finding in model (5), the extended Fung and Hsieh (2004) model, is that emerging market hedge funds significantly outperform the benchmark indices both in the second subperiod (1998 to 2000), the time after the Asian crises, and in the third subperiod (2000 to 2006). Using a comparable model and considering funds of hedge funds, Fung et al. (2008) find that these outperform the market only during the small time window between 1998 and 2000, while at the end of their investigation period alphas of hedge funds decline. While in model (5) the absolute value of alpha declines in the third period (from 0.87% to 0.57%), the significance becomes even stronger. In contrast to Fung et al. (2008), however, Strömqvist (2007) identifies an upward trend in the performance of emerging market hedge funds over time and concludes that emerging market funds might be where future alphas can be found. We cannot confirm either an upward or a downward trend in alphas here, especially since in the emerging market model (6) the results for hedge funds are insignificant for the second and the third subperiods. Note, however, that in model (6) the mutual funds significantly underperform in both these periods. In the fourth period, results are insignificant both for hedge funds and mutual funds. Later results from a rolling regression will help to shed more light on the development of alpha over time and these are more in line with Strömqvist (2007). Table 7 shows the regression results for the equally weighted portfolio in the different subperiods. For the mutual funds, all of the equity indices are

	Equally weighted portfolio		Individual funds						
			Alpha quantiles (%)					Alpha sign. (%)	
	Alpha (%)	t-stat	Min.	25%	Median	75%	Max.	< 0	> 0
Panel A: Mutual Funds									
(1) CAPM	-2.06***	-2.90	-7.74	-3.02	-2.42	-1.13	0.34	49.62	0.00
(2) Fama/French	-1.95***	-2.97	-8.87	-3.00	-2.29	-1.03	1.00	45.80	0.00
(3) Carhart	-1.84**	-2.40	-7.82	-2.86	-2.26	-1.01	1.00	35.88	0.00
(4) Fung/Hsieh (1997)	-0.09	-0.25	-4.93	-0.48	0.02	0.51	2.76	5.34	2.29
(5) Ext. Fung/Hsieh (2004)	0.23	0.66	-4.26	-0.31	0.35	0.96	5.13	3.82	12.98
(6) EM Modell	-0.36	-1.41	-3.91	-0.85	-0.44	0.08	2.44	17.56	0.76
Panel B: Hedge Funds									
(1) CAPM	-1.27	-1.05	-5.12	-2.61	-1.24	-0.17	1.81	19.23	1.92
(2) Fama/French	-1.24	-1.15	-4.21	-2.64	-1.39	-0.15	2.34	15.38	1.92
(3) Carhart	-1.35	-1.14	-4.44	-2.67	-1.32	-0.28	1.94	11.54	1.92
(4) Fung/Hsieh (1997)	0.89	1.23	-1.95	-0.19	0.86	1.61	10.55	0.00	15.38
(5) Ext. Fung/Hsieh (2004)	2.05***	3.28	-2.50	0.36	1.48	3.47	7.42	0.00	30.77
(6) EM Modell	0.44	0.81	-2.90	-0.55	0.09	0.80	3.87	5.77	7.69

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Table 6: Alpha of the performance measurement models in different subperiods. Subperiod: January 1996 to September 1998. Note: * (**, ***) indicates significance at 10% (5%, 1%) level.

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	Equally weighted portfolio		Individual funds						
			Alpha quantiles (%)					Alpha sign. (%)	
	Alpha (%)	t-stat	Min.	25%	Median	75%	Max.	< 0	> 0
Panel A: Mutual Funds									
(1) CAPM	1.51^{**}	2.16	-2.92	0.76	1.43	2.05	7.75	0.56	15.56
(2) Fama/French	1.46^{*}	2.02	-3.75	0.77	1.33	2.04	6.53	0.56	15.56
(3) Carhart	1.46^{**}	2.48	-3.75	0.75	1.35	2.04	6.53	0.56	19.44
(4) Fung/Hsieh (1997)	0.06	0.31	-5.43	-0.74	-0.16	0.55	5.46	11.67	5.56
(5) Ext. Fung/Hsieh (2004)	0.81	1.58	-10.57	-0.29	0.57	1.74	9.44	0.56	9.44
(6) EM Modell	-0.46^{*}	-2.06	-10.30	-1.22	-0.60	0.22	5.02	8.33	1.11
Panel B: Hedge Funds									
(1) CAPM	2.14^{**}	2.60	-4.02	0.72	2.05	3.20	7.83	1.30	23.38
(2) Fama/French	2.20^{**}	2.69	-4.11	0.73	2.38	3.25	8.78	1.30	24.68
(3) Carhart	2.20^{**}	2.62	-4.11	0.73	2.39	3.25	8.78	1.30	27.27
(4) Fung/Hsieh (1997)	0.93	1.26	-6.60	-0.35	0.63	1.74	7.57	1.30	11.69
(5) Ext. Fung/Hsieh (2004)	0.87^{*}	1.90	-9.24	-0.67	0.55	2.00	9.02	1.30	9.09
(6) EM Modell	-0.25	-0.48	-7.14	-2.00	-0.41	0.97	5.63	3.90	3.90

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Table 6: Alpha of the performance measurement models in different subperiods. Subperiod: October 1998 to March 2000. Note: * (**, ***) indicates significance at 10% (5%, 1%) level.

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	Equally weighted portfolio		Individual funds						
			Alpha quantiles (%)					Alpha sign. (%)	
	Alpha (%)	t-stat	Min.	25%	Median	75%	Max.	< 0	> 0
Panel A: Mutual Funds									
(1) CAPM	0.57^{**}	2.10	-1.57	0.21	0.59	0.97	9.39	1.28	22.91
(2) Fama/French	0.26	0.92	-2.68	-0.17	0.20	0.52	9.38	2.57	6.85
(3) Carhart	0.24	0.88	-2.29	-0.15	0.22	0.56	9.37	2.78	7.07
(4) Fung/Hsieh (1997)	-0.12	-0.96	-2.99	-0.54	-0.17	0.17	8.94	10.49	2.36
(5) Ext. Fung/Hsieh (2004)	-0.06	-0.39	-2.39	-0.42	-0.05	0.25	10.28	3.64	3.64
(6) EM Modell	-0.30^{*}	-1.88	-5.04	-0.61	-0.26	0.03	8.56	9.85	1.07
Panel B: Hedge Funds									
(1) CAPM	1.07^{***}	4.18	-7.54	0.45	0.84	1.60	4.49	0.59	48.82
(2) Fama/French	0.78^{***}	3.27	-9.87	0.16	0.50	1.21	4.80	1.76	34.12
(3) Carhart	0.79^{***}	3.22	-10.27	0.17	0.51	1.24	4.73	1.76	33.53
(4) Fung/Hsieh (1997)	0.46^{***}	2.92	-7.56	0.00	0.43	1.00	4.59	2.94	27.65
(5) Ext. Fung/Hsieh (2004)	0.57^{***}	3.50	-9.07	0.06	0.45	1.15	4.22	1.76	31.76
(6) EM Modell	0.05	0.28	-11.90	-0.35	0.16	0.58	2.99	5.88	10.00

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Table 6: Alpha of the performance measurement models in different subperiods. Subperiod: April 2000 to December 2006. Note: * (**, ***) indicates significance at 10% (5%, 1%) level.

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	Equally weighted portfolio		Individual funds						
			Alpha quantiles (%)					Alpha sign. (%)	
	Alpha (%)	t-stat	Min.	25%	Median	75%	Max.	< 0	> 0
Panel A: Mutual Funds									
(1) CAPM	0.21	0.35	-2.16	-0.14	0.20	0.65	4.71	1.76	2.93
(2) Fama/French	0.04	0.08	-2.30	-0.31	0.07	0.44	4.37	2.93	4.11
(3) Carhart	-0.13	-0.28	-2.33	-0.38	-0.09	0.22	4.14	3.23	2.35
(4) Fung/Hsieh (1997)	-0.20	-1.02	-2.70	-0.53	-0.19	0.19	3.92	10.85	2.35
(5) Ext. Fung/Hsieh (2004)	-0.18	-1.18	-2.81	-0.55	-0.26	0.17	4.18	7.33	2.05
(6) EM Modell	-0.04	-0.18	-4.94	-0.35	-0.02	0.37	6.05	5.87	2.64
Panel B: Hedge Funds									
(1) CAPM	0.18	0.31	-2.25	-0.13	0.21	0.58	3.68	1.64	7.38
(2) Fama/French	-0.01	-0.03	-3.18	-0.39	0.09	0.51	3.30	4.10	9.02
(3) Carhart	-0.20	-0.41	-4.15	-0.62	-0.05	0.40	3.43	5.74	6.56
(4) Fung/Hsieh (1997)	0.04	0.20	-2.53	-0.38	0.11	0.55	2.88	4.10	7.38
(5) Ext. Fung/Hsieh (2004)	0.05	0.17	-2.96	-0.45	0.15	0.59	3.82	0.82	9.84
(6) EM Modell	-0.12	-0.27	-3.67	-0.64	0.03	0.43	2.55	1.64	5.74

Table 6: Alpha of the performance measurement models in different subperiods. Subperiod: January 2007 to August 2008. Note: * (**, ***) indicates significance at 10% (5%, 1%) level.

significant except for one index in one subperiod. For the hedge funds the picture is different. The equity factors are often not significant. Only from April 2000 to December 2006 are all of them significant. One problem here could be the relative brevity of the other subperiods. Another possible explanation is that hedge funds in fact have different asset allocations during these periods. With regard to the last period, this interpretation would be in line with Abugri and Dutta (2009) who find a change in the behavior of hedge funds after 2006. To investigate these changing hedge fund patterns, we look at the individual fund level. We find more often a significant exposure towards the JPM EM Bond indices if we compare the complete period from January 1996 to August 2008 to the period from January 2007 to August 2008. On a 5% level and during the whole investigation period, 11.93% of all funds have a significant exposure toward the JPM EM Latin America, 9.88% toward the JPM EM Asia, and 27.98% toward JPM EM Europe. During the post-2006 period, the respective numbers are 7.38%, 9.02%, and 10.66%. For the MSCI EM equity indices, the percentage of funds with significant exposure toward the MSCI EM EMEA or Asia does not decrease substantially. For the MSCI EM Latin America, however, the percentage decreases from 24.28% to 8.20%. These results partly confirm the findings from the correlation analysis as well as those from Abugri and Dutta (2009).

In order to analyze extreme market events and changing return patterns more closely, we follow Fung and Hsieh (2004) and Fung et al. (2008) and use a modified CUSUM test to find structural breakpoints in factor loadings (see Meligkotsidou and Vrontos (2008) for a more detailed analysis of structural breaks in hedge fund returns). Fung and Hsieh (2004) as well as Fung et al. (2008) find that structural breaks coincide with extreme market events (in their case the collapse of Long-Term Capital Management in September 1998 and the peak of the technology bubble in March 2000) and conclude that these events might affect managers' risk-taking behavior. Our findings here are mixed. Using a Rec-CUSUM and an OLS-Cusum test we find a breakpoint on a significance level of at least 10% for neither hedge funds nor mutual funds at the level of the equally weighted portfolio. We also use the Chow test to test for structural breaks with regard to the different dates. Here we find significant breakpoints in October 1998 and April 2000 but not in January 2007 for hedge funds. For mutual funds, all tests reject the existence of breakpoints. On an individual-fund level we test for breakpoints using a Rec-CUSUM and an OLS-CUSUM test. Significant breakpoints are found for mutual funds in 5.76% (9.47%)

	January 1996 to September 1998		October 1998 to March 2000	
	MF	HF	MF	HF
Intercept	-0.360	0.440	-0.460*	-0.250
	(-1.407)	(0.815)	(-2.060)	(-0.481)
MSCI EM Asia	0.261***	0.228**	0.104***	0.137**
	(4.889)	(2.627)	(3.826)	(2.591)
MSCI EM Europe	0.147***	0.130	0.132***	0.192
	(4.648)	(1.482)	(7.305)	(1.651)
MSCI EM Latin Am.	0.130	0.261	0.191**	0.115
	(1.654)	(1.615)	(2.996)	(1.085)
JPM EM Latin Am.	0.349**	0.680	0.325	0.374*
	(2.732)	(0.025)	(0.237)	(2.259)
JPM EM Asia	0.024	-0.853	0.488***	-0.334
	(0.156)	(-0.274)	(4.075)	(-1.305)
JPM EM Europe	-0.247	0.142	0.215***	0.280**
	(-0.354)	(1.374)	(9.259)	(3.168)
JPM EM Latin Am. t-1	0.765	0.419*	0.778**	-0.256
	(0.543)	(1.822)	(2.461)	(-0.164)
JPM EM Asia t-1	-0.440	-0.630**	-0.254***	0.182
	(-0.021)	(-2.127)	(-4.219)	(0.087)
JPM EM Europe t-1	0.511	0.144	0.825**	0.122
	(0.740)	(1.084)	(3.274)	(1.412)
Credit Spread	-2.169	-11.626	-6.466***	-6.499
	(-0.573)	(-1.301)	(-4.360)	(-1.450)

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Table 7: Regression result for mutual funds (MF) and hedge funds (HF) with EM model (6) in subperiods. Note: * (**, ***) indicates significance at 10% (5%, 1%) level, t-stat is given in brackets.

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	April 2000 to December 2006		January 2007 to August 2008	
	MF	HF	MF	HF
Intercept	-0.003*	0.500	-0.400	-0.120
	(-1.878)	(0.279)	(-0.185)	(-0.265)
MSCI EM Asia	0.304***	0.123***	0.284***	0.179**
	(8.476)	(4.536)	(7.913)	(2.300)
MSCI EM Europe	0.145***	0.120***	0.999***	0.164*
	(5.960)	(5.030)	(5.617)	(2.111)
MSCI EM Latin Am.	0.149***	0.147***	0.122**	0.130
	(4.100)	(4.206)	(2.978)	(1.534)
JPM EM Latin Am.	0.241	-0.265	0.149	-0.447
	(0.449)	(-0.509)	(1.084)	(-0.162)
JPM EM Asia	0.847	0.183**	0.289**	-0.125
	(0.956)	(2.270)	(3.045)	(-0.576)
JPM EM Europe	0.183***	0.222***	-0.120	0.449
	(2.698)	(3.547)	(-0.480)	(0.189)
JPM EM Latin Am. t-1	0.745	0.402	-0.340**	-0.157
	(1.535)	(1.176)	(-2.796)	(-0.494)
JPM EM Asia t-1	-0.118	0.104	-0.147	-0.325
	(-1.362)	(1.252)	(-1.127)	(-0.122)
JPM EM Europe t-1	0.158	0.258	0.843***	0.268
	(0.284)	(0.570)	(4.432)	(0.583)
Credit Spread	-2.235	-3.623***	-5.854***	-2.394
	(-1.632)	(-3.901)	(-23.405)	(-1.368)

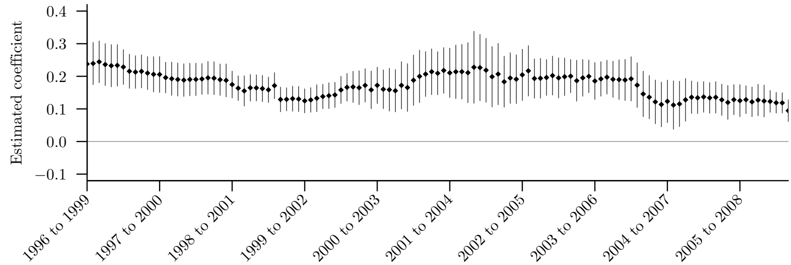
Table 7: Regression result for mutual funds (MF) and hedge funds (HF) with EM model (6) in subperiods. Note: * (**, ***) indicates significance at 10% (5%, 1%) level, t-stat is given in brackets.

of all cases and for hedge funds in 2.85% (5.23%) cases with a Rec-CUSUM (OLS-CUSUM) and a 95% confidence interval. Overall, the results are not clear and depend on the test that is used. Given that we find significant structural breaks using the Chow test in October 1998 and April 2000 for hedge funds but not for mutual funds supports the idea that hedge funds adapt to changing market environments while mutual funds do not.

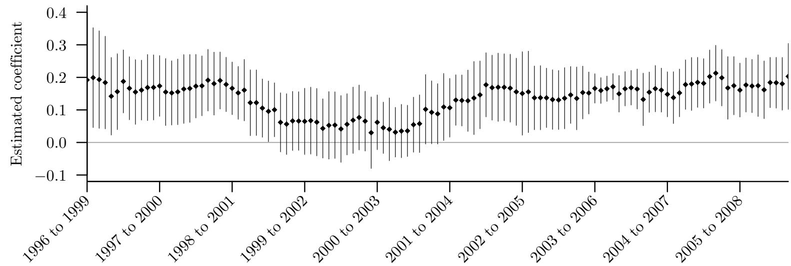
Figures 2 to 4 show rolling regressions using model (6) with a 36-month time window that examines a manager's exposures to the MSCI EM Asia, the MSCI EM Latin America, and the MSCI EM EMEA, i.e. the estimated regression coefficient and a 90% confidence interval over time.[27] The upper (middle) part of the figure presents the analysis for the equally weighted mutual (hedge) fund portfolio. The bottom presents the returns of the respective MSCI EM index in the time period under consideration. In Figure 2 we see that the exposure of hedge funds towards the Asian market declines from mid-1997 to mid-2000. For the mutual funds this effect is weaker. Figure 2 also shows that from 1999 to 2002, mutual funds increased their exposure to the Asian markets while hedge funds kept their exposure low. Exactly during this time, the MSCI EM Asia has negative returns. After this period, we see a rise in the exposure of hedge funds towards the Asian market, a time which was followed by positive returns with the MSCI EM Asia index. All these shifts in exposure suggest the good timing abilities of hedge fund managers. Regarding the exposure to the MSCI EM Latin America index (Figure 3) the interpretations are vague since the confidence band is broader than for the other indices. In general, however, both hedge funds and mutual funds reduced their exposure to Latin American markets after 1998 and increased it again in 2003.

Remarkable in Figure 4 is the strong exposure to the MSCI EM EMEA which hedge funds built up after 2001. After March 2004, however, we see a strong drop in the exposure of hedge funds. In April 2004 the respective index had a negative return of 8.70%. Unfortunately, our data does not allow us to investigate whether the reduced exposure was due to the negative returns or whether the hedge fund managers reduced their exposure before the losses occurred. With respect to the MSCI EM Asia and the MSCI EM EMEA, hedge funds have an exposure which changes more over time than does the exposure of mutual funds. This indicates that hedge funds are more active with respect to geographic asset allocation, perhaps in an effort to time the market.

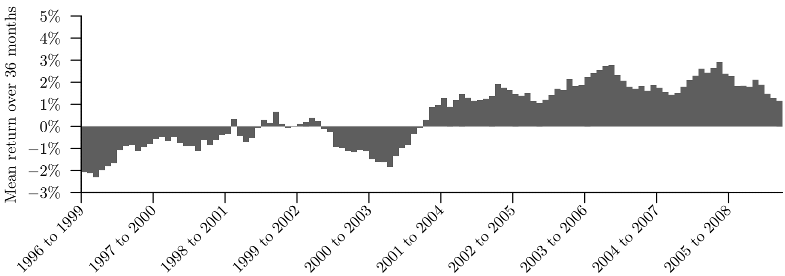
[27] Results from a rolling regression for all other factors are available from the authors upon request.



(a) Mutual funds factor exposure for the MSCI EM Asia.

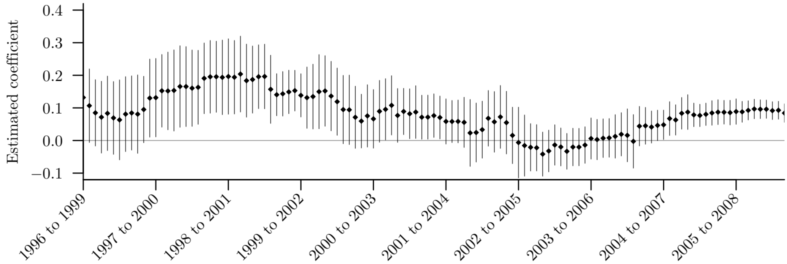


(b) Hedge funds factor exposure for the MSCI EM Asia.

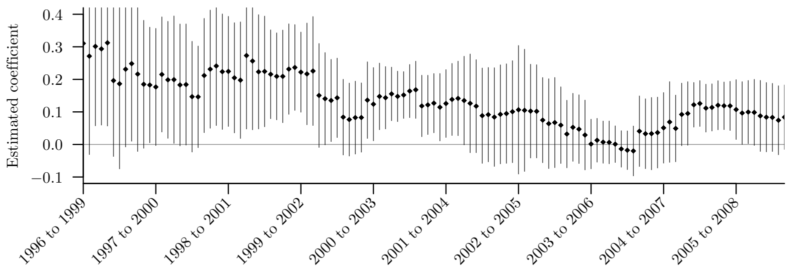


(c) MSCI EM Asia average return.

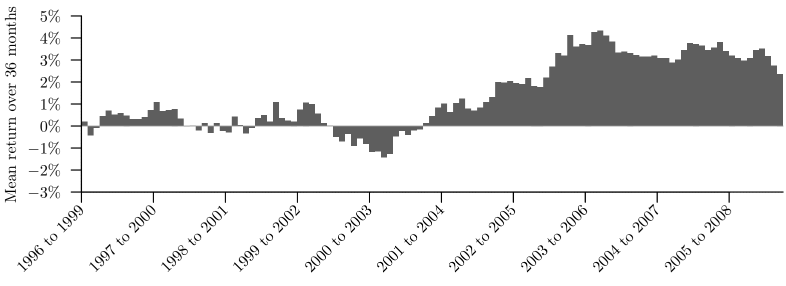
Figure 2: Factor exposure from a rolling regression over 36 months for mutual funds and hedge funds including a 90% confidence interval and the average index return for the MSCI EM Asia.



(a) Mutual funds factor exposure for the MSCI EM Latin America.

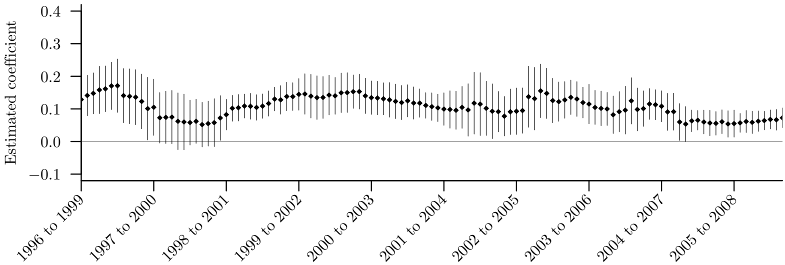


(b) Hedge funds factor exposure for the MSCI EM Latin America.

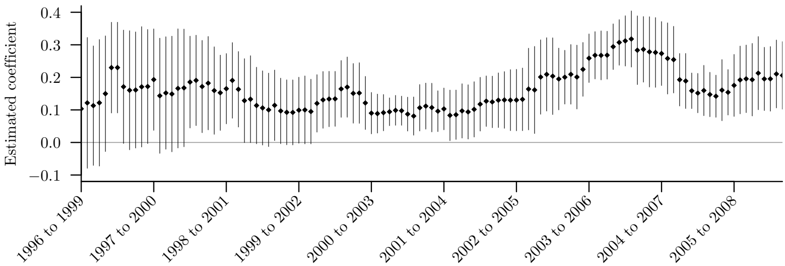


(c) MSCI EM Latin America average return.

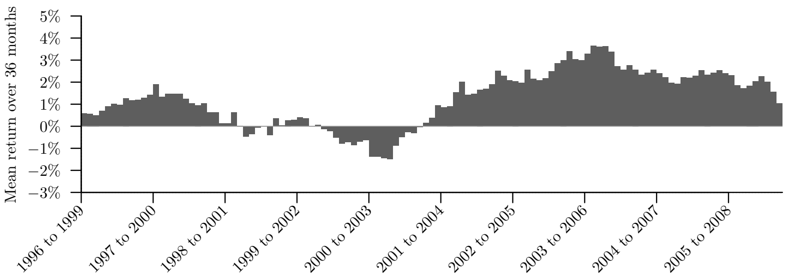
Figure 3: Factor exposure from a rolling regression over 36 months for mutual funds and hedge funds including a 90% confidence interval and the average index return for the MSCI EM Latin America.



(a) Mutual funds factor exposure for the MSCI EM EMEA.

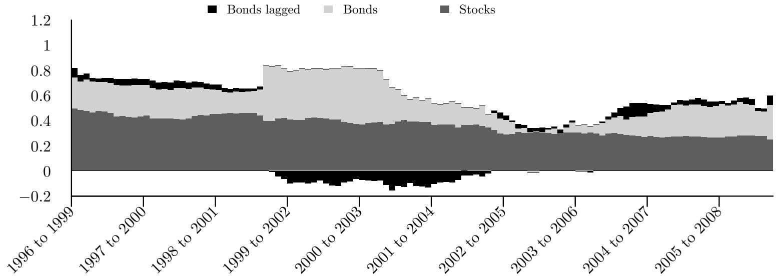


(b) Hedge funds factor exposure for the MSCI EM EMEA.

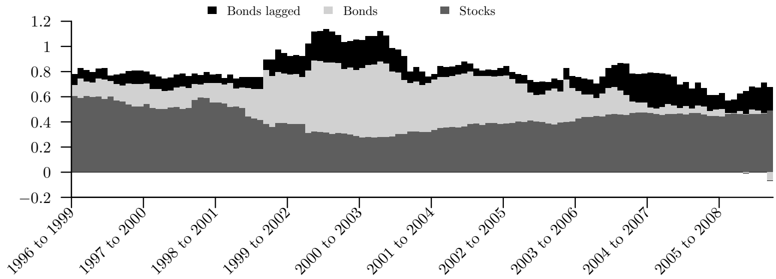


(c) MSCI EM EMEA average return.

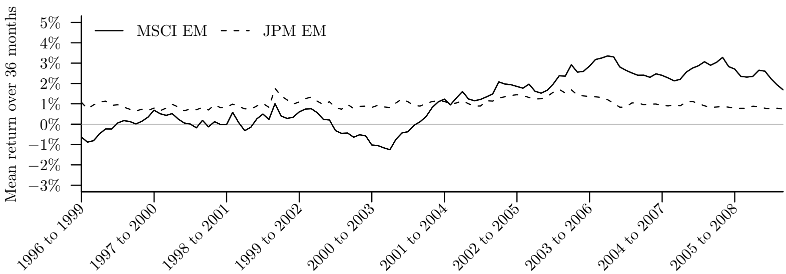
Figure 4: Factor exposure from a rolling regression over 36 months for mutual funds and hedge funds including a 90% confidence interval and the average index return for the MSCI EM EMEA.



(a) Summed exposure of mutual funds.



(b) Summed exposure of hedge funds.



(c) Average return of the MSCI EM and the JP Morgan EMBI Bond indices

Figure 5: Sum of the estimated coefficients from a rolling regression over 36 months for mutual funds (top), hedge funds (middle) and the average return of the MSCI EM and the JP Morgan EMBI Bond indices.

Regarding Figure 5 the exposure of hedge funds to equities seems to go down after the period 1998 to 2001 and stays on a lower level before it increases again two years later. In the period from 2000 to 2003 where emerging market equities had on average negative returns, hedge funds reduced their exposure to equities, an observation which we cannot confirm for mutual funds. In general the mutual funds were holding a nearly constant exposure to equities which was only slightly reduced over time. A possible explanation might be that they are ether obliged by investment policies to do so or that they do not try to time the markets by asset allocation. The exposure to bonds should be interpreted with more caution because the confidence intervals for the bond exposure are larger than those for equities. The hedge funds seem to have a higher exposure to bonds than mutual funds around the period 2000 to 2003 what is again support for the thesis that hedge funds, opposed to mutual funds, were able to time the asset allocation between bonds and equities. While the hedge funds always have a positive exposure to the lagged bond returns, this is not the case for the mutual funds. An explanation for the hedge funds could be illiquid positions which are infrequently priced or not adequately market priced. Another reason might be return smoothing. Another question that has recently been the subject of much research is whether the hedge fund alpha has declined in the last several years. Naik et al. (2007) report that hedge funds generated significant alphas in the decade between 1995 and 2004, but that the level of alpha declined substantially over this period. Their two explanations for this effect are (1) large capital inflows that are followed by negative movements in alpha and (2) that hedge fund fees have increased over this time. Fung et al. (2008) analyze funds of funds and also emphasize that large capital inflows attenuate the ability to produce alpha in the future. According to their study, the average fund of fund delivered a significant positive alpha only between October 1998 and March 2000. To see what light our work can shed on this topic, Figure 6 presents the adjusted R^2 of a rolling regression and Figure 7 the estimated alpha over our sample period.

Our empirical results provide no support either for Fung et al. (2008) or for Naik et al. (2007). First, we do not find that emerging market hedge funds had excellent performance between October 1998 and March 2000; instead, this was a period of declining alpha values. Second, we cannot confirm that hedge funds alpha has decreased over the investigation period as the best alpha values are found in the second half of this timeframe. These empirical findings are in line with Strömqvist (2007), however, who

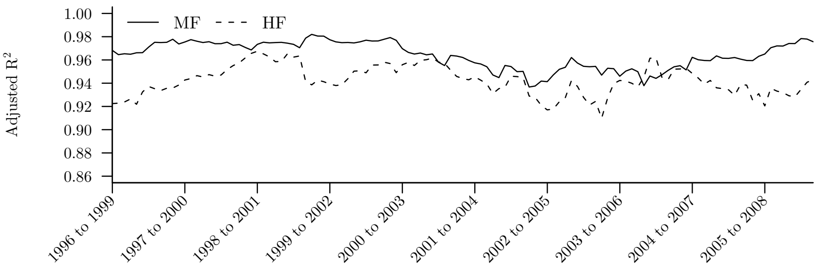
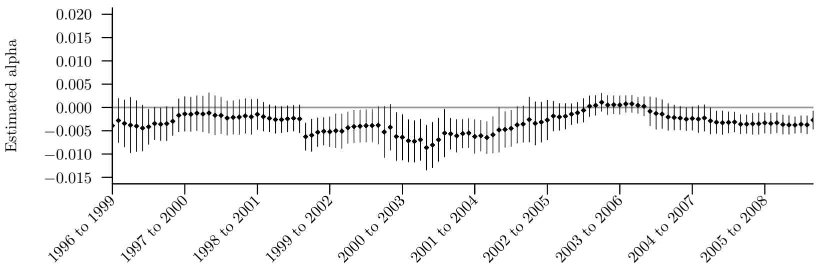
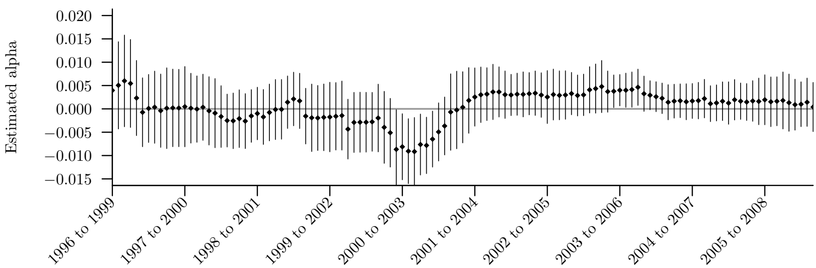


Figure 6: Adjusted R^2 of a rolling regression over 36 months for mutual funds and hedge funds.



(a) Alpha of a rolling regression for mutual funds



(b) Alpha of a rolling regression for hedge funds

Figure 7: Alpha of a rolling regression over 36 months for mutual funds and hedge funds with 90% confidence interval.

also cannot identify a decrease in performance in recent years. Only during the last few years (mid-2003 to 2008, a period not fully considered in Strömqvist (2007)), does alpha decrease slightly, especially for the mutual funds. When comparing hedge funds and mutual funds, we find the latter underperform during the stock market plunge, only beginning to recover starting in 2003. As to explanatory power (adjusted R^2 in Figure 6), we do not see much variation for either type of fund.

4.5 Performance Measurement Results for Different Market Environments

The results so far suggest that hedge funds and mutual funds have different abilities in generating returns during bear markets. To analyze this hypothesis in more detail, we consider fund performance in different market environments. We therefore subdivide the returns of the MSCI emerging market index (we choose this index as a reference because of its high correlation with mutual funds and hedge funds) into four different market environments, ranging from severe declines to sharp rallies, by sorting the monthly returns into four quartiles (see Fung and Hsieh (1997)). Market environment 1 contains the worst 36 months of the MSCI index; market environment 4 the best 36 months. The average returns are then calculated for the MSCI index as well as for mutual fund and hedge fund returns in these months. The results are presented in Figure 8.

Not surprisingly, given the correlation of 0.96, the returns of mutual funds and the market index are very comparable. Overall, the beta of the mutual fund portfolio with regard to the MSCI EM is lower than 1, as the mutual fund portfolio tends to be less extreme, i.e., in the worst months (market environment 1) mutual funds are slightly better than the index and in the best months (market environment 4), mutual funds underperform the market. Hedge fund returns are almost identical to the mutual fund returns in good market environments (market environments 3, 4). Interestingly, however, in bad market environments (market environments 1, 2) hedge funds outperform both the market as well as their mutual fund competitors. It thus appears that mutual funds have a relative constant exposure with regard to different market environments, whereas hedge funds might be able to profit from non-directional strategies, providing, at least to some extent, downside protection in an unfavorable market environment (market environment 1, 2).

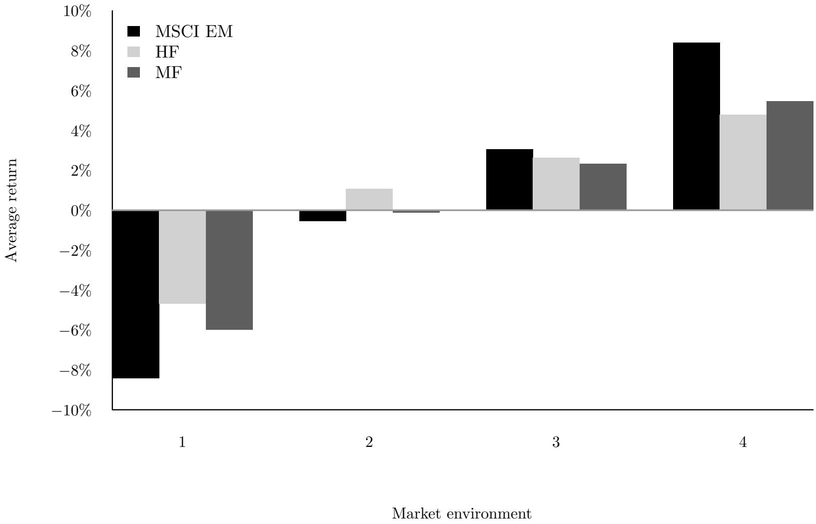


Figure 8: Returns in different market environments (1: worst months for MSCI EM, 4: best months for MSCI EM).

5 Conclusion

The contribution of this paper is twofold: In a first step, we develop an asset class factor model to describe the performance of hedge funds and mutual funds investing in emerging markets. Our results indicate that the market-related factors chosen for our model are much better at explaining the variation in emerging market returns than are non emerging market specific factor models presented in the literature and that they are slightly better than the emerging market specific model of Abugri and Dutta (2009). Our model explains a large proportion of the variation in both mutual fund and hedge fund returns. The second contribution of this paper is to employ various factor models to compare returns of hedge funds and mutual funds active in emerging markets. We find that hedge funds provide both higher returns and alphas than do traditional mutual funds. These findings are in line with other recent literature (see Abel and Fletcher (2004); Strömqvist (2007)). In general, some hedge funds tend to outperform the benchmarks, but most traditional mutual funds do not. One possible reason could be more active management of hedge funds than of mutual funds. We find support for this hypothesis from the tests for structural breaks, the factor exposure, and from the analysis of the performance in different market environments. Regarding structural breaks, we only find significant breakpoints for hedge funds but not for mutual funds. This indicates that hedge funds are adjusting their risk taking while mutual funds are not. The factor exposure of hedge funds, which we reveal using a rolling regression, shows that hedge funds have a more volatile exposure, supporting the idea of a more active management. The analysis of different market environments shows that hedge funds provide to some extent downside protection in contrast to mutual funds that have a rather constant exposure to market movements.

In conclusion, it seems that emerging market hedge funds are more active in shifting their asset allocation, probably since they are less restricted by their investors in investment style and policy. Furthermore, it is plausible that hedge fund style shifts have been especially pronounced in the most recent period (post 2006) since more alternative instruments, such as options and futures, are becoming available in emerging markets and hedge funds are not restricted in using them. It might thus also be that emerging market hedge funds now behave more like other hedge funds (see Abugri and Dutta (2009)), but we believe that additional research with more recent data is necessary to confirm this assertion, since the last, most recent subperiod analyzed is relatively short.

However, investors need to be aware that (aside from the differences in their flexibility regarding asset allocation) there are numerous reasons which might be responsible for the performance difference between mutual funds and hedge funds, including the use of leverage, lock-up periods, and incentive fees for hedge fund managers. Lock-up periods are also a good example to emphasize the higher degree of freedom hedge fund managers enjoy in making investment decisions. For example, hedge funds might invest in illiquid positions and capture liquidity risk premiums, actions not allowed to traditional mutual funds (see Ding et al. (2009), for an analysis of liquidity in the hedge fund context). In case of illiquid investments, investors need to be aware that hedge fund managers might smooth their returns (see Getmansky et al. (2004)), which might bias performance measurement results.[28]

[28]Note that our study design accounts for other biases in hedge fund returns such as survivorship and backfilling bias; these other biases thus do not distort the performance measurement results. Overall, we thus believe that data biases can only partly explain the observed performance differences between hedge funds and mutual funds.

Kouwenberg and Ziemba (2007) illustrate that incentive fees and manager's own investment in the fund substantially affect the investment strategy of hedge fund managers. Both these elements are not widespread with traditional mutual funds. Furthermore, hedge funds are not subject to much regulation. Hedge funds in the United States are usually set up as limited partnerships, a legal form only lightly regulated, and hedge funds outside the United States are usually domiciled offshore, a practice that has both regulatory and tax advantages. All these advantages make hedge funds the more flexible investment scheme, both as to investment strategy and markets in which to invest. During the financial crisis hedge funds have been severely criticized and it is not clear whether future regulation in the financial services sector might diminish these regulatory advantages of hedge funds.[29] Overall, it thus seems that a combination of technical problems (e.g., return smoothing) and economic advantages (e.g., higher flexibility and lower regulation) might account for the observed performance differences between hedge funds and mutual funds.

The factor model developed in this paper can be put to a number of different uses. First, investors can use the model to identify well-performing funds in which to invest. Although past performance is not necessarily an indicator of future returns, investors heavily rely on past performance when making investment decisions (see Capon et al. (1996)). Second, the model can be a tool for determining manager compensation as the model can detect whether a fund's performance is mainly attributable to passive investment style or something more proactive. The model makes it possible to reward managers for only those returns superior to a specific benchmark, and thus attributable to the fund manager's skill. Third, the model can be used for risk management as revealing the underlying assets will help identify the true risk of a fund. This might be especially relevant in identifying a drift in management style; catching any such changes early will help keep a portfolio both safe and profitable.

[29] An interesting application of our model would be to measure performance in the recent times of crisis, e.g. with regard to structural breaks or with regard to shifts in asset allocation. However, due to the substantial data reporting lags such an investigation is not feasible yet. For example, the CISDM database considered in this paper is released with a six to twelve month lag. An analysis of hedge funds in times of financial crisis and its biggest hits (that occurred so far in the second half of 2008) can thus not be undertaken before 2010 or 2011. The analysis of the Asian crisis presented in this paper, however, illustrates the substantial impact of these big events on both hedge fund and mutual fund performance.

Appendix: Performance of Hedge Funds, Mutual Funds, and Passive Investment Strategies

	Panel A: Measurement Value				
	Sharpe Ratio	Modified Sharpe Ratio (Israelsen)	Modified Sharpe Ratio (Gregoriou and Guyie)	Sortino Ratio	Calmar Ratio
Hedge Funds	0.20	0.20	0.08	0.29	0.03
Mutual Funds	0.09	0.09	0.04	0.12	0.01
Market Proxy	0.10	0.10	0.05	0.15	0.02
SMB*	0.06	0.06	0.03	0.10	0.01
HML*	0.12	0.12	0.06	0.18	0.02
Momentum*	0.16	0.16	0.07	0.23	0.02
MSCI North Am.	0.10	0.10	0.05	0.14	0.02
MSCI non-US	0.08	0.08	0.04	0.11	0.02
IFC Emerg. Markets	0.10	0.10	0.05	0.14	0.02
JPM US Gov. Bonds	0.15	0.15	0.07	0.23	0.03

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Table 8: Performance of hedge funds, mutual funds, and passive investment strategies. Note: The Jobson and Korkie (1981) test in Panel C measures the difference between the Sharpe ratio of hedge funds and the alternative indices. * (**, ***) indicates significance at 10% (5%, 1%) level. For example, with a test statistic of 2.86 the performance difference between hedge funds and mutual funds is highly significant at 1% level.

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	Panel A: Measurement Value				
	Sharpe Ratio	Modified Sharpe Ratio (Israelsen)	Modified Sharpe Ratio (Gregoriou and Guyie)	Sortino Ratio	Calmar Ratio
JPM Non-US	0.06	0.06	0.04	0.10	0.01
Eurodollar Deposit	-0.04	0.00	-0.02	-0.06	-0.01
Gold	0.07	0.07	0.04	0.11	0.01
US Dollar*	0.02	0.02	0.01	0.03	0.00
S&P 500	0.10	0.10	0.05	0.14	0.02
Size*	0.03	0.03	0.01	0.04	0.00
Bond*	-0.05	0.00	-0.03	-0.08	-0.01
Credit*	0.07	0.07	0.05	0.12	0.01
TFBond*	-0.13	0.00	-0.10	-0.19	-0.02
TFCur*	0.04	0.04	0.03	0.07	0.01

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Table 8: Performance of hedge funds, mutual funds, and passive investment strategies. Note: The Jobson and Korkie (1981) test in Panel C measures the difference between the Sharpe ratio of hedge funds and the alternative indices. * (**, ***) indicates significance at 10% (5%, 1%) level. For example, with a test statistic of 2.86 the performance difference between hedge funds and mutual funds is highly significant at 1% level.

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	Panel A: Measurement Value				
	Sharpe Ratio	Modified Sharpe Ratio (Israelsen)	Modified Sharpe Ratio (Gregoriou and Guyie)	Sortino Ratio	Calmar Ratio
TFCom*	0.04	0.04	0.04	0.08	0.01
MSCI EM Total	0.09	0.09	0.04	0.13	0.02
MSCI EM Asia	0.03	0.03	0.01	0.04	0.01
MSCI EM EMEA	0.15	0.15	0.07	0.22	0.02
MSCI EM Latin Am.	0.17	0.17	0.08	0.25	0.03
JPM EM Asia	0.23	0.23	0.06	0.32	0.02
JPM EM Europe	0.18	0.18	0.05	0.23	0.02
JPM EM Latin Am.	0.16	0.16	0.06	0.22	0.02

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Table 8: Performance of hedge funds, mutual funds, and passive investment strategies. Note: The Jobson and Korkie (1981) test in Panel C measures the difference between the Sharpe ratio of hedge funds and the alternative indices. * (**, ***) indicates significance at 10% (5%, 1%) level. For example, with a test statistic of 2.86 the performance difference between hedge funds and mutual funds is highly significant at 1% level.

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	Panel B: Ranking					Panel C: Test	
	Sharpe Ratio	Modified Sharpe Ratio (Israelsen)	Modified Sharpe Ratio (Gregoriou and Guyie)	Sortino Ratio	Calmar Ratio	Jobson and Korkie (1981) Test	Sign.
Hedge Funds	2	2	1	2	2	/	
Mutual Funds	15	15	17	16	16	2.86	***
Market Proxy	10	10	11	10	8	1.31	
SMB*	20	20	21	19	22	1.34	
HML*	9	9	7	9	6	0.57	
Momentum*	6	6	4	5	9	0.36	
MSCI North Am.	12	12	12	12	10	1.27	
MSCI non-US	16	16	19	18	15	1.65	*
IFC Emerg. Markets	11	11	14	11	13	2.03	**
JPM US Gov. Bonds	7	7	3	6	3	0.38	

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Table 8: Performance of hedge funds, mutual funds, and passive investment strategies. Note: The Jobson and Korkie (1981) test in Panel C measures the difference between the Sharpe ratio of hedge funds and the alternative indices. * (**, ***) indicates significance at 10% (5%, 1%) level. For example, with a test statistic of 2.86 the performance difference between hedge funds and mutual funds is highly significant at 1% level.

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	Panel B: Ranking					Panel C: Test	
	Sharpe Ratio	Modified Sharpe Ratio (Israelsen)	Modified Sharpe Ratio (Gregoriou and Guyie)	Sortino Ratio	Calmar Ratio	Jobson and Korkie (1981)Test	Sign.
JPM Non-US	19	19	18	20	18	1.03	
Eurodollar Deposit	26	27	26	26	26	1.99	**
Gold	18	18	15	17	19	1.12	
US Dollar*	25	25	25	25	24	1.92	*
S&P 500	13	13	13	13	12	1.28	
Size*	24	24	24	23	25	1.58	
Bond*	27	26	27	27	27	2.24	**
Credit*	17	17	10	15	17	0.87	
TFBond*	28	28	28	28	28	2.26	**
TFCur*	22	22	22	22	20	1.21	

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Table 8: Performance of hedge funds, mutual funds, and passive investment strategies. Note: The Jobson and Korkie (1981) test in Panel C measures the difference between the Sharpe ratio of hedge funds and the alternative indices. * (**, ***) indicates significance at 10% (5%, 1%) level. For example, with a test statistic of 2.86 the performance difference between hedge funds and mutual funds is highly significant at 1% level.

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	Panel B: Ranking					Panel C: Test	
	Sharpe Ratio	Modified Sharpe Ratio (Israelsen)	Modified Sharpe Ratio (Gregoriou and Guyie)	Sortino Ratio	Calmar Ratio	Jobson and Korkie (1981)Test	Sign.
TFCom*	21	21	20	21	21	1.19	
MSCI EM Total	14	14	16	14	14	2.26	**
MSCI EM Asia	23	23	23	24	23	2.52	***
MSCI EM EMEA	8	8	5	8	5	0.90	
MSCI EM Latin Am.	4	4	2	3	1	0.59	
JPM EM Asia	1	1	6	1	4	-0.22	
JPM EM Europe	3	3	9	4	11	0.28	
JPM EM Latin Am.	5	5	8	7	7	0.56	

Table 8: Performance of hedge funds, mutual funds, and passive investment strategies. Note: The Jobson and Korkie (1981) test in Panel C measures the difference between the Sharpe ratio of hedge funds and the alternative indices. * (**, ***) indicates significance at 10% (5%, 1%) level. For example, with a test statistic of 2.86 the performance difference between hedge funds and mutual funds is highly significant at 1% level.

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A Performance Analysis of Participating Life Insurance Contracts

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Participating life insurance contracts are one of the most important products in the European life insurance market. These kind of contracts are characterized by a cliquet-style minimum interest rate guarantee and bonus participation rules with regard to the insurer's return. Even though these contract forms are very common, only very little research has been conducted in respect to their performance. Hence, we conduct a performance analysis to provide a decision support for policyholders. We decompose a participating life insurance contract in a term life insurance and a savings part and simulate the cash flow distribution of the latter. The simulation result is compared with cash flows resulting from a benchmark investing into the same portfolio but without investment guarantees and bonus distribution scheme in order to measure the impact of these two product features. For providing a realistic picture within the two alternatives, transaction costs and distribution effects between policyholders are taken into account. We show how the payoff distribution depends on the initial reserve situation and management's discretion. Our results clarify that policyholders have very little chance to predetermine the cash flow distribution if future behavior of management and the reserve level are unknown.

1 Introduction

As a consequence of the financial crisis, private investors currently seek for safe investments with low downside risk. In this context, minimum interest rate guarantees embedded in financial products are one option for customers. Insurance companies offer investment products with such a downside protection and are often perceived as safe harbor.[1] The participating life insurance (PLI hereafter) is one of the most important products with a built in minimum interest rate guarantee. In most European countries these contracts are typically characterized by an embedded term life insurance, a cliquet-style interest rate guarantee[2], and bonus participation rules with regard to the insurer's annual return. However, administrative costs and complex profit distribution schemes between policyholders and shareholders make it difficult to answer the question whether such products are actually beneficial to customers. In addition, management's discretion with respect to certain parameters and various embedded options make pricing and performance measurement of this product complex.

In this paper we model PLI based on contract forms offered in the German market.[3] We simulate the complete payoff distribution on an ex-ante basis and compare the cash flow distribution of the PLI with a passive portfolio which invests into the same assets. We show how the payoff distribution depends on the initial reserve situation (the surplus fund in our model) and management's discretion. For buyers of PLIs this means that they are not able to predetermine the cash flow distribution unless the future behavior of management and the surplus fund level is known or specific assumptions are made in that respect.

In previous research on PLI, we can distinguish between two major streams of literature. The first one addresses fair pricing of participating life insurance policies based on option pricing theory.[4] Amongst others, bonus distribution rules are often modeled and reproduced in this area of

[1] For example, in the German life insurance market, the estimated increase in premium income in 2009 is 4.8 percent compared to 0.8% in 2008 (see GDV, 2009, Beitragseinnahmen der Versicherungswirtschaft, accessed January, 2010 at `http://www.gdv.de/Downloads/Pressemeldungen_2009/Tabellenanhang_PM_2009.pdf`). This increase might be mainly attributable to an increased risk aversion and/or risk awareness following the financial crisis.

[2] In case of a cliquet-style interest rate guarantee, the guaranteed rate of interest has to be credited to the customer's account on a year-to-year basis.

[3] However, the contract forms in focus are very similar to PLI contracts offered in other European insurance markets.

[4] See for example Grosen and Jørgensen (2000) and Bacinello (2001).

research. For instance, Kling et al. (2007) analyze the numerical impact of interest rate guarantees found in PLI contracts on the shortfall probability of a life insurance company. Gatzert (2008) provides a general framework for pricing and risk management of participating life insurance contracts under different assumptions in respect to asset management and surplus distribution strategies. Gatzert and Schmeiser (2008) assess in particular the risk of different premium payment options typically offered in participating life insurance contracts. Bauer et al. (2006) and Zaglauer and Bauer (2008) derive risk-neutral valuation frameworks while simulating bonus distribution rules of the German regulatory framework. However, these fair pricing approaches only work under the assumption of perfect and frictionless markets.

The second stream of literature mainly analyzes performance by means of the internal rate of return, accounting ratios, and similar performance ratios based on historical cash-flows or numerical examples provided by insurance companies (see, e.g., Ferrari (1968) and Levy and Kahane (1970)). However, these approaches generally ignore embedded options and may misjudge the risk-return profile of the investment. Exceptions are Waldow (2003) and Stehle et al. (2003). In these contributions not only one single performance ratio is derived, but historical cash flows of PLI contracts are compared with those of an alternative portfolio composed of an annual term life insurance and different investment products. Nevertheless, as most of these performance analyses are conducted from an ex-post perspective, they can only indicate whether PLI contracts were advantageous in the past. Implications for the future however might be limited.

In order to get a clearer picture of the performance of PLI, we decompose PLI in a term life insurance and an investment part and simulate the cash flow distribution of the investment part under the real world measure $\mathbb{P}$. Further, we create a benchmark portfolio based on the same underlying to measure the impact of the interest rate guarantee and the bonus distribution rules on the cash flows of the portfolio. By doing so, we are able to show in which cases the interest rate guarantee and the mechanisms applied by the insurance company can be beneficial to the policyholder. In addition, we show how the payoff distribution depends on the initial reserve situation and management's discretion. We do not benchmark the PLI using a fair (risk-neutral) pricing approach, which would mean to compare the observed market price with the calculated fair price, because we believe that the underlying assumption of perfect and frictionless markets is rather not fulfilled in this context. In particular, we doubt that instruments exist that allow the replication of the PLI's cash flows. In practice, we think that consumers will rather judge products depending on personal preferences and actually available alternatives. The contribution of this paper is that we neither rely on a single performance measurement ratio nor do we provide an ex-post analysis. Instead, our framework allows a comparison of the complete payoff distribution on an ex-ante basis. This general framework is subsequently not bonded to one specific subjective preference scheme. Further, we model an insurance company with various insurance collectives which allows us to incorporate distribution effects between policyholders. Only Hansen and Miltersen (2002) analyzed PLI with pooled accounts before, but just for a two-customer case. In addition, the influence of the initial level of the pooled surplus fund on the performance of one single contract is analyzed. Furthermore, we examine how management discretion, in terms of a change of the target rate of return, effects payoff distributions. Results indicate that all of these elements have a strong impact on payoffs and should subsequently not be neglected.

The remainder of the paper is organized as follows: In Section 2, we introduce our general framework. Results from Monte Carlo simulations are discussed in Section 3. We conclude in Section 4.

2 Model Framework

2.1 Premium Investments on a Single Contract Basis

First, we illustrate an insurance company which has only one single insurance contract. We employ a discrete time model with $t \in 1, \ldots, T$ where t determines the elapsed time since inception of the contract (in years) and T denotes the contract's maturity. In section 2.5, the mechanism introduced for the single contract company is applied for an insurer with more than one contract. Our model builds on PLI contracts offered in Germany, but could be easily applied to similar regulatory frameworks (e.g., Switzerland or Austria).

The policyholder pays a constant annual premium P_{t-1} at the beginning of each year given no previous termination of the contract by death, surrender or default of the insurer. The insurance company uses the fraction $P_{c,t-1}$ of the annual premium to cover its costs. Costs are divided into annual operational costs and acquisition costs which are allocated over the first five years of the contract. Another part of the premium $P_{r,t-1}$ is needed to cover the term life insurance. The remaining amount of the annual premium $P_{s,t-1}^{(\mathrm{PLI})}$ is invested in an asset portfolio. This savings fraction of the premium $P_{s,t-1}^{(\mathrm{PLI})}$ features an annual minimum interest rate r_g and builds up the policyholder's savings account $A_{g,t-1}$. The process can be defined as

$$A_{g,t-1} = \sum_{i=1}^{t} P_{s,i-1}^{(\mathrm{PLI})} \exp\left(r_g(t-i)\right).$$

The premium $P_{r,t-1}$ is the annual premium for a term life insurance contract. We calculate this premium using actuarial fair premiums and market loadings (see Appendix). To account for a decreasing sum insured I_t, the term life insurance premium is annually adjusted so that the sum insured equals the guaranteed death benefit D minus the accumulated savings account:

$$I_t = D - \exp(r_g)A_{(g,t-1)}.^5$$

Regarding the investment alternatives to the PLI, we denote with $P_{s,t-1}^{(\mathrm{BM})}$ the amount which is invested annually in the benchmark portfolios. $P_{s,t-1}^{(\mathrm{BM})}$ equals the annual premium P_{t-1} minus the premium for the term life insurance contract $P_{r,t-1}$. In addition, front-end loads Y_U as a proportion of assets invested are subtracted,

$$P_{s,t-1}^{(\mathrm{BM})} = (1 - Y_U)(P_{t-1} - P_{r,t-1}).$$

In order to incorporate management and administrative fees associated with these benchmark portfolios, an annual fee (defined as a percentage of the total assets in t) is deducted at the end of each year.

Because we are interested in the investment result of the PLI and not in the effect of the term life insurance, we analyze only the savings parts of both premiums, $P_{s,t-1}^{(\mathrm{PLI})}$ and $P_{s,t-1}^{(\mathrm{BM})}$. Hence, we assume in what follows that the investor wants to buy a term life insurance contract in both alternatives and hence, this part of the contract does not influence the decision whether to buy a PLI or not.

[5] Note that the premium in t will not be paid if the policyholder dies or surrenders between $t-1$ and t. Hence, we take the savings account in $t-1$ which increases by the guaranteed rate of interest between $t-1$ and t, i.e. $\exp(r_g)A_{(g,t-1)} = A_{(g,t)} - P_{s,t}^{(\mathrm{PLI})}$.

Assets (market values)	Liabilities (market values)
	A_f : surplus fund
A_r: assets attributable to individual policyholders	A_g : policyholders' savings accounts (subject to minimum interest rate guarantee) A_{dp} : policyholders' distributed profits accounts A_{dtb} : policyholders' distributed terminal bonus accounts

Table 1: Balance sheet of a simulated insurance company.

2.2 Portfolio Development

We illustrate a simplified balance sheet of an insurance company with market value accounting in Table 1. The liability side of this balance sheet can be divided into two different parts, the policyholders' accounts, A_g, A_{dp}, and A_{dtb} and the surplus fund A_f. While the policyholders' accounts are attributable to policyholders on an individual basis, the surplus fund is attributable to all policyholders as a group. Although the single contract company has only one policyholder, the surplus fund is still different from the policyholders' accounts: The surplus fund has the function of a risk buffer. That is to say it is built up in times of high returns and reduced in times of low returns. Grosen and Jørgensen (2000) work with a similar account, the so-called bonus reserve, which is determined by the difference between book and market values. Unlike the bonus reserve by Grosen and Jørgensen (2000), our surplus fund contains all assets which are attributable to policyholders on a collective basis, i.e. our surplus fund consists of hidden reserves and of provisions for premium refunds.

In what follows, we describe in more detail how the different balance sheet accounts evolve. We assume that the insurance company invests in a diversified portfolio of stocks and bonds and that returns on both asset classes are independently and normally distributed.[6] The percentage of assets invested at the beginning of each year in bonds is denoted by B (with $0 \leq B \leq 1$) and the fraction invested in stocks by $1 - B$. Rebalancing of the portfolio weights between bonds and stocks is performed on an annual

[6]In the historical time series used later on to calibrate the model, the correlation between stock and bond returns was close to zero ($\rho = -0.0432$) and not significant on a 5% level. As a consequence, we assume independence.

basis. Using an annual time interval (i.e. $\Delta t = 1$), earnings $e_{a,t}$ on invested assets $A_{r,t-1}$ are given by

$$e_{a,t} = A_{r,t-1}\left[B\left(\exp\left(\mu_B - \frac{\sigma_B^2}{2} + \sigma_B r_{1,t}\right) - 1\right)\right.$$
$$\left. +(1-B)\left(\exp\left(\mu_S - \frac{\sigma_S^2}{2} + \sigma_S r_{2,t}\right) - 1\right)\right],$$

whereas σ_B (σ_S) denotes the standard deviation of bonds (stocks). The expected bond (stock) return is given by μ_B (μ_S). The random variates $r_{1,t}$ and $r_{2,t}$ are drawn from a standard normal distribution. As common in German PLI contracts, the minimum interest rate guarantee is granted on a year-to-year basis and only applies to the savings part of the premium $P_{s,t-1}^{(\mathrm{PLI})}$. The guaranteed minimum interest earned in period t is thus

$$e_{g,t} = (\exp(r_g) - 1)\, A_{g,t-1},$$

where r_g denotes the guaranteed rate of interest. In our model, the return on the insurer's asset portfolio $e_{a,t}$ is first used to cover this interest rate guarantee. Subsequently, the achieved earnings on assets after covering the guaranteed minimal interests are

$$e_{s,t} = e_{a,t} - e_{g,t}.$$

If the achieved return is insufficient to cover the guarantee, $e_{s,t}$ will be negative and additional capital will be required to cover the interest rate guarantee. We assume that the insurance company is always able to cover this required amount of capital by equity capital.[7] If earnings on assets are positive after covering the interest rate guarantee, then the remaining profit is distributed to the surplus fund A_f, to shareholders in form of dividends, and to the insurer's equity capital (retentions of earnings). The fraction F will be allocated to the surplus fund (i.e. the policyholders). We can express this as

[7] By doing so, we exclude the case of insolvency. This is reasonable in the German regulatory framework since article 125 of the German law for insurance control (German: "Versicherungsaufsichtsgesetz", VAG) defines that all policyholders' claims, i.e. savings, distributed profit, and distributed terminal bonus accounts, should be secured by and transferred to a safety fund in case of insolvency. The safety fund continues the contracts as before. Hence, insolvency of the insurer does not have any impact from the policyholder's financial point of view as long as the safety fund can be financed by solvent market participants.

$$f_t = \begin{cases} 0 & \text{if } e_{s,t} \leq 0, \\ F e_{s,t} & \text{if } e_{s,t} > 0 \end{cases}$$

under the constraints that $0 \leq F \leq 1$. The remaining fraction $(1 - F)$ is distributed as dividends or to equity capital.

2.3 Bonus Distribution

In participating policies, the insurance company is obligated to give policyholders a share in profits. The surplus fund A_f provides an intermediate mechanism with the goal to stabilize returns to policyholders over time. We introduce a decision rule based on the framework presented in Bauer et al. (2006) and Kling et al. (2007) in order to establish a bonus distribution mechanism in our model.[8] The insurance company defines a certain target rate of interest $r_z > r_g$ which is planned to be granted to the policyholders' accounts annually in order to maintain returns for policyholders stable. This target rate of interest is given to the policyholders as long as the surplus fund quota $Q_t = A_{f,t}/A_{g,t}$ stays within a defined range $[Q^L, Q^U]$. Let $Q_{x,t}$ be the surplus fund quota before any distribution of profits,

$$Q_{x,t} = (A_{f,t-1} + f_t)/A_{g,t},$$

and $e_{z,t}$ be the additional amount which is required to achieve the target rate of interest after covering the interest rate guarantee,

$$e_{z,t} = (\exp(r_z) - 1)\left(A_{g,t-1} + A_{dp,t-1} + A_{dtb,t-1}\right) - e_{g,t}.$$

Finally, we define z_t as the bonus distributed each year based on our decision rule. Then, four different cases can be distinguished:

[8] Bauer et al. (2006) and Kling et al. (2007) use the respective decision rule in a similar context. However, their quota is calculated by means of hidden reserves and the book value of liabilities. As our portfolio is composed differently, we calculate our quota based on the surplus fund and the policyholders' savings accounts. This quota retains the idea that reserves are build up in times of high returns and reduced in times of low returns in order to smooth the result and the contract's participation. In addition, Bauer et al. (2006) and Kling et al. (2007) differentiate between an is-case and a must-case while we only focus on their is-case.

- If crediting the target interest $e_{z,t}$ leads to a surplus fund quota above its upper limit Q^U, the amount leading to a surplus fund quota at its upper limit is distributed.
- If distributing the target interest $e_{z,t}$ leads to surplus fund quota between its upper and lower limit, the target interest is granted.
- If crediting the target interest $e_{z,t}$ leads to a surplus fund quota below its lower limit Q^L, the amount leading to a surplus fund quota at its lower limit is distributed.
- No additional bonus is distributed if the surplus fund quote before the distribution of any bonus is already below its lower limit Q^L.

Formally, this can be expressed as follows:

$$z_t = \begin{cases} (Q_{x,t} - Q_U)A_{g,t} & \text{if } Q^U + e_{z,t}/A_{g,t} < Q_{x,t} \\ e_{z,t} & \text{if } Q^L + e_{z,t}/A_{g,t} \leq Q_{x,t} \leq Q^U + e_{z,t}/A_{g,t} \\ (Q_{x,t} - Q_L)A_{g,t} & \text{if } Q^L < Q_{x,t} < Q^L + e_{z,t}/A_{g,t} \\ 0 & \text{if } Q_{x,t} \leq Q^L \end{cases}$$

In this context, z_t stands for the profit distribution assigned to the policyholders in addition to the minimum interest rate guarantee. These profits are allocated between the policyholders' terminal bonus accounts $A_{dtb,t}$ and the policyholders' distributed profits account $A_{dp,t}$. We assume that a percentage M (with $0 \leq M \leq 1$) of z_t should be distributed to $A_{dtb,t}$. Hence, the policyholders' terminal bonus accounts evolve as follows:

$$A_{dtb,t} = \begin{cases} Mz_t & \text{if } t = 1 \\ A_{dtb,t-1} + Mz_t & \text{if } t > 1. \end{cases}$$

The remaining amount of z_t is allocated to $A_{dp,t}$. In addition, $A_{dp,t}$ increases by annually distributed profits on expenses d_t. Thus the distributed profits account develops according to

$$A_{dp,t} = \begin{cases} (1-M)z_t + d_t & \text{if } t = 1 \\ A_{dp,t-1} + (1-M)z_t + d_t & \text{if } t > 1. \end{cases}$$

After the distribution of profits, the surplus fund is

$$A_{f,t} = A_{f,t-1} + f_t - z_t.$$

The benchmark portfolio does not involve any bonus distribution scheme or interest guarantee. Earnings $e_{b,t}$ on invested assets $A_{b,t-1}$ for the benchmark portfolio are given by

$$\begin{aligned} e_{b,t} = {} & A_{b,t-1}B\left(\exp\left(\mu_B - \frac{\sigma_B^2}{2} + \sigma_B r_{1,t}\right)(1-Y_B) - 1\right) \\ & + A_{b,t-1}(1-B)\left(\exp\left(\mu_S - \frac{\sigma_S^2}{2} + \sigma_S r_{2,t}\right)(1-Y_S) - 1\right), \end{aligned}$$

where Y_B (Y_S) are annual fees (in percent) for the bond (stock) fraction of the portfolio. The bond fraction is given by B, the expected returns by μ_B (μ_S), and the volatility by σ_B (σ_S). The random variates $r_{1,t}$ and $r_{2,t}$ are the same as those used for the return of the PLI ($e_{a,t}$). The invested assets amount $A_{b,t-1}$ evolves according to

$$A_{b,t-1} = \begin{cases} P_{S,0}^{(\mathrm{BM})} & \text{if } t = 1 \\ \sum_{i=1}^{t}\left(P_{s,t-1}^{(\mathrm{BM})} + e_{b,t-1}\right) & \text{if } t > 1. \end{cases}$$

2.4 Cash Flows

We distinguish between three possible events which lead to a payoff to the policyholder (or his heirs respectively). Namely, surrender of the policy before maturity, death before maturity, or survival until maturity. In case of death between $t-1$ and t, policyholders receive the total amount on their accounts, i.e. their savings accounts[9], their distributed profits accounts, and their distributed terminal bonus accounts.

$$\mathrm{Payoff}_{t,\mathrm{death}} = \exp(r_g)A_{g,t-1} + A_{dp,t} + A_{dtb,t}.$$

If a policyholder cancels his policy between $t-1$ and t, he receives the amount on his savings account, on his distributed bonus account, and the fraction W of his distributed terminal bonus account. The policyholder

[9] In the case of death or surrender of the insured between $t-1$ and t, no premium in t is paid by the policyholder. Hence, the policyholders' savings account subject to the minimum interest rate guarantee in t is given by $\exp(r_g)A_{g,t-1} = A_{g,t} - P_{s,t}^{(\mathrm{PLI})}$.

does not receive the total amount on his distributed terminal bonus account because policyholders are motivated to continue their contract until maturity,

$$\text{Payoff}_{t,\text{surrender}} = \exp(r_g)A_{g,t-1} + A_{dp,t} + WA_{dtb,t}.$$

Finally, if a policyholder continues the contract until maturity, the insurer pays the total amount of his different accounts. As we employ a discrete time model, death and cancellation between $T-1$ and T are assumed to lead to equal payoffs at maturity,

$$\text{Payoff}_{\text{maturity}} = \exp(r_g)A_{g,T-1} + A_{dp,T} + A_{dtb,T}.$$

Unlike the PLI contract, the benchmark does not differentiate between death of the policyholder, surrender, and survival until maturity. Hence, the current value of the benchmark portfolio is paid out in all three possible events,

$$\text{Payoff}_{t,\text{benchmark}} = A_{b,t-1} + e_{b,t}.$$

2.5 Modeling the Insurer's Portfolio

After introducing our model for a single contract insurance company, we apply it to an insurance company with more than one contract. We simulate a life insurance company's underwriting portfolio with T insurance collectives. The contract duration is the same for all collectives (T years) but the different collectives vary in their remaining time to maturity. Each insurance collective is homogenous, i.e. contains policyholders of same age and mortality whose contracts have the same remaining time to maturity. The insurance company starts with one single insurance collective at point in time 0. Then, every year a new collective is initiated. After $T-1$ years, T collectives exist. From then on, every year one new collective is initiated with T years to maturity and one is terminated so that there will always be T insurance collectives. The basic mechanisms introduced remain the same. However, there is only one surplus fund account A_f for all contracts whereas the policyholders' accounts ($A_g^{(i)}$, $A_{dp}^{(i)}$, and $A_{dtb}^{(i)}$) remain on an individual basis. As the surplus fund is not individually attributable to the policyholders, we introduce a mechanism in order to distribute the amount z_t source-related.

Given n policyholders, each policyholder i participates in profits distributed additionally to the minimum interest with

$$z_t^{(i)} = \frac{A_{g,t-1}^{(i)} + A_{dp,t-1}^{(i)} + A_{dtb,t-1}^{(i)}}{A_{g,t-1} + A_{dp,t-1} + A_{dtb,t-1}} z_t$$

whereas

$$A_{g,t-1} = \sum_{i=1}^{n} A_{g,t-1}^{(i)},$$
$$A_{dp,t-1} = \sum_{i=1}^{n} A_{dp,t-1}^{(i)}, \text{ and}$$
$$A_{dtb,t-1} = \sum_{i=1}^{n} A_{dtb,t-1}^{(i)}.$$

One additional difference between the previously introduced single contract company and the various insurance collectives has to be noted, namely that with more than one contract cash outflows occur every year based on how many members of each collective die or cancel their policy.[10] If one policyholder i surrenders, the amount on his terminal bonus account which is not paid out $(1 - W)A_{dtb,t}^{(i)}$ is distributed to the joint surplus fund A_f. Hence, policyholders profit from the cancellation of others. In our numerical analysis, we will focus on single contracts out of the T collectives given the surplus fund in order to analyze payoffs obtained by individual policyholders.

2.6 Model Calibration

We apply our model to contracts with a maturity of twelve years ($T = 12$).[11] We assume that policyholders start premium payments at the beginning of age 53 so that they would receive their survival benefit at the beginning of age 65 (retirement). We use the current mortality tables,

[10]In the single contract company, only one cash flow will occur after which the insurance company ceases to exist (as the single contract was paid out).

[11]PLIs in Germany feature tax benefits if the duration of the policy is at least 12 years (Art. 20 sec. 6 no. 2 of the income tax law (in German: "Einkommenssteuergesetz (EStG)").

loadings of 34% (so called first order mortality), and probabilities of cancellation published by the German Actuary Association.[12] The data provided by the German Actuary Association typically serves as the basis of product calculation of German life insurance companies.

We base our contract parameters on the actual offering of a German life insurance company.[13] The policyholder pays an annual premium of $P_{t-1} = 5000€$ and has a guaranteed death benefit of $D = 61491€$. Acquisition costs of 1487.7€ are allocated over the first five years. Annual administrative costs are 202.97€. Hence,

$$P_{c,t-1} = \begin{cases} 500.51€ \text{ if } t \leq 5 \\ 202.97€ \text{ if } t > 5 \end{cases}$$

The guaranteed death benefit and the guaranteed terminal payment are equal (i.e. $D = A_{g,T-1}\exp(r_g)$). To achieve this, the minimum interest rate needs to be set to $r_g = 2.20\%$.[14] To obtain estimates for volatility and drift, we use monthly data from January 1990 to December 2009 of German Federal Securities with a remaining time to maturity of 10 years[15] and a Euro countries based stock index (MSCI EMU total return index), i.e. $\mu_S = 6.74\%$, $\sigma_S = 19.00\%$, $\mu_B = 3.50\%$, and $\sigma_B = 0.47\%$.[16]

Note that we reduced the drift for bonds from 5.45% to $\mu_B = 3.50\%$ in order to account for the current low interest rate environment.[17] The drift μ_B we apply equals the return on German Federal Securities as of December 2009. As the stock ratio in insurance companies' portfolios is

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[12] DAV, 2008, Raucher- und Nichtrauchersterbetafeln für Lebensversicherungen mit Todesfallcharakter and DAV, 1995, Stornoabzüge in der Lebensversicherung, DAV-Mitteilung Nr. 5. We use the DAV 2008 T mortality table.

[13] We used a contract offered by the HUK Coburg (cf. `www.huk.de`). The information used for our simulation in respect to the contract calibration are publicly available.

[14] This number is close to the current maximum permitted guaranteed rate of 2.25% under the German law (Art. 2 sec. 1 of the German directive for the calculation of policy reserves (in German: "Deckungsrückstellungsverordnung", DeckRV)).

[15] We use the time series WZ3409 as published by the German central bank and available at `http://www.bundesbank.de/statistik/statistik_zeitreihen.php?lang=de&open=zinsen&func=row&tr=WZ3409`.

[16] The MSCI EMU covers the European Economic and Monetary Union. We use this Euro countries based index because the German directive for investments (in German: "Anlageverordnung", AnlV) requires that the currencies of assets and liabilities match (congruency rule).

[17] Further note that the current maximum permitted guarantee rate given by law (2.25%) should not exceed 2/3 of the current interest rate level, namely the current yield on ten-year German Federal Securities.

approximately 8.5% [18], we apply a stock ratio of $1 - B = 8.5\%$ and a corresponding bond ratio of $B = 91.5\%$.

We assume that each insurance collective consists of $n = 10000$ contracts and simulate 100000 paths. The initial surplus fund is assumed to be $A_{f,\text{initiation}} = 0$. We set the fraction distributed to the surplus fund to $F = 90\%$ which is the minimum amount that has to be credited to policyholders according to German law (legal quote).[19] We assume that a percentage $M = 10\%$ of the profits which are to be distributed to the policyholders are distributed to their terminal bonus accounts. This is close to what we observe on average in the German market.[20] As terminal bonus payments aim at motivating policyholders to continue their contract until maturity, we assume that only $W = 50\%$ of the terminal bonus account is paid out in case of cancellation. For our surplus fund quota, we use the bounds $[Q^L, Q^U] = [2.5\%, 7.5\%]$. Unless stated otherwise, we apply a target rate of interest $r_z = 3.5\%$.

Finally, we calculate fees for the benchmark portfolios based on fees reported by Khorana et al. (2007) for mutual funds sold in Germany and based on calculations provided by Frankfurt Stock Exchange for ETFs[21]. Thus we apply annual fees of $Y_B \in \{0.91\%, 0.17\%\}$ for the bond fraction, $Y_S \in \{1.47\%, 0.17\%\}$ for the stock fraction, and averaged upfront fees of $Y_U \in \{3.22\%, 0.36\%\}$, whereas the first element stands for the fees associated with the mutual fund and the second with the ETF portfolio.

[18] GDV, 2008, Kennzahlen zur Kapitalanlage der Versicherer. Accessed February 2010 at `http://www.gdv.de/Downloads/Veranstaltungen_2008/KAPLV_2007_Koll_2008.pdf`.

[19] cf. Art. 4 sec. 3 of the German directive for minimum premium refund in life insurance (in German: "Mindestzuführungsverordung", MindZV)

[20] In Germany, terminal bonus payments policyholders receive are between 5.25% and 30.68% of total interest earnings with an arithmetic mean of 13.27% (see Assekurata, 2010, Marktstudie 2009: Die Überschussbeteiligung in der Lebensversicherung, accessed January, 2010 at `http://www.assekurata.de/content.php?baseID=130&dataSetID=703`). For simplicity, we assume that 10% of annual distributed profits are distributed to the terminal bonus account.

[21] See `http://www.boerse-frankfurt.de/DE/MediaLibrary/Document/Sonstiges/etf_handbuch.pdf`.

3 Numerical Results

3.1 Surplus Fund

Besides the function of stabilizing profits over time, the surplus fund is also an additional source of interest income for policyholders. If a policyholder enters an insurance company possessing a high amount of assets in the surplus fund, this policyholder will profit from interest earnings of a surplus fund which was built up by others. On the other hand, if the policyholder enters a contract when the surplus fund is comparably low, he will tend to build it up whereof future policyholders will profit. Hence, there is a kind of cross-subsidization between policyholders. Thus, from a policyholder's perspective the level of the surplus fund is crucial. However, individuals who enter a PLI contract do in general not know whether the surplus fund of the insurance company is rather stable or not. Figure 1 shows how the surplus fund develops on average over time in our sample case.

The dashed lines provide the lower and upper bounds in each year, which are constant in our setting once the 12th insurance collective has been set up. Based on the convergence behavior observable, we analyze contracts with three different starting points. Contract 1 starts at point in time 0 when the surplus fund is empty ($A_{f,\text{initiation}} = 0$). Contract 2 is established at the end of the 12th year when 12 collectives exist and the surplus fund has partially been built up. At point in time 24, when the surplus fund is rather stable, contract 3 is initiated.

Costumers benefit if they enter when the surplus fund has already been built up (contract 3). Then they will (on average) earn interest on assets others paid for and do not have to pay for assets which others will benefit of. Certainly, it is less beneficial if policyholders still have to build up the surplus fund (contract 1, contract 2). However, entering the contract when the surplus fund is greater than zero (contract 2), the policyholders might still profit from this mechanism due to earnings provided by assets already in the surplus fund.

In Table 2 to 5 we provide descriptive statistics of the payoff distribution of contract 1, contract 3, and of the two benchmark portfolios (mutual fund (MF) and exchange traded fund (ETF)). As results for contract 2 are just between those of contract 1 and 3, they are omitted and are available upon request. Reported results are for all T periods conditional upon being paid out during the respective period. The last column gives the probability of payout in each period.

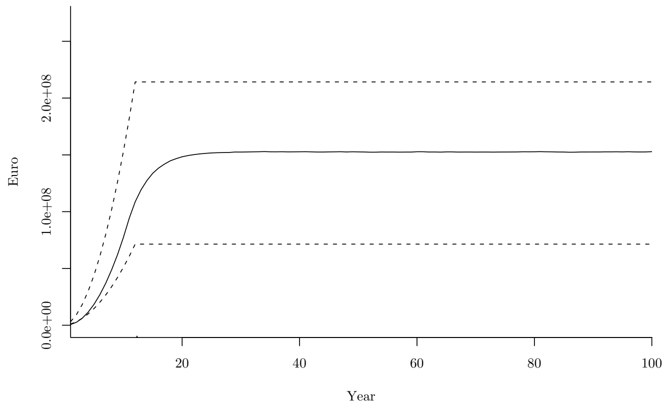


Figure 1: Development of the expected surplus fund in the sample case.

Regarding the contract's mean payoff, the life insurance payouts are dominated by the mutual fund in most periods. Only in the last three periods the mean payoff of contract 3 is higher than the one of the mutual fund. However, as the last three periods cover 73.7% of all cases, the mean is in favor of PLI contract 3 in the most likely periods. On the other hand, the relative difference is much higher in the first periods than in the last periods. In period 1, the mean payoff of contract 3 is 8.371% lower than the one of the mutual fund but only 2.489% higher in the last period. Comparing median payoffs yields the same structure. Concerning contract 1, mean and median are worse compared to the mutual fund in all periods.

Although some investors might be more concerned with the mean of the payoff distribution, others may care more about the distribution's dispersion and its shape, i.e. standard deviation, skewness, and kurtosis. Concerning the standard deviation, the mutual fund shows always higher values than the different PLI contracts. Looking at the third and fourth moment, contract 3 has a higher skewness and a higher kurtosis than the mutual fund during all periods. Contract 1 possesses a higher skewness in periods 2 to 7 and a lower kurtosis in periods 5 to 11. However, it is not straight possible to draw general conclusions about possible preferences solely based on these moments.

Besides considering the first four moments and the median, Table 2 to 5 also report the 5%, 25%, 75%, and the 95% quantile. For contract 1, all reported quantiles are higher for the mutual fund. This suggests that contract 1 is - at least down to the 5% quantile - dominated by the mutual fund for all periods. Concerning contract 3, all quantiles are lower than those of the mutual fund in early periods (1 to 8). However, from period 9 on the 5% and the 25% quantile of contract 3 and from period 11 on the 75% and the 95% quantile contain higher payoffs compared to the mutual fund portfolio. This supports results reported with respect to the mean payoff, namely that contract 3 appears to be favorable in late periods.

The ETF dominates PLI contract 1 and 3 concerning mean payoffs and all reported quantiles. The standard deviation of the ETF portfolio is higher whereas skewness and kurtosis are approximately the same like those of the mutual fund.

In order to clarify results with respect to the last period which accounts for more than 70% of all outcomes, we illustrate the payoff distributions (histograms) of the PLI contracts and the benchmark portfolios for period 12 in Figure 2. The figure shows how peaked the PLIs' payoff distributions are compared to the mutual fund and the ETF. The payoff distributions of the ETF is very similar to the one of the mutual fund but is shifted to the right due to the lower transaction costs. Comparing contract 1 and 3 shows that the payoff distribution of contract 1 is shifted to the left with a lower upside potential. From these results we can draw two major conclusions. First, the payoff distribution of the PLI depends on the level of the surplus fund at inception of the contract. If the surplus fund equals 0 when the contract is started (contract 1), the payoff distributions of both benchmark portfolios dominates the one of the PLI contract in all quantiles reported. If the surplus fund at inception is high (contract 3), the payoff distribution of the mutual fund dominates in early periods but is dominated later on (with regard to the quantiles reported). Second, it is not possible to draw general conclusions about the question whether PLI is beneficial to customers or not solely by considering moments or quantiles of the payoff distributions. While the mutual fund dominates the PLI in early periods for all contracts, this effect is reversed during the last four periods regarding contract 3. Hence, survival until maturity without surrender appears advantageous. However, results reported suggest that the ETF portfolio might be most beneficial as it dominates all PLI contracts with regard to mean and all quantiles analyzed.

Period	Mean	SD	Skewness	Kurtosis	5%	25%	Median	75%	95%	Prob.
1	4347	1.163	37.992	1551.293	4347	4347	4347	4347	4347	0.023
2	8787	17.301	5.356	28.648	8783	8783	8783	8783	8795	0.042
3	13339	56.713	2.354	4.760	13314	13314	13314	13314	13487	0.039
4	18028	120.750	1.379	1.009	17946	17946	17946	18111	18285	0.035
5	22876	207.049	0.880	-0.142	22685	22685	22817	22995	23264	0.031
6	28207	310.859	0.561	-0.576	27845	27900	28188	28434	28794	0.028
7	33746	431.047	0.350	-0.662	33141	33393	33707	34045	34510	0.025
8	39514	563.347	0.189	-0.623	38581	39089	39514	39940	40457	0.022
9	45521	712.180	0.113	-0.493	44326	44982	45509	46040	46690	0.019
10	51799	875.588	0.065	-0.311	50345	51166	51809	52433	53211	0.016
11	58376	1061.656	0.067	-0.037	56623	57613	58390	59141	60059	0.014
12	65424	1293.041	0.101	0.202	63275	64528	65440	66326	67442	0.706

Table 2: Descriptive statistics for the payoff distributions of PLI contract 1 conditional upon payout in the respective period. The probability of payout is given in the last column.

Period	Mean	SD	Skewness	Kurtosis	5%	25%	Median	75%	95%	Prob.
1	4422	36.951	2.339	9.807	4373	4411	4415	4419	4499	0.023
2	9012	95.183	1.678	5.696	8884	8978	8990	9025	9205	0.042
3	13779	178.199	1.372	3.913	13530	13709	13735	13834	14135	0.039
4	18734	283.425	1.146	2.783	18334	18609	18661	18846	19291	0.035
5	23886	410.989	1.011	2.201	23299	23688	23786	24071	24685	0.031
6	29563	564.995	0.948	2.061	28751	29268	29435	29837	30638	0.028
7	35477	742.128	0.831	1.527	34406	35064	35325	35859	36885	0.025
8	41647	942.925	0.781	1.334	40275	41101	41471	42146	43410	0.022
9	48100	1169.332	0.727	1.122	46397	47395	47900	48747	50260	0.019
10	54855	1427.806	0.681	0.950	52765	53963	54634	55658	57496	0.016
11	61956	1729.874	0.664	0.887	59424	60855	61703	62945	65138	0.014
12	69542	2067.277	0.603	0.695	66490	68201	69266	70755	73308	0.706

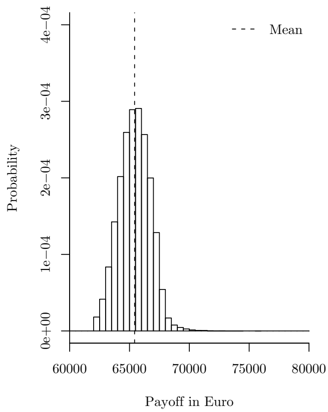
Table 3: Descriptive statistics for the payoff distributions of PLI contract 3 conditional upon payout in the respective period. The probability of payout is given in the last column.

Period	Mean	SD	Skewness	Kurtosis	5%	25%	Median	75%	95%	Prob.
1	4826	83.347	0.522	0.488	4702	4767	4819	4877	4974	0.023
2	9771	188.598	0.426	0.357	9485	9639	9758	9889	10101	0.042
3	14843	321.417	0.386	0.277	14352	14619	14823	15046	15404	0.039
4	20049	477.354	0.360	0.258	19317	19714	20023	20352	20881	0.035
5	25395	659.055	0.345	0.242	24377	24937	25359	25814	26541	0.031
6	30891	861.528	0.333	0.237	29556	30295	30842	31440	32385	0.028
7	36555	1082.281	0.314	0.214	34872	35803	36501	37254	38414	0.025
8	42397	1328.488	0.306	0.189	40332	41473	42333	43245	44684	0.022
9	48425	1596.633	0.313	0.206	45956	47312	48347	49447	51179	0.019
10	54665	1888.341	0.307	0.178	51725	53350	54568	55877	57920	0.016
11	61136	2212.389	0.311	0.205	57688	59594	61026	62552	64947	0.014
12	67853	2559.604	0.296	0.168	63870	66065	67737	69506	72259	0.706

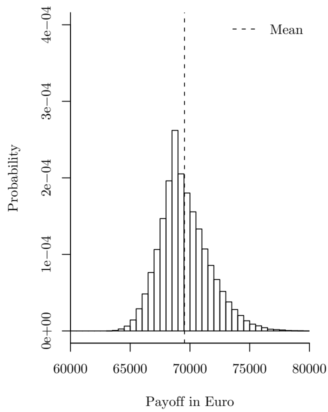
Table 4: Descriptive statistics for the payoff distributions of MF conditional upon payout in the respective period. The probability of payout is given in the last column.

Period	Mean	SD	Skewness	Kurtosis	5%	25%	Median	75%	95%	Prob.
1	4858	84.458	0.522	0.478	4733	4799	4851	4910	5008	0.023
2	9890	192.310	0.425	0.356	9597	9755	9876	10010	10226	0.042
3	15102	329.901	0.388	0.276	14598	14872	15082	15310	15678	0.039
4	20510	493.151	0.355	0.266	19752	20164	20483	20824	21368	0.035
5	26120	685.900	0.344	0.249	25060	25643	26082	26556	27310	0.031
6	31948	903.316	0.333	0.232	30549	31324	31895	32523	33513	0.028
7	38013	1140.024	0.321	0.224	36240	37222	37956	38745	39972	0.025
8	44333	1408.309	0.305	0.180	42147	43352	44266	45231	46766	0.022
9	50919	1703.969	0.314	0.193	48290	49729	50836	52008	53867	0.019
10	57800	2031.720	0.315	0.214	54640	56387	57690	59098	61299	0.016
11	65001	2390.649	0.314	0.208	61284	63338	64876	66530	69127	0.014
12	72551	2789.714	0.297	0.169	68211	70601	72421	74351	77353	0.706

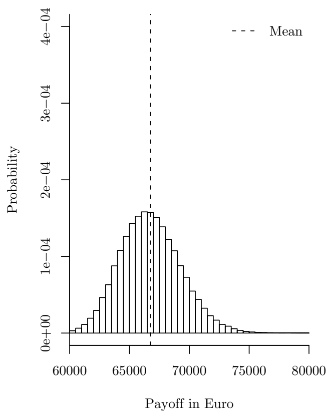
Table 5: Descriptive statistics for the payoff distributions of ETF conditional upon payout in the respective period. The probability of payout is given in the last column.



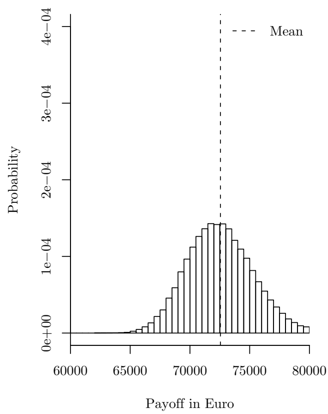
(a) PLI payoffs contract 1



(b) PLI payoffs contract 3



(c) MF payoffs



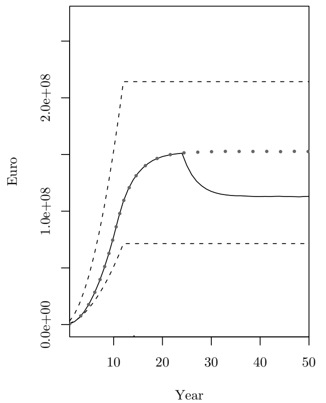
(d) ETF payoffs

Figure 2: Histograms and mean for the payoff distributions conditional upon payout in the last year for each contract.

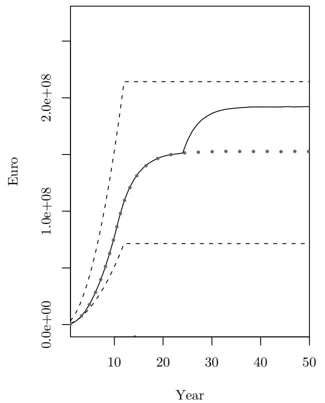
3.2 Management Discretion

Our previous results have shown that the surplus fund has an important impact on the payoff distribution. However, we assumed parameters to be constant and differences with respect to the different contracts were caused by the initial level of the surplus fund. In what follows, we analyze the effects of management's discretion with regard to contract 3. We examine the effect on the PLI's payoff distribution if management changes the target rate of interest directly after the policyholder's first premium payment. We focus on an increase of the target rate to $r_z = 4.0\%$ and a decrease to $r_z = 3.0\%$. Similar to Figure 1, Figure 3(a) and 3(b) show how the surplus fund develops on average over time given the change of the target rate of interest in year 24. The dashed lines provide the lower and upper bounds in each year, the dotted line displays the level of the surplus fund given no change in target interest rate. If the target rate increases to $r_z = 4.0\%$, the surplus fund first decreases and then stabilizes at a lower level. On the contrary, with a decrease to $r_z = 3.0\%$, the surplus fund first increases and then stabilizes at a higher level. Figure 3(c) and 3(d) show the payoff distribution in the last period (similar to Figure 2). The dotted line denotes the density function given no target rate change. Both rate changes, $r_z = 3.0\%$ and $r_z = 4.0\%$, lead to a much less peaked payoff distribution compared to the contract without a change of the target rate. In addition, the rate change to $r_z = 3.0\%$ causes the payoff distribution to be more skewed than the change to $r_z = 4.0\%$. In Table 6 and 7 we provide descriptive statistics of the payoff distribution of contract 3 with the target return increase and decrease. Reported results are for all T periods conditional upon being paid out during the respective period. The probability of payout in each period is reported in the last column.

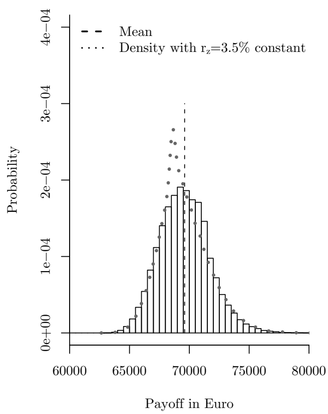
The target rate increase to $r_z = 4.0\%$ results in a higher mean, a higher median, a lower kurtosis, and a lower skewness in all periods compared to the constant target rate. The standard deviation with the increased target rate is lower in periods 1 to 3 and higher in periods 4 to 12. The 5% and the 95% quantile are higher for the contract with the constant target rate (except of period 1). On the contrary, in most periods the 25% and the 75% quantile are higher for the contract with the changed target return. Hence, the target rate increase to $r_z = 4.0\%$ appears to be beneficial around the expected payoff, i.e. between the 25% and the 75% quantile. However, the higher target rate results in a lower upside potential as the equilibrium level of the surplus fund gets closer to the lower bound. Subsequently,



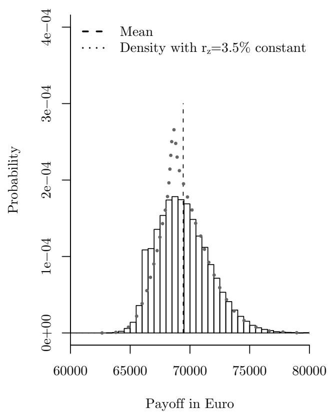
(a) Surplus fund for $r_z = 4.0\%$



(b) Surplus fund for $r_z = 3.0\%$



(c) Payoff distributions for $r_z = 4.0\%$



(d) Payoff distributions for $r_z = 3.0\%$

Figure 3: Histograms and mean for the payoff distributions conditional upon payout in the last year for contract 3 if the target rate of interest is changed at the beginning of the contracts life and the corresponding expected level of the surplus fund.

Period	Mean	SD	Skewness	Kurtosis	5%	25%	Median	75%	95%	Prob.
1	4436	34.938	1.321	8.357	4373	4432	4436	4440	4497	0.023
2	9048	92.671	0.619	4.456	8875	9026	9054	9068	9203	0.042
3	13839	176.102	0.360	2.627	13525	13755	13861	13897	14133	0.039
4	18815	284.612	0.278	1.733	18323	18648	18862	18936	19283	0.035
5	23985	418.984	0.273	1.309	23275	23720	24049	24188	24674	0.031
6	29673	573.991	0.249	0.944	28716	29293	29728	29980	30621	0.028
7	35597	753.985	0.252	0.681	34367	35087	35639	36027	36845	0.025
8	41770	960.568	0.296	0.618	40221	41113	41790	42340	43380	0.022
9	48219	1189.749	0.309	0.557	46314	47398	48219	48955	50208	0.019
10	54963	1447.987	0.315	0.443	52661	53950	54947	55873	57399	0.016
11	62040	1739.032	0.319	0.348	59291	60821	62006	63149	64995	0.014
12	69609	2081.328	0.318	0.296	66338	68147	69549	70957	73164	0.706

Table 6: PLI contract 3, target return changing to 4%.

Period	Mean	SD	Skewness	Kurtosis	5%	25%	Median	75%	95%	Prob.
1	4407	40.820	2.511	8.141	4373	4390	4393	4403	4497	0.023
2	8976	108.957	1.853	4.298	8870	8915	8926	9013	9206	0.042
3	13721	206.747	1.481	2.509	13519	13584	13633	13820	14145	0.039
4	18654	328.994	1.229	1.612	18310	18406	18553	18836	19305	0.035
5	23787	475.186	1.054	1.142	23259	23397	23677	24065	24703	0.031
6	29450	646.797	0.915	0.802	28694	28903	29330	29842	30678	0.028
7	35354	840.084	0.815	0.575	34331	34666	35225	35868	36915	0.025
8	41528	1060.833	0.745	0.508	40183	40687	41390	42184	43481	0.022
9	47978	1297.929	0.673	0.380	46266	46974	47828	48787	50340	0.019
10	54741	1572.455	0.633	0.348	52596	53549	54570	55720	57593	0.016
11	61845	1868.678	0.590	0.273	59210	60448	61665	63015	65233	0.014
12	69446	2230.646	0.557	0.226	66227	67793	69235	70855	73465	0.706

Table 7: PLI contract 3, target return changing to 3%.

the probability to reach the upper bound of the surplus fund and thus the probability to receive return attributions which are higher than r_z are reduced.

The decrease of the target rate of interest to $r_z = 3.0\%$ leads to a lower mean, a lower median, a higher standard deviation, and a lower kurtosis in all periods. The 5% and the 25% quantile are lower for the decreased target rate (except of period 1). On the contrary, the 75% quantile is higher from period 6 to 12 and the 95% quantile is higher for all period except of period 1. Thus, the decreased target rate of interest leads to a higher upside potential as the equilibrium level of the surplus fund gets closer to the upper bound. However, the lower target rate leads to lower expected payoffs. These results let us draw two conclusions. First, management's discretion have an important influence in respect to the payoff distribution. Second, it depends on customer's preferences if a change of the target rate is found beneficial or not. While expected payoffs increase with an increase in target rate, a reduction leads to a higher upside potential in later periods.

3.3 Performance Measurement

Next, we derive a preference dependent valuation of the different investment opportunities based on the payoff distributions shown. In order to do so, assumptions regarding the state and time preferences of the policyholder are needed. In this subsection, we assume that whenever payments take place before the end of maturity T (because of surrender or death of the investor), the corresponding cash-flows are reinvested and compounded with the annual minimum interest rate r_g. This yields one single cash flow distribution L_T at time T for each investment alternative. We provide descriptive statistics of the payoff distribution L_T of the different investment alternatives in Table 8. Regarding the mean payoff, the median, and the different quantiles shown in Table 8, the ETF benchmark leads to the highest payouts compared to all other alternatives.

The premiums paid into the different saving products (i.e., after detaching the term life insurance) are the same for all alternatives: $P_{t-1} - P_{r,t-1}$. Compounding the premium payments $(P_{t-1} - P_{r,t-1})$ with the interest rate r_g while taking surrender and survival probabilities of the policyholder into account, leads to a (deterministic) terminal value of premium payments of $Y_T = 55518$. As it is done in Gatzert and Schmeiser (2009), we perform a comparison of the four different cases by using modified forms of three

Contract type	Mean	SD	Skewness	Kurtosis	5%	25%	Median	75%	95%
PLI contract 1	54441	19070	-1.397	0.355	10942	48253	64695	65950	67250
PLI contract 3	57748	20491	-1.374	0.310	11209	50802	68419	70059	72822
MF	55884	19142	-1.395	0.436	11899	49861	65327	67610	70622
ETF	60527	21085	-1.377	0.370	12398	53484	70972	73493	76816

Table 8: Descriptive statistics of the payoff distribution L_T derived under the assumption that payouts before T had been invested to the annual minimum interest rate r_g.

Contract type	Sharpe ratio	Omega	Sortino ratio
PLI contract 1	-0.057	-0.132	-0.056
PLI contract 3	0.109	0.285	0.108
MF	0.019	0.048	0.019
ETF	0.238	0.688	0.231

Table 9: Modified performance measures for the valuation of four different investment opportunities.

different classical performance measures. First, an adaption of the Sharpe ratio (see Sharpe (1966)) can be defined in the following way:

$$\text{Sharpe ratio}(L_T) = \frac{E(L_T) - Y_T}{\sigma(L_T)}$$

For instance, in the case of the ETF benchmark portfolio, this will lead to

$$\text{Sharpe ratio}(L_T) \approx \frac{60527 - 55518}{21085} \approx 0.238$$

Following Gatzert and Schmeiser (2009), a modified form of Omega and the Sortino ratio can be defined by (see Shadwick and Keating (2002), Sortino and van Der Meer (1991))

$$\text{Omega}(L_T) = \frac{E\left(max\left(L_T - Y_T, 0\right)\right)}{E\left(max\left(Y_T - L_T, 0\right)\right)}$$

and

$$\text{Sortino ratio}(L_T) = \frac{E\left(max\left(L_T - Y_T, 0\right)\right)}{\sqrt{E\left(max\left(Y_T - L_T, 0\right)^2\right)}}.$$

Table 9 provides an overview of the different performance ratios of the four investment opportunities in focus. The used performance measurements of the investment alternatives give a clear picture: The contract type ETF dominates all other investment forms analyzed. PLI contract 3 dominates MF and PLI contract type 1, whereas contract 1 is dominated by all other alternatives. In addition, we further tested for first degree stochastic dominance (FSD).[22] In our simulation results a FSD is only given for

[22]See Bawa (1975).

investment form ETF in comparison to PLI contract 1. More precisely, let F_1 denote the cumulative distribution function of L_T^{C1} (PLI contract 1) and let F_2 stand for the cumulative distribution function of L_T^{ETF} (ETF portfolio). Then L_T^{ETF} dominates L_T^{C1} by FSD since $F_1(x) \geq F_2(x)$ for all x and $F_1(x) > F_2(x)$ for at least some x. Performance ratios are best for the ETF portfolio and worst for PLI contract 1 as already implied by our previous results. Further, performance ratios for PLI contract 3 are higher than for the mutual fund portfolio. Hence, PLI contract 3 appears to be superior to the mutual fund portfolio given our underlying assumptions about preferences.

4 Conclusion

In this paper, we develop in a first step a framework to estimate payoffs from PLI contracts. We decompose PLI into an investment part and a term life insurance. Thus we are able to analyze the benefits of the minimum interest rate guarantee in combination with the profit distribution rules separately from the term life insurance. In addition, we model more than one single contract which allows us to incorporate distribution effects between policyholders. In a second step we simulate the payoff distributions and benchmark the complete payoff distribution on an ex-ante basis. We show how the payoff distribution depends on the level of the surplus fund at inception of the contract and analyze the effect of management discretion. PLI contracts are popular - especially in the context of old-age provisions. This popularity might be to a large extent attributable to the downside protection. However, it is controversial if these products are actually beneficial for customers. More precisely, even though these contract forms are very common in insurance practice, only very little research has been conducted in respect to its performance. We show that PLI can be beneficial depending on the initial reserve situation and preferences. A low initial reserve situation of the insurer appears to be disadvantageous. Individuals continuing their contract until maturity without death or surrender will in general profit from a better payoff distribution compared to the MF benchmark portfolio but not the ETF benchmark portfolio. Further, investors do not know ex ante whether and when they will die or surrender. Hence, product preferences will depend on risk aversion and the rate of intertemporal substitution. Management's discretion changes payoff distributions but it depends on preferences whether the changed payoff distribution is perceived to be better or worse. To conclude, policyholders have very little chance to predetermine the cash flow distribution as long as the future behavior of management and the current level of the surplus fund are unknown or realistic assumption cannot be derived in this respect. Also, our preference dependent performance analysis shows that in most cases an ETF portfolio will assumedly perform better than each possible PLI contract.

Appendix

The following formulas illustrate briefly how the annual term life insurance premium can be calculated. The insured sum I_t in year t equals the guaranteed death benefit minus the accumulated savings account at the end of year t,

$$I_t = D - A_{g,t-1}\exp(r_g).$$

Recall the formulas for the savings part of the premium and the accumulated savings account:

$$P_{s,t-1}^{(\mathrm{PLI})} = P - P_{c,t-1} - P_{r,t-1}$$
$$A_{g,t-1} = \sum_{i=1}^{t} P_{s,i-1}^{(\mathrm{PLI})}\exp\left(r_g(t-i)\right).$$

Given the probability q_{x+t} of a $(x+t)$-years old individual to die within the next years, the term life insurance premium is (assuming that payouts only take place at the end of year t)

$$P_{r,t-1} = q_{x+t-1} I_t \exp(-r_g).$$

Insertion yields

$$\begin{aligned}
P_{r,t-1} &= q_{x+t-1} I_t \exp(-r_g) \\
&= q_{x+t-1}\left(D - A_{g,t-1}\exp(r_g)\right)\exp(-r_g) \\
&= q_{x+t-1}\left(D\exp(-r_g) - A_{g,t-1}\right) \\
&= q_{x+t-1}\left(D\exp(-r_g) - (A_{g,t-2}\exp(r_g) + P - P_{c,t-1} - P_{r,t-1})\right) \\
&= \frac{q_{x+t-1}}{1-q_{x+t-1}}\left(D\exp(-r_g) - (A_{g,t-2}\exp(r_g) + P - P_{c,t-1})\right).
\end{aligned}$$

Under the constraint that the guaranteed death benefit equals the guaranteed terminal payment,

$$D = A_{g,T-1}\exp(r_g).$$

Thus

$$P_{r,t-1} = \frac{q_{x+t-1}}{1-q_{x+t-1}}\left(A_{g,T-1} - (A_{g,t-2}\exp(r_g) + P - P_{c,t-1})\right).$$

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Corporate Risk, Diversification, and Shareholder Value

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In a contingent claims approach, equity is expressed as a call option on the assets of a company with debt being the strike. Depending on option type and parameters, a reduction in the volatility of assets could imply a value reduction. If corporate diversification leads to a reduction in the volatility of assets this reasoning might explain the diversification discount. We assume that equity is a down-and-out call option on a companies assets and propose a two-step regression framework to empirically test for a large sample of US companies whether the insight from option pricing can explain the observed diversification discount. While our results show that assets of single-line companies have a higher volatility compared to multi-line companies they reject that the contingent claims approach could explain the observed diversification discount. This finding does not change if we model equity as a European call option. However, we find a significant relationship between the barrier level of the down-and-out call option and shareholder value.

*Acknowledgements: We are grateful to Marc Arnold, Alexander Braun, Daniel Buncic, Christina Felfe, Michel Habib, Przemysław Rymaszewski, Hato Schmeiser, René Stulz, Paolo Tasca, Joël Wagner, participants in the 22nd Australasian Finance and Banking Conference (Sydney, December 2009), participants in the 9th German Operations Research Society Workshop on Finance and Financial Institutions (St. Gallen, March 2010), and participants in the 9th Swiss Doctoral Workshop in Finance (Gerzensee, June 2010) for valuable comments and suggestions.

1 Introduction

Lang and Stulz (1994) show that firms which are diversified over more than one business line trade at a discount compared to single-line firms. Similar findings are provided by Berger and Ofek (1995). Subsequently there has been a large body of literature on the diversification discount.[1] Mansi and Reeb (2002) argue with a contingent claims approach and interpret the discount of diversified firms as a loss of shareholder value due to volatility reduction. In a contingent claims framework the value of equity is expressed as a call option on the assets of a company with the book value of debt being the strike. This means that equity holders get the residual claims once debt holders have been paid out or zero in the case that assets are insufficient to pay off debt holders. Assuming that the assets of different business lines have a correlation coefficient below one, the conglomerate's combined assets will have a lower volatility because of the diversification effect. The option on the sum of the assets is worth less than the sum of options on the assets of the individual business lines.[2] Mansi and Reeb (2002) show that while equity trades at a discount, bonds of diversified firms trade at a surplus compared to single-line firms. Their interpretation is that diversification shifts wealth from shareholders to bondholders because of a volatility reduction.[3] Our goal in this paper is to test empirically whether there is an effect on shareholder value due to changes in volatility.

Using the classical Black and Scholes framework for European call options to value equity it is ignored that companies could become bankrupt during the life-time of the option. To overcome this shortcoming, Brockman and Turtle (2003) propose a down-and-out call option (hereafter DOC) for corporate security valuation. By using a DOC to value equity it is possible to account for the fact that the firm could be eliminated during

[1] See for example Martin and Sayrak (2003) for an overview of the literature which appeared until 2001.

[2] See for example Ammann and Verhofen (2006) for this argument in the context of the diversification discount.

[3] Because most companies do not have publicly traded debt, the used subsample of Mansi and Reeb (2002) contains only 2487 firm years which is rather small compared to their whole sample of 18898 firm years. Eberhart (2005) shows that the Merton (1974) model provides more accurate estimates for the market value of debt than the book value of debt. This can help to overcome the problem of having only a small sample of observed market values of debt. Glaser and Müller (2010) for example use the Merton (1974) model to estimate the market value of debt and to test whether the book value bias helps to explain the diversification discount.

the lifetime of the option. The logic is based on the reasoning that the company will become liquidated once the value of its assets falls below a specific level. It is not only at maturity but during the whole lifetime of the option that the value of assets matters. This difference is important: If we model equity as a European call option, the value of assets can approach zero, stay there for some time, and recover until maturity. In reality, this seems implausible since the company would most likely become bankrupt. For a DOC Vega is not always strictly positive. Thus an increase in assets volatility will not always improve equity holders wealth. This is a very different property compared to a classical call option and contradicts even within the theoretical framework the assumption that shareholders would always prefer as risky projects as possible.

The DOC approach provides a rather flexible framework and allows to take various different settings into account. For example, it is possible that upon default equity holders might still receive a proportion of the assets. Within the DOC pricing framework this can be modeled as a cash rebate which is paid out once the barrier is broken. Extending the framework of Duan (1994), Wong and Choi (2009) propose a maximum likelihood estimation (hereafter MLE) to estimate the barrier, the assets' drift term, and the volatility of the assets within a DOC framework. We rely on this MLE to estimate the three parameters. In the structural corporate bond pricing literature the general superiority of the MLE framework of Duan (1994) over alternative estimation methods like the proxy approach and the volatility-restriction approach has been for example documented by Ericsson and Reneby (2005) and Li and Wong (2008). An overview on different estimation methods and different models is given by Li and Wong (2008).

The contribution of this paper is that we empirically test whether the diversification discount often reported in the literature is explainable by the contingent claims approach. For this purpose we use a measure for a companies' relative valuation compared to its peers as dependent variable and the expected effect of a change in volatility as independent variable in a regression. Following Berger and Ofek (1995) the firm's actual value compared to the sum of stand-alone values of its business segments is used as a measure for the firms excess value. This allows us to show empirically the relationship between the expected effect of a change in volatility and excess value. We find that the assets of single-line firms have a higher volatility than the assets of multi-line firms. However, we find no significant relationship between excess value and the expected effect of a change in volatility. Thus our results reject the contingent claims approach as explanation for the observed diversification discount. This should not be interpreted as a test of the contingent claims approach itself. It is a test, whether the diversification discount can be explained with the contingent claims approach, i.e. whether the diversification discount is attributable to a change in the volatility of a companies assets. An additional finding is that we show a significant relationship between the barrier level and shareholder value indicating that the effect of the barrier level could be more important than the effect of volatility. Also, we report a significant relationship between the drift of assets and excess value.

The remainder of the paper is as follows: In section 2 we explain the used DOC model, the estimation of its parameters through MLE, the measurement of excess value, the measurement of the expected effect of volatility, and the second-step regression. In section 3 we present our data sample. Empirical results are presented in section 4 and in section 5 we conclude.

2 Framework

2.1 The DOC Framework

Merton (1973) has developed a closed formula to value barrier options. Within the contingent claims approach, the value of the DOC is equal to the value of equity V_E. Under the assumption of no rebate and no drift of the barrier, the value of a DOC is given by[4],

$$\begin{aligned} DOC &= V_E \\ &= VN(a) - Xe^{-rT}N(a - \sigma\sqrt{T}) \\ &\quad - V(H/V)^{2\eta}N(b) + Xe^{-rT}(H/V)^{2\eta-2}N(b - \sigma\sqrt{T}) \end{aligned} \tag{1}$$

where T is the time to maturity, the underlying is given by assets V, σ is the volatility of assets, X is the strike which is given by the book value of debt, r is the risk free interest rate, and $N(\cdot)$ is the cumulative standard normal distribution. The option is knocked out if the underlying reaches the barrier H. In addition, a, b, and η are given by

[4] Note that both Brockman and Turtle (2003) and Wong and Choi (2009) present a formula which accounts for a rebate but set the rebate to zero. To simplify the equation, we drop the terms which account for the rebate directly.

$$a = \begin{cases} \dfrac{\ln(V/X) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} & \text{if } X \geq H, \\ \dfrac{\ln(V/H) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} & \text{if } X < H, \end{cases}$$

$$b = \begin{cases} \dfrac{\ln(H^2/(VX)) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} & \text{if } X \geq H, \\ \dfrac{\ln(H/V) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} & \text{if } X < H, \end{cases}$$

and

$$\eta = \frac{r}{\sigma^2} + \frac{1}{2}.$$

2.2 First-Step Estimation

To estimate the parameters, i.e the assets' volatility σ, the barrier H, and the assets' drift μ, we use the MLE approach of Wong and Choi (2009). If the conditional probability density function for the observable market value of equity V_E at time t is given by

$$f(V_E(t_i)|V_E(t_{i-1}), \boldsymbol{\theta})$$

with $\boldsymbol{\theta} = (\mu, \sigma, H)$, then the likelihood is maximized by maximizing the log-likelihood function

$$L(\boldsymbol{\theta}) = \sum_{i=2}^{n} \ln f(V_E(t_i)|V_E(t_{i-1}), \boldsymbol{\theta}) \tag{2}$$

with respect to vector $\boldsymbol{\theta}$. The number of daily stock closing prices is given by n. Further,

$$f(V_E(t_i)|V_E(t_{i-1}), \boldsymbol{\theta}) = \left(g(w_i|w_{i-1}, \boldsymbol{\theta}) \left(\frac{\partial V_E}{\partial w} \right)^{-1} \right)_{w_i = w(V_E^i, t_i, \sigma, H)}$$

whereas $w_i = \ln(V_i)$. The density function can be found in Rubinstein and Reiner (1991). It is

$$g(w_i|w_{i-1}, \boldsymbol{\theta}) = \varphi(w_i - w_{i-1}) - \exp(2\eta^*(\ln(H) - w_{i-1}))\varphi(w_i + w_{i-1} - 2\ln(H))$$

if $V > H$ and zero otherwise. The time interval between two observations is given by Δt. Further

$$\varphi(x) = \frac{1}{\sigma\sqrt{2\pi\Delta t}} \exp\left(-\frac{(x-(\mu-\sigma^2/2)\Delta t)^2}{2\sigma^2\Delta t}\right)$$

and

$$\eta^* = \frac{\mu}{\sigma^2} - \frac{1}{2}.$$

The derivative

$$\frac{\partial V_E}{\partial w}$$

can be calculated by using the Delta of the DOC pricing formula (1):

$$\left.\frac{\partial V_E}{\partial w}\right|_{w=w_i} = V_i \left.\frac{\partial V_E}{\partial V}\right|_{V=V_i}.$$

Once the parameter vector $\boldsymbol{\theta}$ is estimated as $\hat{\boldsymbol{\theta}}$ it can be used together with the given market value of equity V_E to solve the DOC pricing formula for the underlying assets V to receive the estimated value of assets $\hat{V}$.

2.3 Excess Value

Excess value can be measured as ratio between market value of equity plus book value of debt and the sum of an accounting item which is multiplied for every business line of the company with a respective multiplier. We follow Brockman and Turtle (2003) and define debt as total book value of assets less book value of total common equity whereas Berger and Ofek (1995) use the book value of debt as stated in the balance sheet. The SIC code specific multipliers are calculated as the median of the ratios between the market value of equity plus the book value of debt and the book value of an accounting item of single-line firms which only have operations within the specific SIC code. We use the market to sales ratio to measure excess value of a company. We calculate excess value similar to Berger and Ofek (1995) for each firm year as

$$E = \ln \left(\frac{\text{market value of common equity} + \text{book value of debt}}{d \sum_{j=1}^{J} \text{sales}_j \text{MSR}_{t,j}} \right) \tag{3}$$

whereas $\text{MSR}_{t,j}$ is the market-to-sales ratio for industry j at time t and sales_j are the sales of the company in business line j for the respective firm year. The term d adjusts for cases where the summed up sales of the business lines do not equal the total reported sales. It is calculated as total sales divided by the sum of the sales of all business lines. Berger and Ofek (1995) make this adjustment for market-to-asset ratios. While differences between total assets and the sum of all business lines assets' exist more often and are in general larger than this is the case if one relies on sales we still decided to consequently correct differences.

2.4 Expected Effect of a Change in Volatility

The expected effect of a change in volatility on the price of an option can be approximated by Vega, i.e. its first derivative with respect to volatility:

$$\nu = \frac{\partial V_E}{\partial \sigma}.$$

The change in volatility within one year is given by $\Delta\sigma_t = \sigma_t - \sigma_{t-1}$. Ceteris paribus, an approximation for the effect of a change in value due to a change in volatility of an option is given by $\nu\Delta\sigma_t$. To scale this absolute measure we divide it by the reported sales and introduce the measure ς:

$$\varsigma = \frac{\nu\Delta\sigma_t}{\text{Sales}}, \tag{4}$$

which we evaluate with the estimated parameters $\hat{\boldsymbol{\theta}}$ to receive $\hat{\varsigma}$.

2.5 Second-Step Estimation

We want to examine the relationship between diversification -measured as a dummy variable which is one for multi-line firms-, ς, μ, H/X, and excess value. For this purpose we use OLS. As control variables EBIT over sales to control for profitability, capital expenditures over sales to control for growth opportunities, and the natural logarithm of assets to control for size are added. The last three control variables are used by Berger and Ofek (1995) as control variables in regressions with excess value as dependent variable and diversification measures as independent variables. Additionally we add the debt proportion as explanatory variable. Following Brockman and Turtle (2003) we define the debt proportion as debt divided by total market value. Debt is calculated as total book value of assets minus book value of total common equity. Total market value of the company is calculated as the sum of the market value of equity and debt.

Since excess value is a relative measure, we also compute relative measures for all independent variables except the diversification dummy and finally use this measures in our regression. The relative value is obtained by subtracting the median value of single-line firms in the same primary industry. This approach is employed by Denis et al. (2002). We will use the index r for this relative measures.

While the first-step estimates from a MLE can be used in general directly in subsequent models without affection point estimates, inference in a second-step should be adjusted for the first step (Murphy and Topel, 1985). To correct inference results for the first-step estimation, we bootstrap 100 times the returns of the used equity prices using the resampling technique of Politis and Romano (1994). We set the block length to 10 what is in general appropriate for daily equity returns, see for example Sullivan et al. (1999). Next we estimate all parameters $\boldsymbol{\theta}$ for all bootstrapped series. Inference results are subsequently based on the 100 samples of bootstrapped estimates and the original estimates.

3 Data

We select publicly listed companies which are domiciled in the US. Balance sheet data is obtained from Worldscope[5,6] on an annual basis and daily stock market closing prices are obtained from Datastream. In accordance with Brockman and Turtle (2003) and Wong and Choi (2009) we restrict our sample to industrial companies for which all reported SIC codes are between 2000 and 5999. We apply this restriction upon all business segments. This means that we exclude firm years, where any reported business segment has a SIC Code not within the specified range. The annual company data cover the ten year period between 1999 and 2008. This time period includes both bear and bull markets which enables us to perform our analysis with data from different stock market environments. We delete all firm years with missing SIC codes for the segment sales, where the sum of the segment sales is bigger than total reported sales as well as firm years for which the sum of segment sales is less than 99% of total sales. We adjust the remaining cases which have a difference between the sum of business lines sales and total sales, see formula (3). Following both Berger and Ofek (1995) and Mansi and Reeb (2002) we also delete all firm years with total sales of less than $20 million.

We set a minimum requirement of at least five single-line firms within a given SIC code to calculate the market-to-sales ratio. Multiples are calculated based on a four digit SIC code level for each individual year. If data is insufficient we switch to a three digit SIC code level and subsequently to a two digit level. If we have insufficient data on the two digit level we drop all companies in the respective year for which sales of any business segment are attributed to the respective SIC code. The reason for this is that we would not be able to calculate the implied value for these companies. The median for the calculation of the relative variables is based on either a four or a three digit SIC code level with at least five firm years of

[5]The Worldscope database and its segment data has for example been used by Lins and Servaes (1999) or Mansi and Reeb (2002).

[6]Villalonga (2004) shows that segment data from Compustat (the same should apply to Worldscope) gives different results regarding the conglomerate discount than data from the Business Information Tracking Series (BITS), a census database. Compared to data from BITS, Compustat data suffer under strategic accounting and inconsistency across firms (Villalonga, 2004). However, it can also be argued that managers (which report the segment description to Compustat, SIC codes are subsequently assigned by Compustat) "have better information than the econometrician about the strategic extent of diversification" (Villalonga, 2004).

	Mean	Quantiles Min.	5%	25%	50%	75%	95%	Max.	SD
Interest rate	0.035	0.012	0.015	0.019	0.036	0.048	0.056	0.061	0.017

Table 1: Summary statistic for the risk free interest rate proxy per year.

single-line firms. After calculating the excess value, we follow Berger and Ofek (1995) and Mansi and Reeb (2002) and delete any firm year in which the absolute excess value is larger than 1.386, i.e. where the actual value is more than four times or less than one fourth of the imputed. Extreme values can have a strong impact on non robust regression methods like to one we use. In our data set, extreme values might not only exist due to for example wrong data of the data provider but particular due to the calculation of $\hat{\nu}$ which can take extreme values and subsequently often leads to extreme values for $\hat{\varsigma}$. In such cases $\hat{\varsigma}$ can be a rather bad approximation for the effect which we want to measure. Further, the calculation of the barrier level can become rather inaccurate for low debt levels (see also Wong and Choi (2009)). Thus, we finally delete all firm years for which the squared robust Mahalanobis distance[7] is larger than $\chi^2_{8,0.99} \approx 20.100$. The final sample consists of 1616 different companies and 5227 firm years. The data cover 3663 firm years from single-line and 1564 from multi-line companies.

Following both Brockman and Turtle (2003) and Wong and Choi (2009) we choose ten years as time to maturity T of the option. Both of the former authors show -within two different frameworks- that the estimation of remaining parameters is rather robust with respect to maturity T. As proxy for the risk free rate we use the market yield on U.S. treasury securities at 1-year constant maturity. The respective summary statistics are given in Table 1.

[7] The robust Mahalanobis distance is calculated as proposed by Rousseeuw and van Zomeren (1990), using the algorithm of Rousseeuw and van Driessen (1999) to calculate the minimum ellipsoid estimator and a subset of $h = 0.75M$, i.e. a breakdown value of about 25%, with M being the number of total firm years.

4 Empirical Results

4.1 First-Step Estimations and Sample Statistics

We maximize the log-likelihood function given in equation (2) by imputing the needed data to estimate the parameters $\boldsymbol{\theta}$ for each firm year. We do this by using the algorithm of Nelder and Mead (1965) which is the same as used by Wong and Choi (2009). We restrict μ to be smaller (higher) than 10 (-10), σ to be smaller than 10, and the barrier level H/X to be below 3.[8] The reason for doing this is that we consider values out of this range to be implausible from an economic viewpoint.

In Table 2 summary statistics for the variables used in the second-step regression are given for single-line firms and multi-line firms. Further we show the results of a (corrected) t-test for the difference between the mean of the single and multi-line companies. The mean of the excess value of single-line firms is higher than the one of multi-line firms, indicating that single-line firms have on average a higher excess value than multi-line firms. However, the difference is not significant. Table 2 further shows that multi-line firms are larger and have a higher debt proportion, i.e. they depend more on debt financing. The mean of these two variables is significantly different between single-line and multi-line companies.

Interesting with respect to the results from the first-step regression is that we can see that single-line companies have more volatile assets. This supports the idea that diversification along business lines leads to a volatility reduction. The difference of the mean is significant. For the drift and the barrier level we do not find a significant difference of the mean. Wong and Choi (2009) report that in the financial troublesome years of 1998 and 2002 they find a lower proportion of barrier levels below one than in all other years. We can confirm this finding for our data sample. While we report a proportion of 0.510 of all barriers to be below one, this is only the case for 0.210 (0.449) in 2008 (2002) and in no other year the number is lower than these two. The interpretation is that in times of financial crisis investors price equities with a higher default barrier. For the years in which our sample overlaps with the period covered by Wong and Choi (2009) we find a similar trend of a declining proportion of barrier levels below one. We (Wong and Choi (2009)) find that in 2000, 2001, and 2002

[8] More technically speaking, we penalize the values during the maximization of the log-likelihood function since the original algorithm of Nelder and Mead (1965) does not support constraints.

	Mean	Quantiles							SD
		Min.	5%	25%	50%	75%	95%	Max.	
Excess value (EV)									
Single line firms	-0.022	-1.382	-1.036	-0.412	0.003	0.373	0.922	1.381	0.571
Multi line firms	-0.037	-1.385	-0.963	-0.398	-0.025	0.343	0.851	1.380	0.542
t-test	0.909								
EBIT / sales									
Single line firms	0.065	-1.747	-0.189	0.004	0.071	0.140	0.288	0.624	0.145
Multi line firms	0.066	-0.480	-0.157	0.017	0.075	0.132	0.244	0.566	0.119
t-test	-0.117								
Capex /sales									
Single line firms	0.048	0.000	0.005	0.016	0.033	0.060	0.148	0.478	0.051
Multi line firms	0.048	0.000	0.008	0.020	0.035	0.058	0.137	0.297	0.043
t-test	0.150								

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Table 2: Descriptive statistics for single and multi-line firms and t-statistic from a t-test for the difference of mean between single and multi-line firms, * indicates significance on a 10%, ** on a 5%, and *** on a 1% level. To correct for the first-step estimation, the t-statistic for $\hat{\sigma}$, $\hat{H}/X$, and $\hat{\mu}$, is calculated as follows: We bootstrap 100 times the returns of the used equity prices using the resampling technique of Politis and Romano (1994). We set the block length to 10 what is in general appropriate for daily equity returns, see for example Sullivan et al. (1999). Next we estimate all parameters $\boldsymbol{\theta}$ for all bootstrapped series. The provided t-statistic is the averaged value based on the 100 samples of bootstrapped estimates and the original estimates.

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	Mean	Quantiles							SD
		Min.	5%	25%	50%	75%	95%	Max.	
Ln of asset									
Single line firms	5.566	1.474	3.136	4.285	5.334	6.600	8.929	11.334	1.744
Multi line firms	6.161	2.088	3.351	4.821	6.041	7.401	9.405	12.505	1.831
t-test	-10.979***								
Debt proportion									
Single line firms	0.343	0.000	0.039	0.122	0.276	0.514	0.876	1.000	0.262
Multi line firms	0.392	0.004	0.063	0.170	0.347	0.577	0.910	1.000	0.258
t-test	-6.212***								
$\hat{\sigma}$									
Single line firms	0.405	0.000	0.049	0.233	0.369	0.526	0.882	4.138	0.261
Multi line firms	0.372	0.000	0.040	0.203	0.318	0.482	0.876	2.005	0.260
t-test	4.173***								

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Table 2: Descriptive statistics for single and multi-line firms and t-statistic from a t-test for the difference of mean between single and multi-line firms, * indicates significance on a 10%, ** on a 5%, and *** on a 1% level. To correct for the first-step estimation, the t-statistic for $\hat{\sigma}$, $\hat{H}/X$, and $\hat{\mu}$, is calculated as follows: We bootstrap 100 times the returns of the used equity prices using the resampling technique of Politis and Romano (1994). We set the block length to 10 what is in general appropriate for daily equity returns, see for example Sullivan et al. (1999). Next we estimate all parameters $\boldsymbol{\theta}$ for all bootstrapped series. The provided t-statistic is the averaged value based on the 100 samples of bootstrapped estimates and the original estimates.

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		Quantiles							
	Mean	Min.	5%	25%	50%	75%	95%	Max.	SD
$\hat{\mu}$									
Single line firms	0.081	-1.908	-0.575	-0.148	0.040	0.285	0.863	1.964	0.436
Multi line firms	0.084	-1.490	-0.483	-0.117	0.041	0.259	0.760	1.871	0.382
t-test	-0.052								
$\hat{H}/X$									
Single line firms	1.055	0.000	0.003	0.151	0.985	1.426	3.000	3.000	0.976
Multi line firms	1.031	0.000	0.003	0.177	0.991	1.358	3.000	3.000	0.913
t-test	0.847								

Table 2: Descriptive statistics for single and multi-line firms and t-statistic from a t-test for the difference of mean between single and multi-line firms, * indicates significance on a 10%, ** on a 5%, and *** on a 1% level. To correct for the first-step estimation, the t-statistic for $\hat{\sigma}$, $\hat{H}/X$, and $\hat{\mu}$, is calculated as follows: We bootstrap 100 times the returns of the used equity prices using the resampling technique of Politis and Romano (1994). We set the block length to 10 what is in general appropriate for daily equity returns, see for example Sullivan et al. (1999). Next we estimate all parameters $\boldsymbol{\theta}$ for all bootstrapped series. The provided t-statistic is the averaged value based on the 100 samples of bootstrapped estimates and the original estimates.

a proportion of 0.649 (0.614), 0.533 (0.558), 0.449 (0.431) of all firms years within the respective year have a barrier below one.[9]

In Table 3 the correlations between the various variables are given. We see that volatility has a negative correlation with the multi-line dummy. What we would like to point out is the rather high negative correlation between volatility and the natural logarithm of assets, i.e. size is negatively related to volatility: big companies have less risky assets. It could be possible that large firms engage more often in risk management activities which reduce the volatility of their assets. Such risk management activities may for example include hedging of currency risk or credit insurance.

4.2 Second-Step Estimation

In Table 4 result from two OLS regressions on the pooled data sample are shown. OLS 1 shows results without $\hat{\varsigma}_r$, $\hat{\mu}_r$, and $(\hat{H}/X)_r$. In OLS 2 we add these variables. The Fixed Effects regression controls for firm and year fixed effects. Fixed effects allow to control for endogeneity (see for example Campa and Kedia (2002)). To correct for the first-step estimation, the t-statistic is calculated as follows: We bootstrap 100 times the returns of the used equity prices using the resampling technique of Politis and Romano (1994). We set the block length to 10 what is in general appropriate for daily equity returns, see for example Sullivan et al. (1999). Next we estimate all parameters $\boldsymbol{\theta}$ for all bootstrapped series. We perform the regression using the 100 samples of bootstrapped estimates and the original estimates. The covariance matrix of each regression is corrected following Driscoll and Kraay (1998). The finally reported t-statistic is the averaged value based on the bootstrapped samples and the original sample. OLS 1 is not corrected using bootstrapping since no first-step estimates are used in this regression.

The coefficient of the multi-line dummy has in both OLS models a negative sign and is significant. This indicates a negative relation between diversification and shareholder value. The general finding of a negative relationship between excess value and the multi-line dummy is in line with prior literature like Berger and Ofek (1995) or Mansi and Reeb (2002). However, in the fixed effect model the coefficient becomes insignificant, supporting the idea that the reported diversification discount might be

[9] We provide statistics for the barrier level for all years upon request. Note that 1999 is not included since we have to calculate $\Delta\sigma_t$ and thus the first year of our sample is not directly included in our analysis.

	EV	Multi-line	EBIT / Sales	Capex / Sales	Ln of Assets	Debt Proportion	$\hat{\sigma}$	$\hat{\mu}$	$\hat{H}/X$
EV	1.000								
Multi-line	-0.012	1.000							
EBIT / Sales	0.284	0.002	1.000						
Capex / Sales	0.174	-0.002	0.217	1.000					
Ln of Assets	0.307	0.153	0.351	0.376	1.000				
Debt Proportion	-0.332	0.085	-0.205	0.044	0.131	1.000			
$\hat{\sigma}$	-0.159	-0.058	-0.268	-0.181	-0.457	-0.063	1.000		
$\hat{\mu}$	0.254	0.001	0.157	-0.027	-0.092	-0.226	0.149	1.000	
$\hat{H}/X$	-0.013	-0.011	0.017	0.007	0.039	-0.242	-0.138	-0.170	1.000

Table 3: Correlations of variables.

	OLS 1	OLS 2	Fixed Effects
Intercept	-0.033	-0.037	
	(-0.874)	(-1.862*)	
Multi-line	-0.068	-0.076	-0.012
	(-3.110***)	(-5.364***)	(-0.759)
(EBIT / Sales)$_r$	0.283	0.150	-0.087
	(6.286***)	(3.272***)	(-3.244***)
(Capex / Sales)$_r$	1.613	1.702	0.972
	(15.852***)	(12.884***)	(7.745***)
(Ln of Assets)$_r$	0.108	0.118	0.191
	(20.390***)	(23.818***)	(6.494***)
Debt Proportion$_r$	-0.998	-0.960	-1.049
	(-15.422***)	(-18.199***)	(-14.253***)
$\hat{\varsigma}_r$		0.110	0.023
		(1.130)	(0.262)
$\hat{\mu}_r$		0.221	0.243
		(9.698***)	(17.824***)
$(\hat{H}/X)_r$		-0.056	-0.028
		(-2.728***)	(-3.719***)
Adj. R^2	0.276	0.316	0.832

Table 4: Regression results with excess value as dependent variable. In the Fixed Effects model we control on firm and year level. The independent variables except for the multi-line dummy are relative measures and are obtained by subtracting the median value of single-line firms in the same primary industry. The t-statistic is given in brackets below the parameter estimates, * indicates significance on a 10%, ** on a 5%, and *** on a 1% level. To correct for the first-step estimation, the t-statistic is calculated as follows: We bootstrap 100 times the returns of the used equity prices using the resampling technique of Politis and Romano (1994). We set the block length to 10 what is in general appropriate for daily equity returns, see for example Sullivan et al. (1999). Next we estimate all parameters $\boldsymbol{\theta}$ for all bootstrapped series. We perform the regressions using the 100 samples of bootstrapped estimates and the original estimates. The covariance matrix of each regression is corrected following Driscoll and Kraay (1998). The finally reported t-statistic is the averaged value based on the bootstrapped samples and the original sample. OLS 1 is not corrected using bootstrapping since no first-step estimates are used in this regression.

attributable to endogeneity.

The coefficient of EBIT over sales is positive and significant on a 1% level in both OLS models, indicating a positive relationship between profitability and excess value. In the Fixed Effect model it becomes negativ but is insignificant. The coefficients of Capex over sales and the logarithm of assets are significant on a 1% level and are positive in all used models. The implication is that capital expenditures and firm size are both positively related to shareholder value. Both of the former findings are in line with Berger and Ofek (1995). The coefficient for debt proportion is signifacnt and negative in all cases.

Comparing the results of OLS 1 with OLS 2 shows that adding the three variables $\hat{\varsigma}_r$, $\hat{\mu}_r$, and $(\hat{H}/X)_r$ has hardly any effect on the coefficients of the other variables. Only the control variable $(\text{EBIT/Sales})_r$ is affected. The coefficient of the diversification dummy is hardly affected. The results thus reject the hypothesis that changes in volatility might explain the observed diversification discount. Results in Table 4 for OLS 2 and Fixed Effects show a significant and positive coefficient for the drift of assets. This implies a positive relationship between growing assets of a company and excess value. The coefficient of the barrier level is significant and negative. Within the contingent claims framework this result is what we would expect. A high barrier level will reduce the value of a DOC.

4.3 Robustness

Since our results might be influenced by the decision to use a DOC framework we estimate $\hat{\boldsymbol{\theta}} = (\hat{\sigma}, \hat{\mu})$ assuming equity would be a normal European call option on a companies assets. Again we calculate $\hat{\varsigma}_r$ and perform the same regression as shown in Table 4.[10] Results show that our qualitative findings are not affected:[11] Again the coefficient of $\hat{\varsigma}_r$ is insignificant and the coefficient of $\hat{\mu}_r$ is positive and highly significant. Since results could also be affected by the decision to use relative values instead of absolute values, we perform our test using absolute values for the DOC model and the European call option model. Again our findings are confirmed: The coefficient of $\hat{\varsigma}_r$ is insignificant, the coefficient of $\hat{\mu}_r$ is positive and highly significant, and for the DOC model the coefficient of $\hat{H}/X$ is significant and negative. The coefficient of the diversification dummy however is not

[10] Since there exists no barrier for a normal European call option it is omitted in the regression.

[11] All robustness regression results are available upon request.

affected by the addition of the explanatory variables $\hat{\varsigma}_r$, $\hat{\mu}_r$, and $(\hat{H}/X)_r$.

5 Conclusion

A possible explanation for the diversification discount is based on the contingent claims approach. If the assets of different business lines have a correlation coefficient below one, the conglomerate's combined assets will have a lower volatility because of the diversification effect. A call option on the sum of the assets can -depending on the type of option and /or parameters- be worth less than the sum of options on the assets of the individual business lines. Our contribution to the literature is that we empirically test whether this can explain the observed diversification discount. To test the hypothesis, we propose a two-step regression framework. Our approach allows to test whether a change in risk might explain the observed diversification discount.

Using MLE we first estimate the three parameters volatility and drift of a companies assets and the barrier level within a DOC framework. Based on these estimates, we calculate the expected effect of a change in volatility on the value of the DOC. The estimated effect, the estimated drift of assets, and the barrier level are then used in a second-step regression with excess value as dependent variables. For our sample of companies domiciled in the US the results reject the hypothesis that the expected effect of a change in volatility might explain the observed diversification discount. This finding remains robust once we assume equity would be a normal European call option on a companies assets. However, we find a significant positive relationship between the drift of assets and excess value. Furthermore, results indicate that there is a significant negative relationship between excess value as measure of shareholder value and the barrier level. Within the DOC framework this seems reasonable since a high barrier level increases the risk of default and reduces the value of the DOC. This finding also emphasizes the importance of the barrier.

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Curriculum Vitae

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