Essays on Asset Management and Asset Liability Management

D I S S E R T A T I O N
of the University of St. Gallen,
School of Management,
Economics, Law, Social Sciences
and International Affairs
to obtain the title of
Doctor of Philosophy in Finance

submitted by

Lidia Bolla

from

Ittigen (Bern) and Castro (Tessin)

Approved on the application of

Prof. Dr. Manuel Ammann

and

Prof. Dr. Martin Eling

Dissertation no. 4448

Difo-Druck GmbH, Bamberg, 2016

The University of St. Gallen, School of Management, Economics, Law, Social Sciences and International Affairs hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St. Gallen, October 21, 2015

The President:

Prof. Dr. Thomas Bieger

Acknowledgements

I would like to express my sincere gratitude to all the people that have supported and encouraged me throughout my doctoral studies. First, I would like to thank Prof. Dr. Manuel Ammann and Prof. Dr. Martin Eling for the supervision of this dissertation, the highly appreciated openness towards my ideas and the fruitful discussions on the topics. I also owe earnest thankfulness to my co-authors Dr. Alexander Kohler and Dr. Hagen Wittig for their helpful support and the lively exchanges of ideas, from which this dissertation benefited considerably. Furthermore, I am deeply grateful to my friends and colleagues, in particular to Anina Lauber and Katharina Pytlik for their long-standing friendship, for their continuous advice and for always putting things in perspective.

Finally, I would like to thank my family, to whom I dedicate this thesis. Antonia Bolla and Gion Bolla, for being my closest allies throughout my life, who stuck with me through thick and thin. Lukas Zölch, for being my guiding star and for having an unbelievable understanding that knows no limits. My parents, Dr. Claudia Bolla-Vincenz and Antonito Bolla for their continuous encouragement, all-embracing support and, most importantly, for being my greatest inspiration. And, last but not least, Marie-Claire Bucher and Albert Jansen, for being the rock in turbulent waters for my parents. I am sure, without my family, this dissertation would not have been possible.

Zurich, December 2015

Lidia Bolla

Contents

List of Tables iv

List of Figures v

Summary vii

Zusammenfassung viii

Part I The Liability Market Value as Benchmark in Pension Fund Performance Measurement 1

1. Introduction 2

2. Methodology 5

2.1. The ALR Model 5

2.2. Yield curve model 10

3. Data 12

3.1. Pension framework inputs 13

3.2. Country-specific inputs 14

3.3. Technical inputs 15

3.4. Asset inputs 16

4. Results 17

4.1. Interest rate movements 17

4.2. The movement of the replicating portfolio 18

4.3. The ALR 20

4.4. Robustness checks 22

4.5. Yearly ALR analysis 24

5. Conclusion 27

References 29

Part II Fundamental Indexing in Global Bond Markets – the Risk Exposure Explains it All.. 31

1. Introduction 32

2. Data and methodology 35

2.1. Return indices 35

2.2. Fundamental factors..37

2.3. Methodology...37

3. Performance statistics 41

3.1. Full observation period 41

3.2. Subperiod analysis 44

4. Risk factor analysis...47

4.1. Risk factor exposure 47

4.2. Initial risk factor regression...48

4.3. Extended risk factor regression 50

5. Conclusion 60

References 62

Part III Index Linked Investing – A Curse for the Stability of Financial Markets around the Globe? 65

1. Introduction 66

2. Methodology...69

2.1. Description of risk commonalities...70

2.2. Within-region regression analysis 71

2.3. Cross-regional regression analysis 71

3. Data...72

4. Results...75

4.1. Risk commonality measures..75

4.2. Quartile analysis 79

4.3. Within-region regression analysis 82
4.4. Cross-regional regression analysis 85

5. Conclusion 88

Appendix 90

References 94

Curriculum Vitae 96

List of Tables

Part I: The Liability Market Value as Benchmark in Pension Fund Performance Measurement

Table 1: Largest pension fund markets.......... 2
Table 2: Variable description.......... 7
Table 3: Summary inputs.......... 15
Table 4: Asset classes and benchmarks.......... 16
Table 5: Yearly ALR analysis.......... 26

Part II: Fundamental Indexing in Global Bond Markets – the Risk Exposure Explains it All

Table 1: Overview country indices.......... 36
Table 2: Overview factor data.......... 38
Table 3: Performance statistics.......... 42
Table 4: Regression output.......... 44
Table 5: Subperiod analysis.......... 46
Table 6: Average bond risk factors.......... 48
Table 7: Initial risk factor regression.......... 50
Table 8: Extended risk factor regression – composite index.......... 54
Table 9: Extended risk factor regression – GDP weighted index.......... 58
Table 10: Extended risk factor regression – population weighted index.......... 58
Table 11: Extended risk factor regression – land area weighted index.......... 59
Table 12: Extended risk factor regression – energy weighted index.......... 59
Table 13: Extended risk factor regression – equally weighted index.......... 60

Part III: Index Linked Investing – A Curse for the Stability of Financial Markets around the Globe?

Table 1: Growth in ETF assets under management by region.......... 66
Table 2: Within-region regression results – main markets.......... 83
Table 3: Within-region regression results – quartile analysis.......... 85
Table 4: Cross-regional regression results.......... 87

List of Figures

Part I: The Liability Market Value as Benchmark in Pension Fund Performance Measurement

Figure 1: ALR Model summary 5
Figure 2: Yield curve fitting – Convergence Model (left) versus Nelson-Siegel Model (right) 11
Figure 3: Extrapolation of yield curve – Convergence Model (left) versus Nelson-Siegel Model (right) 12
Figure 4: Development of the assumed strategic asset allocation (SAA) 17
Figure 5: Recent development of interest rates and its consequences on the pricing of zero-coupon bonds 18
Figure 6: The liability benchmark and the change in duration 20
Figure 7: From the asset performance to the ALR 21
Figure 8: Conversion rate robustness check 23
Figure 9: Capital option percentage (cash-out rate) robustness check 24

Part II: Fundamental Indexing in Global Bond Markets – the Risk Exposure Explains it All

Figure 1: Country weights 40
Figure 2: Index plots 42
Figure 3: Subperiods 45
Figure 4: Bond risk factors – difference to market value weighted index 48

Part III: Index Linked Investing – A Curse for the Stability of Financial Markets around the Globe?

Figure 1: US index linked investing: Institutional vs. ETF assets 73
Figure 2: ETF assets under management and proportion of index linked investing by region 74
Figure 3: Commonalities in trading patterns (volume change dispersion and volume change correlation) 76
Figure 4: Commonalities in price returns (price correlation und return beta) 77

Figure 5: Commonalities in liquidity risk (liquidity correlation and liquidity beta) 78
Figure 6: Risk commonality measures for different quartiles – Eurozone............... 79
Figure 7: Risk commonality measures for different quartiles – UK 80
Figure 8: Risk commonality measures for different quartiles – Switzerland........... 80
Figure 9: Risk commonality measures for different quartiles – US......................... 81
Figure 10: Risk commonality measures for different quartiles – emerging markets81
Figure 11: Cross-regional comparison of risk commonality and index linked investing (June 2014)... 86

Summary

The dissertation comprises three articles from the fields of asset liability management and asset management. In the first article, we create a liability benchmark for referencing the asset allocation performance of pension funds and introduce the Asset-Liability-Result (ALR) – the relative performance of the strategic asset allocation (SAA) with respect to the performance of the market value of the liabilities. We apply our approach to the Swiss market and are able to show that the pension funds' recovery from the recent financial crisis took much longer than the value increase of the asset portfolios suggests. The ALR does not intend to benchmark the performance of asset managers, but rather to provide an instrument for analyzing the performance of entire pension fund markets and to present an operational asset liability management tool for individual pension funds.

In the second article, we investigate whether fundamental indexing – an alternative to the predominant market value weighting methodology – is able to generate an outperformance in fixed income markets when accounting for differences in the risk factor exposure. The findings of the study suggest that fundamental indexing is able to generate higher returns in the long term. However, our results show statistically significant and economically relevant exposures of the fundamentally weighted indices towards the previously studied risk factors term and default and, in particular, towards the newly introduced risk factors duration, convexity, liquidity and carry trade risk. The elevated risk exposure is able to fully explain the outperformance.

The third article analyzes risk commonalities within equity markets around the globe and tests the hypothesis that index linked investing is a major driver for increasing co-movements within equity markets. We find substantial evidence that the growth in index linked investing is related to increased co-movements in trading patterns, price returns and liquidity risk. The results suggest a significant increase in market fragility around the globe, leading to an increased danger of more severe reactions to unanticipated events going forward. Portfolio managers are well advised to account for the increased proportion of index linked investing within their risk management tools, diversification approaches and active management strategies.

Zusammenfassung

Die Dissertation umfasst drei Artikel aus den Bereichen Asset Liability Management und Asset Management. Im ersten Artikel entwerfen wir einen Liability Benchmark, welcher zur Beurteilung der Anlage von Pensionskassen dient. Die relative Rendite der Strategischen Asset Allokation (SAA) im Vergleich zur Rendite der marktbewerteten Verpflichtungen ergibt das Asset-Liability-Result (ALR). Wir wenden den Ansatz auf den Schweizer Markt an und zeigen auf, dass die Erholung der Pensionskassen von der letzten Finanzkrise mehr Zeit in Anspruch genommen hat, als die Anlagerenditen suggerieren. Das ALR beabsichtigt nicht, die Renditen externer Vermögensverwalter zu referenzieren, sondern dient als Mittel für die Analyse der Renditen ganzer Pensionskassenmärkte sowie als operatives Asset Liability Management Instrument für individuelle Pensionskassen.

Im zweiten Artikel untersuchen wir, ob Fundamental Indexing – eine Alternative zum vorherrschenden Ansatz der Marktwertgewichtung – in Anleihenmärkten eine Überperformance generiert, auch wenn die Risikounterschiede berücksichtigt werden. Die Studie zeigt auf, dass Fundamental Indexing Strategien in der langen Frist eine höhere Rendite generieren können. Jedoch zeigen die Resultate ebenfalls ein statistisch signifikantes und wirtschaftlich relevantes Exposure der Renditen gegenüber den bereits früher untersuchten Risikofaktoren Laufzeit und Ausfall sowie den neu eingeführten Risikofaktoren Duration, Konvexität, Liquidität sowie Carry Trade Risiken. Das erhöhte Risiko erklärt die Überperformance vollständig.

Der dritte Artikel analysiert Aktienmärkte verschiedener Regionen und testet die Hypothese, dass indexiertes Investieren ein zentraler Treiber für eine erhöhte Gleichbewegung ist. Wir finden substantielle Beweise, dass das Wachstum von indexiertem Investieren in Verbindung mit einem stärkeren Gleichschritt bei Handelsaktivitäten, Preisrenditen und Liquiditätsrisiken steht. Die Resultate deuten auf eine signifikante Erhöhung der Marktfragilität hin, wodurch die Marktreaktionen auf unvorhergesehene Ereignisse in Zukunft stärker ausfallen könnten. Portfoliomanager sollten folglich den Anteil des indexierten Investierens in ihre Risiko-, Diversifikations- und aktiven Strategieüberlegungen miteinbeziehen.

Part I
The Liability Market Value as Benchmark in Pension Fund Performance Measurement

Lidia Bolla[1], Alexander Kohler[2], Hagen Wittig[3]

Publication status: Published (Bolla, L., Kohler, A. and Wittig, H. The Liability Market Value as Benchmark in Pension Fund Performance Measurement. *Journal of Pension Economics and Finance*, available on CJO2014. doi:10.1017/S147474721400033X)

Abstract

Often performance of pension funds is assessed based on the development of the assets only, neglecting the simultaneous development of the liabilities. This especially is the case in Switzerland, one of the world's largest markets for corporate pension funds. We create a new liability benchmark for referencing the asset performance. Measuring the asset performance with respect to the liability benchmark yields the Asset-Liability-Result. We apply the model to (i) the Swiss pension fund market as a whole and (ii) an individual Swiss pension fund. With our new approach, we are able to show that the pension funds' recovery from the recent financial crisis took much longer than the value increase of the asset portfolios suggests. We strongly advocate the use of a liability benchmark for analyzing the entire pension fund markets' performance and specifically as operational tool for individual pension funds.

[1] Lidia Bolla, M.A. HSG, CFA, is Managing Partner at Algofin AG, Webergasse 15, 9000 St. Gallen, Switzerland, lidia.bolla@algofin.ch.

[2] Alexander Kohler, PhD, is Manager at Deloitte Consulting AG, General Guisan-Quai 38, 8022 Zurich, Switzerland, akohler@deloitte.ch.

[3] Hagen Wittig, M.A. HSG, CFA, is Managing Partner at Algofin AG, Webergasse 15, 9000 St. Gallen, Switzerland, hagen.wittig@algofin.ch.

1. Introduction

With growing assets under management, the importance of pension funds as investors increases all around the world. Owing to the design of the social security system and as illustrated in Table 1, in particular the Anglo-Saxon region and – in Continental Europe – the Netherlands and Switzerland are known for their large pension fund markets. The Swiss pension fund market, having a size of USD 732 billion, by asset volume is the seventh largest market worldwide. When measuring the pension fund markets with respect to the countries' GDP, the Swiss pension fund market was the largest in 2002 and the second largest in 2012. The market represented 118% of the Swiss GDP in 2012. The pension fund markets shown in Table 1 are all growing markets, illustrated by the high compound annual growth rates as well as the increase in proportion of GDP from 2002 to 2012 (with the only exception being South Africa).

Table 1: Largest pension fund markets

Country	Total assets 2012 (USD bn)		In % GDP 2012*		In % GDP 2002*		10-year CAGR**	
US	16'851	(1)	108%	(4)	84%	(3)	6.5%	(9)
Japan	3'721	(2)	62%	(8)	57%	(8)	5.0%	(10)
UK	2'736	(3)	112%	(3)	70%	(4)	9.3%	(5)
Australia	1'555	(4)	101%	(5)	69%	(5)	18.2%	(2)
Canada	1'483	(5)	84%	(6)	65%	(7)	7.0%	(8)
Netherlands	1'199	(6)	156%	(1)	114%	(2)	9.1%	(6)
Switzerland	732	(7)	118%	(2)	116%	(1)	8.2%	(7)
Germany	498	(8)	15%	(9)	9%	(10)	10.3%	(4)
Brazil	340	(9)	14%	(10)	10%	(9)	20.4%	(1)
South Africa	252	(10)	64%	(7)	66%	(6)	13.2%	(3)

Notes: Ranking in brackets. Source: Tower Watson (2013). *Local currency; **CAGR = Compound Annual Growth Rate.

Pension fund markets not only increased in size, but also extended their influence. Several authors, starting with Drucker (1976) in the 1970s and continued by Clark (2000) in the new century, describe the influence of pension funds on corporate policies. The work was broadened among others by Cronqvist and Fahlenbrach

(2009), showing that if US pension funds are blockholders of a company, they significantly influence its investment, financial and compensation policies. A study by Dixon (2008) brought the topic to the European market by describing recent developments in the French pension system.

With the growing importance of pension funds as investors, the interest with regard to the performance of the funds and the industry as a whole increases. Thereby, we advocate to taking on a comprehensive point of view by considering both the asset and the liability side in performance measurement. Decisions on the asset side, such as the construction of the investment portfolio, can significantly be improved when being in full knowledge with regard to the risk factors on both sides of the balance sheet. In particular, only when measuring the change in market value on both the asset and the liability side, we can assess the effect that a liability matching investment strategy might have.

Whereas the asset side of the balance sheet usually receives large attention in academia and financial practice, the liability side has been considered by fewer authors until today. A range of work has been conducted in the field of asset liability management (ALM). First and foremost is the collected edition by Ziemba and Mulvey (1998), containing the most relevant papers on the topic up to that point. A range of further studies were conducted on ALM simulation and the topic of portfolio optimization strategies using an ALM perspective. The first stochastic model for a comprehensive simulation of a pension fund, called “Plasm” (Pension Liability and Asset Simulation Model), was provided by Winklevoss (1982). The model is based on a stochastic asset return and liability simulator and allowed to analyze a range of future scenarios and strategies. With regard to further information on ALM portfolio optimization strategies, we refer to the studies contributed by Boender (1997), Bogentoft, Romeijn and Uryasev (2001), Kouwenberg (2001) and Chen, Yang and Yin (2008). The inclusion of liabilities as a benchmark in performance measurement however lacks significant research.

Our contribution to the literature is manifold. First, we build a liability benchmark for pension funds, which is used as an index for referencing the asset performance.

Furthermore, by introducing the Asset-Liability-Result (ALR) as performance measure and thus measuring the pension funds' asset performance with respect to a liability benchmark, we implement a comprehensive performance view that takes into account the pension fund's total balance sheet. In particular, due to the recent drop in yields, the liability benchmark has exhibited a substantial increase in value. The ALR illustrates that the recovery of pension funds from the recent financial crisis took much longer than one would anticipate when looking at the asset side only. We furthermore contribute to the literature by applying the model to the Swiss pension fund market. Analyzing the Swiss pension fund market is important not only due to the significant size of the market, but also because of distinctive features, such as different types of legal guarantees (e.g., minimal conversion rate, minimal investment return, capital guarantees) that cannot be found in other markets. Those legal guarantees lock the plan participants' claims for benefit at some future point in time in and therefore have a substantial effect on the liability side of the pension funds' balance sheet. The Swiss application illustrates that the existence of such legal guarantees requires the pension funds to pay close attention to the liability market value and to include the liabilities in performance measurement considerations. When reforming their pension systems, other countries need to be aware of the effects that such legal guarantees have on the liability market value. The introduction of similar social policy instruments will lead to more stringent pension claims and consequently to less flexible liability structures of the pension funds, which finally makes the modeling of the liabilities much more crucial.

We chose two applications. First, we apply the model to the Swiss pension fund market as an aggregate in order to add insights with regard to the performance of the industry as a whole. Second, we calibrate the model for a specific Swiss pension fund, highlighting the added value of the model also in an operational context. By additionally applying the model to a specific pension fund, a robustness check for the overall market is provided. Given the differences in the parameters of the individual pension fund and the overall market (especially with regard to the plan participant structure or the asset distribution), the impact of those differences on the ALR can be analyzed.

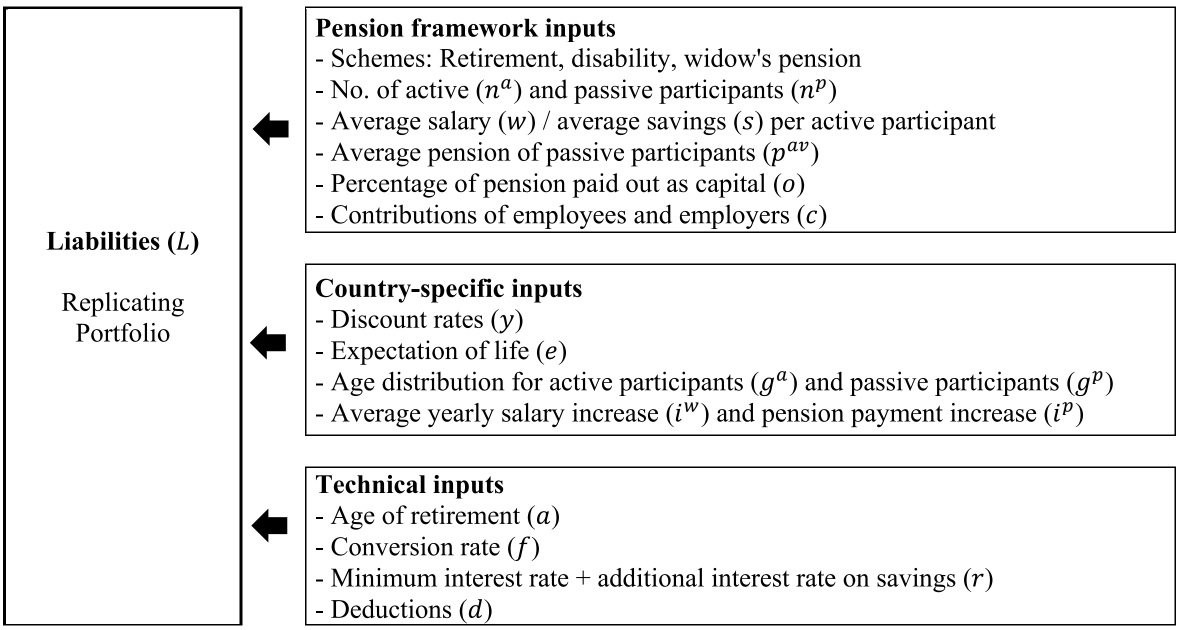
The structure of the remaining paper is as follows. Section 2 describes the methodology and highlights in detail, how the model to calculate the ALR (ALR Model) is constructed. Section 3 discusses the data used for both applications, i.e., on one side the calibration to the Swiss pension market and on the other side the calibration to one specific pension fund. Section 4 discusses the results and, finally, Section 5 concludes.

2. Methodology

2.1. The ALR Model

The following section describes the ALR Model, which reproduces the liability side of a pension fund's balance sheet from a mark-to-market perspective. Although this is an everyday procedure for the asset side, the methodology is usually not applied on the liability side. Figure 1 provides a first overview of the ALR Model.

Figure 1: ALR Model summary



The liabilities are valued with a replicating portfolio approach. The replicating portfolio is constructed as a portfolio of zero-coupon bonds, recreating the payout pattern of a pension fund. To simulate the payout pattern, a range of input variables out of three different categories is required. First, the model requires pension framework inputs, such as the number of active and passive participants ('passive participants' refer to the plan participants in payment status, i.e., retirees, persons with disability as well as widows and widowers[4]). Additionally, the model considers the average salary and the average savings per active participant, the average pension of passive participants, the percentage of pension paid out as capital at retirement as well as the contributions made by employees and employers as inputs. Furthermore, several country-specific inputs need to be provided. Those mainly are the discount rates applied (which are discussed further below), information on the expectation of life per age group, the age distribution of the active and passive participants and the yearly increases in salaries and pensions. Last, the ALR Model does also take specific features of the Swiss pension market, such as the age of retirement, the conversion rate,[5] the minimum plus any additional interest rates on the savings[6] and any deductions due to the coordination of different social security schemes, into account. Where necessary, differences between female and male plan participants are incorporated.

Table 2 provides a definition of the parameters included in the model and describes the effects of those parameters on the liability benchmark (ceteris paribus). It is important to note that the described effects always refer to a pension fund that comprises both active participants as well as retirees. If a pension fund would only consist of active participants, some of the implications might not be valid. A change in variable that leads to an increase in the liability duration increases the interest rate sensitivity and therefore also the volatility of the liability benchmark (and vice versa).

---

[4] Passive participants do not include deferred participants, i.e., former employees that kept their savings within the plan of their former employer after termination of the work contract (this is not common in the Swiss pension system as the accumulated savings have to be transferred to the pension scheme of the new employer).

[5] In Switzerland, the conversion rate determines an individual's annuity in percentage of his savings.

[6] In Switzerland, pension funds have to credit all active members a minimum investment return on the mandatory part of their savings. Currently this minimum investment returns amounts to 1.75%.

Table 2: Variable description

n^a	**Number of active participants, i.e., the number of employees providing contributions to the pension scheme in order to benefit from the scheme at a later point in their life** *A higher number of active participants leads to a higher market value of the liabilities in absolute terms. Furthermore, a higher number of active participants increases the average liability duration.*
n^p	**Number of passive participants, i.e., the number of participants in payment status (retirees, persons with disability as well as widows and widowers)** *A higher number of passive participants leads to a higher market value of the liabilities in absolute terms. However, a higher number of retirees also reduces the average liability duration.*
w	**Average yearly salary of an active participant in Swiss Francs** *A higher yearly salary leads to higher contribution payments but also to a higher pension liability per person and a higher average duration of the liability benchmark.*
s	**Average stock of savings per active participant in pension scheme** *A higher stock of savings leads to higher interest paid in absolute terms. However, the effect on the duration depends on the savings' distribution over the age groups.*
p^{av}	**Average pension of passive participants** *A higher average pension increases the market value of the liabilities in absolute terms. An increase in the average pension of currently retired persons additionally reduces the average duration of the liability benchmark.*
o	**Capital option percentage, i.e., the average percentage of the pension savings paid out as capital at retirement (cash-out rate)** *An increase in cash-out rates reduces the market value and the average duration of the liabilities.*
c	**Sum of contributions of employee (active participant) and employer in percentage of employee's salary** *Higher contributions increase the liability value as well as the average duration of the liability benchmark.*
y	**Discount rates, i.e., bootstrapped and extrapolated zero yields of Swiss government bonds for the maturities 1 to over 70 years** *An increase in discount rates reduces the discounted pension liabilities and therefore also the market value of the liabilities.*
e	**Remaining expectation of life in years depending on the age group** *An increase in the expectation of life leads to a longer pension payment period after retirement and therefore to an increase in the market value of the liabilities as well as to an increase in the average duration.*
g^a	**Age distribution for active participants** *The more the age distribution is tilted towards older people, the lower the average duration of the liabilities.*
g^p	**Age distribution for passive participants** *The more the age distribution is tilted towards older people, the lower the average duration of the liabilities.*

Table 2 (continued): Variable description

i^w	**Average yearly salary increase in percentage of the previous year's salary level** *A salary increase leads to higher contribution payments but also to a higher pension liability per person and therefore to an increased market value and average duration of the liabilities.*
i^p	**Average yearly pension payment increase in percentage of the previous year's pension** *A pension payment increase directly leads to an increase in the liabilities as well as an increase in the average liability duration.*
a	**Age of retirement for female and male plan participants** *An increase in the age of retirement extends the number of contribution years and reduces the number of years, the participant receives benefits. Whereas the pension payment per year increases due to the higher contribution payments, the overall liability might decrease due to the reduced number of benefit years (depends on the other variables).*
f	**Conversion rate, i.e., the determinant of an individual's annuity in percentage of his savings** *A higher conversion rate leads to a higher pension payment and therefore to a higher liability market value. Furthermore, a higher conversion rate increases the average duration of the liability benchmark.*
r	**Yearly statutory minimum interest rate plus yearly additional interest rate paid on savings** *An increase of the interests paid on savings leads to an increase in the savings and consequently to a higher liability market value.*
d	**Deductions due to the coordination of different social security schemes, i.e., amount in Swiss Franc deducted from the salary before calculating the contributions of the active participants** *Higher deductions lead to a lower liability value and a lower average liability duration.*

The input variables are used to calculate the liability value with respect to time t as illustrated in formulas (1)-(6). The formulas show the calculation of the retirement benefits, which represent the largest fraction of pension payments.

First, the expected yearly pension payments of the active (p_t^a) participants at retirement and the current yearly pension payments for the passive (p_t^p) participants are calculated.

$$\boldsymbol{p}_t^a = \left[\boldsymbol{s}_{t-1} \times (1 + r_t)^l + \sum_{i=1}^{l} [(\boldsymbol{w}_i \times (1 + i^w)^{i-1} - d) \times \boldsymbol{c}_t \times (1 + r_t)^{l-i}]\right] \times \boldsymbol{n}_t^a \times (1 - o) \times f \qquad (1)$$

$$\boldsymbol{p}_t^p = p_t^{av} \times \boldsymbol{n}_t^p \tag{2}$$

The variable l accounts for the remaining worklife of the active participants and the vectors (marked in bold) contain the information for the different age groups used in the calculation.

$$\boldsymbol{l} = a - \boldsymbol{g}^a \tag{3}$$

We translate the yearly pension payments into expected cash flows ($CF_{t,m}$) for different maturities m, which are discounted by the respective discount factor for each maturity ($DF_{t,m}$). The matrix I takes on a value of either zero or one, indicating the future years, i.e., maturities m, in which the different age groups of active or passive participants obtain a pension. The value of I depends on the age group ($\boldsymbol{g}^a$, $\boldsymbol{g}^p$), the age of retirement (a) and the life expectation (e) of the participants.

$$\boldsymbol{CF}_{t,m} = \boldsymbol{p}_t^a \times (1 + i^p)^{(m-\boldsymbol{l})} \times \boldsymbol{I}_{t,m} + \boldsymbol{p}_t^p \times (1 + i^p)^m \times \boldsymbol{I}_{t,m} \tag{4}$$

$$\boldsymbol{DF}_{t,m} = \frac{1}{(1+y_{t,m})^m} \tag{5}$$

The sum of all discounted expected cash flows yields the mark-to-market liability value, which is dependent on time t.

$$L_t = \sum_{m=0}^{M} \boldsymbol{CF}_{t,m} \times \boldsymbol{DF}_{t,m} \tag{6}$$

Given the inclusion of those variables, the ALR Model allows the generation of a pension fund specific replicating portfolio. The ALR Model also enables the simulation of entire pension fund markets instead of specific pension funds. This gives us the powerful tool to calculate the pension promises on a mark-to-market basis for entire economies.

With the exception of the discount rates, which are available on a daily basis, the inputs are usually obtainable on a yearly frequency. The liability benchmark will however be calculated on a daily frequency while applying the yearly available inputs on an ex-ante basis. The simultaneous use of daily and yearly frequencies is possible in this setting due to the fact that the yearly available inputs are changing slowly.

Some inputs, as for example the retirement age of men, do not change at all during the observation period. The resulting replicating portfolio is therefore rebalanced to the actual liability structure on a yearly basis. During the year, the replicating portfolio's value is behaving according to the movements in discount rates, i.e., in our case the change in the level, slope and curvature of the term structure of interest rates.

2.2. Yield curve model

Since the applied discount rates are the main factors influencing the change in value of the liability benchmark, they warrant further discussion. We use bootstrapped zero yields of Swiss government bonds for the maturities 1–30 years. However, since pension liabilities are characterized by maturities of over 70 years, an extrapolation of yields is conducted. We tested two different theories: a simplistic theory of convergence and the more sophisticated three-factor model by Nelson and Siegel (1987). The theory of convergence uses the simplifying assumption that the term structure of interest rates converges to the 30-year rate. The Nelson-Siegel Model on the other hand is a more sophisticated three-factor model that can be illustrated as follows (Nyholm, 2008):

$$y_t(\tau) = H \times \beta_t + e_t \tag{7}$$

β_t represents the three yield curve factors: (i) level, (ii) slope and (iii) curvature. The variable e_t adds a normally distributed error term to the equation. The factor sensitivities H are represented in the following way, whereby τ determines the maturity and λ represents the speed of time decay:

$$H = \begin{bmatrix} 1 & \frac{1-\exp(-\lambda\tau_1)}{\lambda\tau_1} & \frac{1-\exp(-\lambda\tau_1)}{\lambda\tau_1} - \exp(-\lambda\tau_1) \\ \vdots & \vdots & \vdots \\ 1 & \frac{1-\exp(-\lambda\tau_T)}{\lambda\tau_T} & \frac{1-\exp(-\lambda\tau_T)}{\lambda\tau_T} - \exp(-\lambda\tau_T) \end{bmatrix} \tag{8}$$

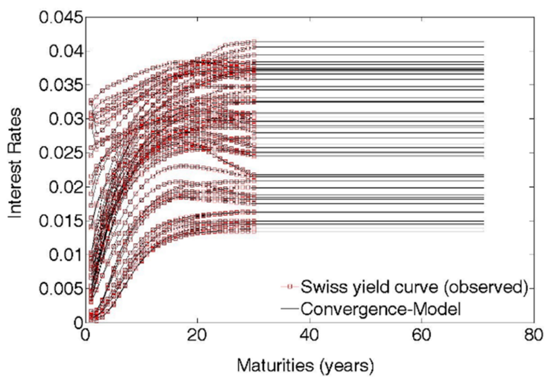
A further extension could be implemented by using the four-factor model of Söderlind and Svensson (1997), whereby the fourth factor represents a second curvature term (representation by Nyholm, 2008):

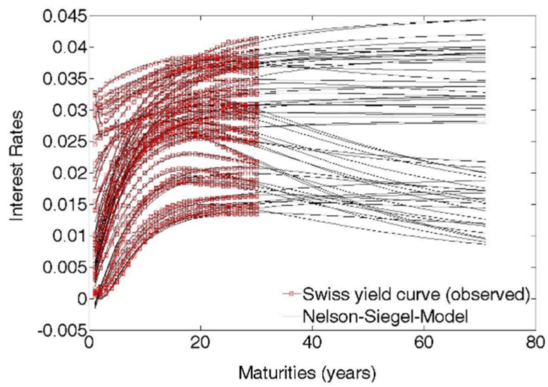
$$H = \begin{bmatrix} 1 & \frac{1-\exp(-\lambda_1\tau_1)}{\lambda_1\tau_1} & \frac{1-\exp(-\lambda_1\tau_1)}{\lambda_1\tau_1} - \exp(-\lambda_1\tau_1) & \frac{1-\exp(-\lambda_2\tau_1)}{\lambda_2\tau_1} - \exp(-\lambda_2\tau_1) \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \frac{1-\exp(-\lambda_1\tau_T)}{\lambda_1\tau_T} & \frac{1-\exp(-\lambda_1\tau_T)}{\lambda_1\tau_T} - \exp(-\lambda_1\tau_T) & \frac{1-\exp(-\lambda_2\tau_T)}{\lambda_2\tau_T} - \exp(-\lambda_2\tau_T) \end{bmatrix} \quad (9)$$

The fitting process of both models to the yield curve is illustrated in Figures 2 and 3. For illustrative purposes, Figure 2 shows the yield curve of every 50$^{\text{th}}$ day in the time period 2003–2013. The dots mark the bootstrapped zero yields obtained from Datastream, whereas the lines show the inter- and extrapolated yield curves. The left graph represents the assumption of convergence to the 30-year rate. The right graph, on the other hand, shows the more sophisticated fitting process applying the three-factor Nelson-Siegel Model.

Our tests show that the extrapolation models yield similar conclusions with respect to the ALR. Throughout the further discussion, we therefore refrain from showing the results of both extrapolation models and, if not noted otherwise, show the results obtained based on the extrapolation via the Nelson-Siegel Model.

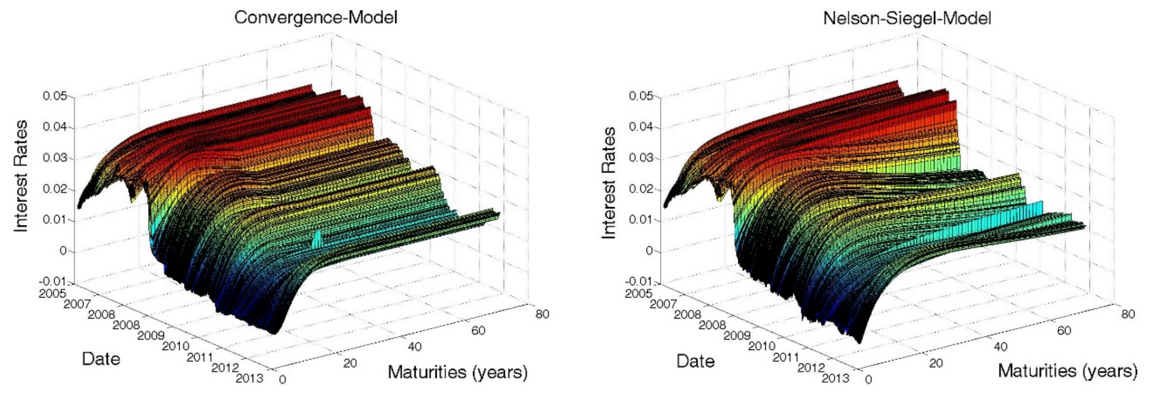
Figure 2: Yield curve fitting – Convergence Model (left) versus Nelson-Siegel Model (right)





Notes: The left graph shows the simplistic Convergence Model (assumes convergence of the yield curve to the 30-year rate). The right graph shows the three-factor Nelson-Siegel Model, which takes into account the level, the slope and the curvature of the whole term structure of interest rates. For illustrative purposes, the graphs show the yield curve of every 50$^{\text{th}}$ day in the time period 2003–2013.

Figure 3: Extrapolation of yield curve – Convergence Model (left) versus Nelson-Siegel Model (right)



Notes: The left graph shows the simplistic Convergence Model, whereas the right graph shows the three-factor Nelson-Siegel Model. The graphs show the extrapolated yield curves for the observation period (31.12.2005–31.12.2013) on a daily basis.

3. Data

We calibrate the ALR Model to the Swiss market based on two different frameworks: first, on an economy-wide level (hereafter called Market Model) and, second, on a pension fund level (hereafter called Pension Fund Model). For the former, we applied the model to the entire Swiss pension fund market. For the latter model, we selected one of the largest Swiss pension funds.[7] Given the differences in the parameters of the individual pension fund and the overall market, the two applications allow the analysis of the parameter differences and their impact on the ALR.

We make two simplifying assumptions. First, for the Market Model we assume that all Swiss pension funds follow a defined contribution[8] plan. This assumption is justified, as 85% (in 2004) to 91% (in 2012) of the funds in the market are defined contribution plans. Second, we disregard the splitting of the pension schemes into its mandatory and super-mandatory part. Swiss pension funds are required to insure a person's income only up to a certain fixed amount, which represents the mandatory

[7] The Pension Fund Model is calibrated to the BVK Personalvorsorge (pension fund of the canton of Zurich), which has 110'258 participants and USD 23 bn assets under management (as of 31 December 2013).

[8] The definition of defined contribution plans follows the Swiss law (as opposed to IFRS).

part of the pension scheme. Insured income above this level falls into the super-mandatory regime and follows other legal requirements, in particular the possibility for pension funds to apply a conversion rate below the statutory fixed rate. We perform robustness checks by applying assumed lower conversion rates, which reflect blended rates for the mandatory and super-mandatory income. Although a lower conversion rate influences the value of the liability benchmark, it does not impact the conclusions drawn in this study. Please refer to Section 4 for the results on the robustness checks.

The replicating portfolio of both data sets takes on a comprehensive view and thus includes pension benefits for retired, disabled and widowed persons. The analysis disregards children pensions due to its small impact. As described in the previous chapter, a broad range of data is required to calculate the liability benchmark. In this section, we will highlight the sources of those variables. An overview of the descriptive statistics is shown in Table 3.

3.1. Pension framework inputs

Majority of the pension framework inputs for the Market Model are obtained from the Swiss Federal Statistical Office.[9] The data required is available for end of year values from 2004 to 2012. Majority of the pension framework inputs for creating the Pension Fund Model are obtained from publicly available annual reports for the time period 2005 to 2012. We apply the liability setting ex-ante and perform the analysis for both the Market Model and the Pension Fund Model from 31 December 2005 to 31 December 2013.

Bütler and Staubli (2010) estimate cash-out rates in autonomous Swiss pension funds to range from 10% to 30% and in collective funds from 50% to 60%. In 2012, collective funds accounted for 8% of the total number of funds and – owing to their larger size with respect to the number of plan participants per fund – for 26% of the active plan participants and for 15% of the passive plan participants in the Swiss

[9] www.statistik.admin.ch

market.[10] We therefore assumed the average portion of the retirement pension paid out as capital instead of yearly benefits to be at the higher end of the cash-out rates for autonomous funds, i.e., 30%, for both models. However, in order to account for the even higher rates of collective funds, we run several robustness checks by increasing the cash-out rates stepwise to 60%. Please refer to Section 4 for the results on the robustness checks.

For the Market Model, we do not have average contribution rates of employees and employers and therefore use the statutory defined minimum rates.[11]

3.2. Country-specific inputs

The replicating portfolio is built based on synthetic Swiss government zero-coupon bonds. As discount rates, we therefore use daily bootstrapped zero yields of Swiss government bonds obtained from Datastream and extrapolated with the models described in the previous chapter. We receive the data on life expectation from country-specific life tables published by the WHO.[12] We then get the age distribution for both the labor force and the retired population, as well as the average age of disabled and widowed persons from the Swiss Federal Statistical Office.[13] The future average salary increase is calculated from the Swiss Wage Index,[14] by taking the average historical wage increase over the period analyzed. Last, the future pension payment increases are set to zero. This is based on the fact that retirement benefits are generally not indexed and disability and widow's pension benefits can only be indexed if the financial health of the pension fund allows it.

[10] www.statistik.admin.ch

[11] The contribution rates depend on the age group selected. For the sake of brevity, we abstain from showing them in detail.

[12] http://who.int/gho/data

[13] www.statistik.admin.ch

[14] Published by the Swiss Federal Statistical Office; www.statistik.admin.ch

3.3. Technical inputs

As for the age of retirement, we do not consider early retirement and use the statutory age of 65 for men and 64 for women for observations after 2005 and 63 for women for observations before 2005.[15] We use the statutory conversion rates, which continuously decreased in the last decade. The minimum interest rate for savings is fixed on a yearly basis by the Federal Council.

Table 3: Summary inputs

Pension framework inputs	Market Model	Pension Fund Model
Number of active participants	3'615'786	69'578
% Female	41%	61%
Number of passive participants	871'609	24'514
% Female	47%	56%
Ratio active participants to passive particpants	4.15	2.84
Average pension passive particpants (retired)	27'551	33'842
Average pension passive particpants (disabled)	16'177	24'539
Average pension passive particpants (widowed)	16'036	19'287
Capital option percentage	30.0%	30.0%
Time period analyzed	31.12.2005 - 31.12.2013	31.12.2005 - 31.12.2013
Country-specific inputs	Market Model	Pension Fund Model
Average salary increase	1.3%	1.3%
Pension payment increase (retired)	0.0%	0.0%
Pension payment increase (disabled)	0.0%	0.0%
Pension payment increase (widowed)	0.0%	0.0%
Technical inputs	Market Model	Pension Fund Model
Average conversion rate*	7.1%	7.1%
Average interest rate on savings p.a.	2.2%	2.2%

Notes: This table reports the descriptive statistics of both the Market Model (applied to the Swiss pension market as a whole) and the Pension Fund Model (applied to one of the largest Swiss pension funds). The statistics represent averages over the time period specified. *The conversion rate is shown as average over the study period. The conversion rate on the mandatory part of the pension scheme was gradually reduced to currently 6.8%.

[15] The temporary arrangements implemented for women close to retirement are not taken into account in the analysis.

3.4. Asset inputs

Furthermore, we require financial market data for modelling the asset side of the Market Model and the Pension Fund Model. The asset side is replicated with nine different asset classes, represented by well-known benchmarks (see Table 4).

Table 4: Asset classes and benchmarks

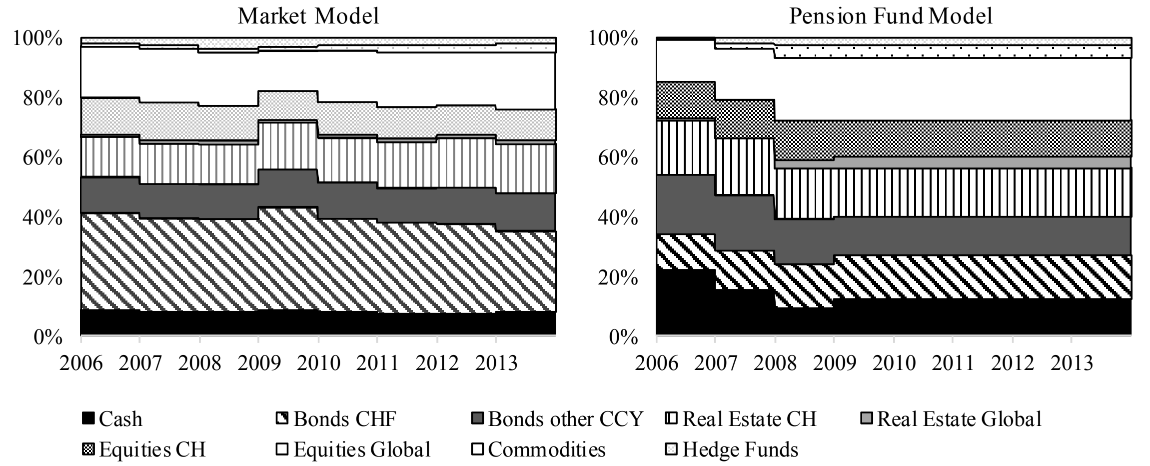
Asset class	Benchmark
Cash	Citigroup 3 Mth Eurodeposit CHF
Bonds CHF	SBI AAA-BBB
Bonds other CCY	JPM World Government Bond Index
Real Estate CH	SXI Real Estate Index
Real Estate Global	FTSE EPRA/NAREIT Global Index
Equities CH	SPI
Equities Global	MSCI World ex Switzerland
Commodities	S&P GSCI Commodity Total Return
Hedge Funds	HFRX Equal Weighted Strategies

Notes: This table reports the benchmarks used for each asset class. The asset class separation reflects the typical classification seen for Swiss pension funds.

All financial market data is obtained from Datastream with a daily frequency (exception: Hedge Fund Index on a monthly frequency). The selected time period corresponds to the time period of the pension framework observations.

Furthermore, we require information about the asset class allocation. For the Market Model, we use the actual total asset distribution across all pension funds at the beginning of the year as a proxy for the strategic asset allocation (SAA). When looking at a single pension fund, as in our Pension Fund Model, we can directly use the SAA published in the annual report. We therefore do not take amendments to the SAA, which have taken place within the year, into account. Figure 4 illustrates the development of the assumed SAA during the study period.

Figure 4: Development of the assumed strategic asset allocation (SAA)



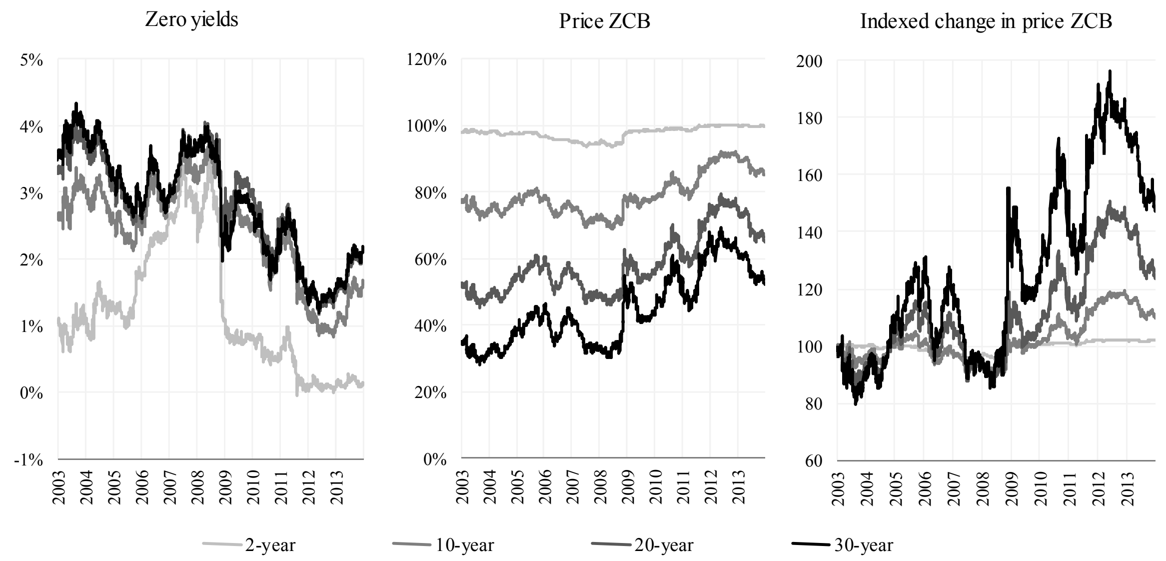
Notes: This figure illustrates the development of the asset class distribution. For the Market Model, we use the actual total asset distribution across all pension funds at the beginning of the year as a proxy for the strategic asset allocation (SAA). For the Pension Fund Model, we directly use the SAA published in the annual report. Amendments to the SAA during the year are not taken into account.

4. Results

4.1. Interest rate movements

In order to understand the development of the replicating portfolio's value, we first need to consider the movements on the interest rate market in the recent decade. Figure 5 illustrates three connected developments based on the Swiss term structure of interest rates. Similar term structure developments can be observed in most developed countries. The figure illustrates several noteworthy points. First, in the graph on the left, we see the falling trend of 2-, 10-, 20- and 30-year interest rates, particularly in the aftermath of the recent financial crisis. The middle graph illustrates the corresponding increase in synthetic prices of zero-coupon bonds. The prices are called synthetic since they have not been observed in the market but were calculated by discounting the cash flows with the zero yield curve. Last, the graph on the right indexes the change in price of zero-coupon bonds of different maturities, starting at an index value of 100 in the beginning of the year 2003. We can see that, due to the long-term discounting effect, in particular the prices of 20- to 30-year zero-coupon bonds increased heavily until 2012. Understanding this significant effect of a drop in long-term interest rates, which are used as discount rates in the valuation of the liabilities, on the price of zero-coupon bonds is crucial for understanding the movement in the replicating portfolio's value discussed in this paper.

Figure 5: Recent development of interest rates and its consequences on the pricing of zero-coupon bonds



Notes: The graph on the left illustrates the falling trend of 2-, 10-, 20- and 30-year interest rates since 2003. The middle graph illustrates the corresponding increase in synthetic prices of zero-coupon bonds (not directly observable in the market). The graph on the right indexes the change in price of zero-coupon bonds starting at an index value of 100 in the beginning of the year 2003.

4.2. The movement of the replicating portfolio

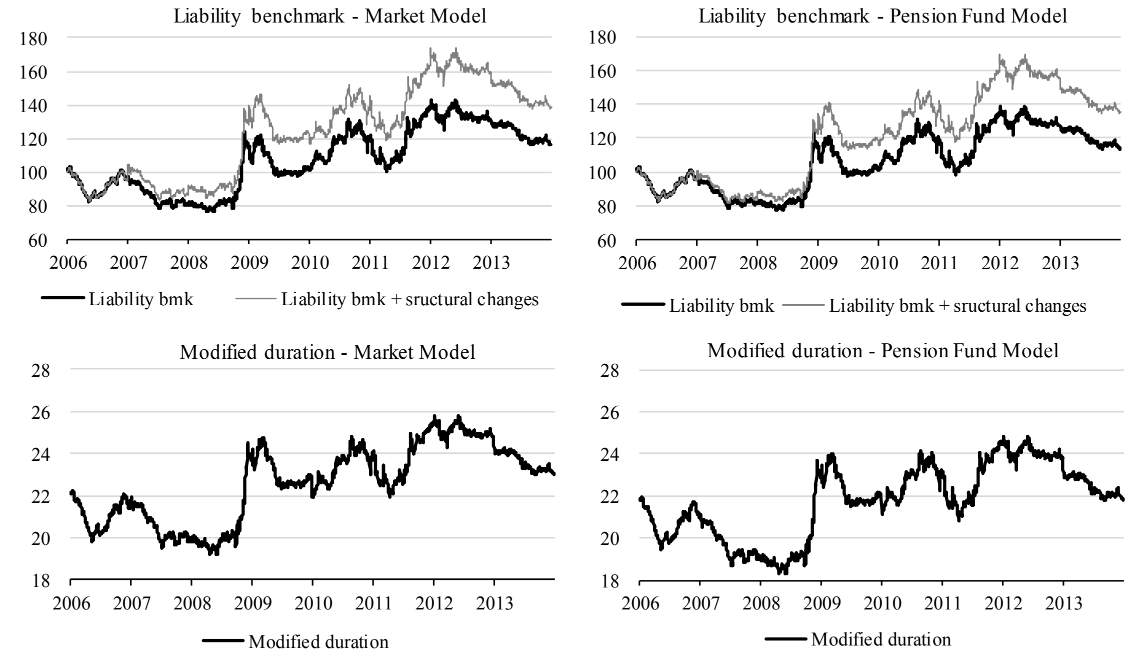
We use the ALR Model to estimate the expected cash flows of the Swiss pension fund market and a specific Swiss pension fund. We assume a horizon as long as the highest expectation of life of the plan participants. In general, this horizon amounts to slightly above 70 years. We do not implement a going concern assumption in our model – rather we are aiming at measuring the currently existing liabilities, which also represents the common approach applied in practice for the valuation of a pension fund's liabilities.

The replicating portfolio then rebuilds the expected pension cash flows over the maximum horizon with synthetic zero-coupon bonds. It thereby takes the specific maturities of the pension liabilities into account. Consequently, also a movement in the slope of the yield curve is reflected by the ALR Model. Since we use synthetic zero-coupon bonds of the Swiss government, we assume maturity-dependent risk-free rates as discount rates. This does not correspond with the valuation of Swiss pension liabilities in reality: pension funds value their liabilities with a single interest rate, which is often related to a combination of the 10-year risk-free rate and a market return, and are thus ignoring the true maturity structure of the liabilities.[16]

Finally, the value of the replicating portfolio is based on the discounted value of the synthetic zero-coupon bonds. In light of this paper's goal, the discounted value of the replicating portfolio is called the liability benchmark. The first row of Figure 6 illustrates the development of the liability benchmark for the two pension frameworks. The indexed liability benchmark reflects the current pension framework structure at any given date; however, it explicitly excludes the yearly changes in the pension framework structure. As an example, the liability benchmark will always take the current number of plan participants and the respective age structure into account. However, at the beginning of every year, the liability benchmark will be rebalanced in order to account for the new number of plan participants and the new age structure. This structural change can lead to a one-time jump in the liability value. Since structural changes are not relevant for performance measurement, they will be excluded in the liability benchmark. As illustration, Figure 6 additionally shows the liability benchmark plus the effect of the structural changes. Furthermore, the second row of the figure shows the movement in the replicating portfolio's modified duration in the course of the study period.

[16] This valuation methodology is referring to the *Fachrichtlinie* FRP 4, which is published by the Swiss Chamber of Pension Actuaries. Another valuation methodology is provided for example by IFRS within the regulation of IAS 19.

Figure 6: The liability benchmark and the change in duration



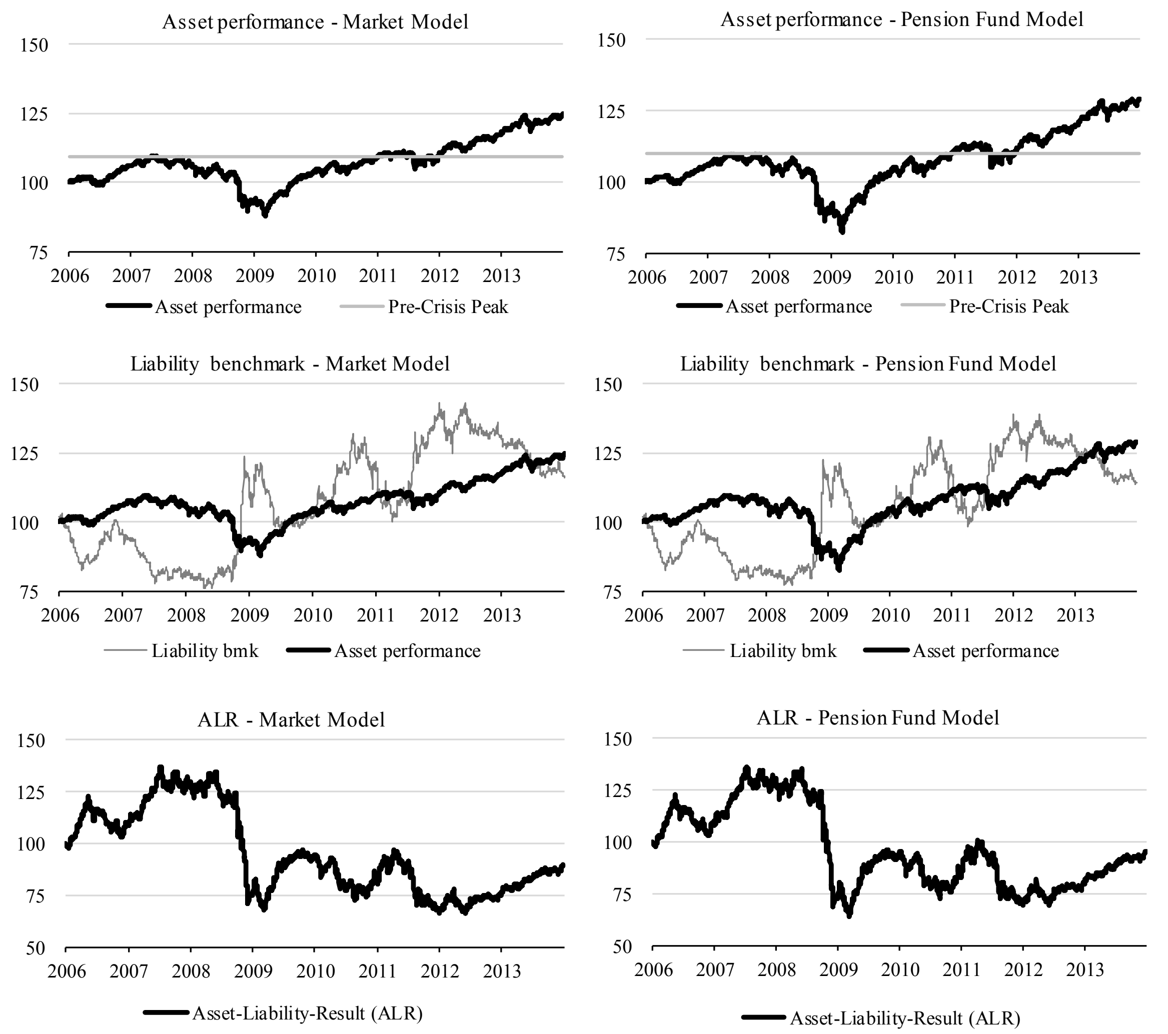
Notes: The graphs in the first row illustrate the development of the replicating portfolio's value for the Market Model and the Pension Fund Model – with and without taking structural changes into account. The graphs in the second row show the movement in the replicating portfolio's modified duration with time.

4.3. The ALR

In a next step, we use the liability benchmark as index for the performance on the asset side of the balance sheet. To approximate the asset performance on a daily basis, we use the actual total asset class distribution across all pension funds at the beginning of the year for the Market Model and the SAA for the Pension Fund Model. Based thereon, we calculate the investment portfolio performance.

Figure 7 illustrates the calculated asset performance in the top row and shows that the asset side of the Swiss pension funds has recovered from the financial crisis in 2009, while it reached the pre-crisis peak again in 2010. Furthermore, as illustrated in the middle row of Figure 7, we add the liability benchmark as comparison. We can see that, while the assets decreased in value during the financial crisis, the liabilities of the Swiss pension funds increased due to the substantial drop in interest rates at that time. Although the asset side recovered in 2009, the liabilities continued to increase in value until 2012 based on the ongoing pressure on interest rates.

Figure 7: From the asset performance to the ALR



Notes: The performance of the investment portfolio (asset performance) is illustrated in the graphs of the top row. To approximate the asset performance on a daily basis, we use the actual total asset class distribution across all pension funds at the beginning of the year for the Market Model and the SAA for the Pension Fund Model. The middle row shows both the asset performance and the liability benchmark (without structural changes) in comparison. Finally, the bottom row shows the ALR – i.e., the asset performance measured with respect to the liability benchmark.

Combining these two effects, whereby the asset performance is measured with respect to the liability benchmark, yields the ALR. The liability benchmark (without structural changes) and the asset performance are compared on a daily frequency without applying a weight to either of them. As an alternative, the asset performance and the liability benchmark could be weighted with a funding ratio. However, we refrain from such a procedure in order not to mix up different valuation approaches – which would be required for the introduction of the funding ratio.

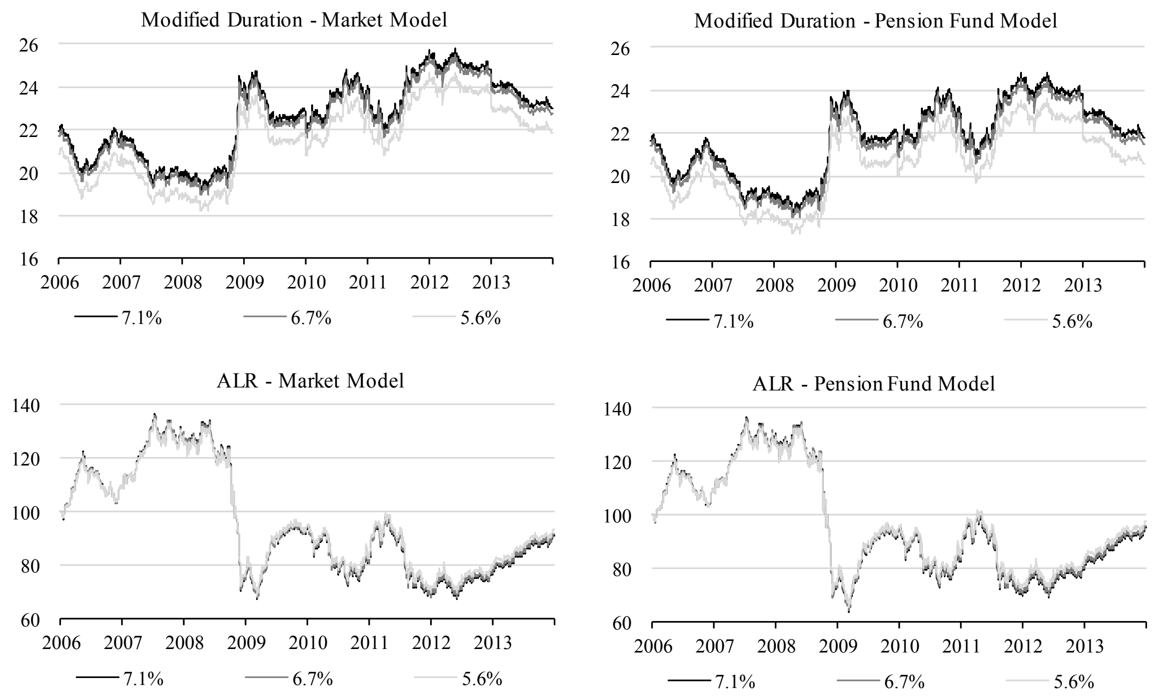
The ALR is illustrated in the bottom row of Figure 7. It can be highlighted that the drop in performance during the financial crisis was even higher when it is measured against the liability side. Both the Market Model and the Pension Fund Model illustrate that the Swiss pension market has not recovered from the financial crisis until the end of 2013 when looking at the comprehensive ALR measure. The recovery in 2013 is due to both the increase in long-term interest rates and the positive performance of equity markets in the same year.

4.4. Robustness checks

Given that we disregard the splitting of the pension schemes into its mandatory and super-mandatory part, we perform robustness checks on the assumed conversion rate. In the standard model, we used the statutory minimum conversion rates, which averaged at 7.1% over the study period. Pension funds that provide benefits beyond the statutory minimum are allowed to apply a lower conversion rate. The average blended conversion rate from 2006 to 2013 for the mandatory and the super-mandatory regimes amounted to 6.7%, whereas the average minimum value amounted to 5.6%.[17] We run the model with both alternative assumptions and thereby provide a lower bandwidth of possible outcomes. Figure 8 illustrates that the modified duration of the liabilities decreases with a lower conversion rate, whereas the ALR exhibits a slightly less volatile development. However, given the limited impact on the ALR, it does not impact the conclusions drawn in this study.

[17] Swisscanto (2014)

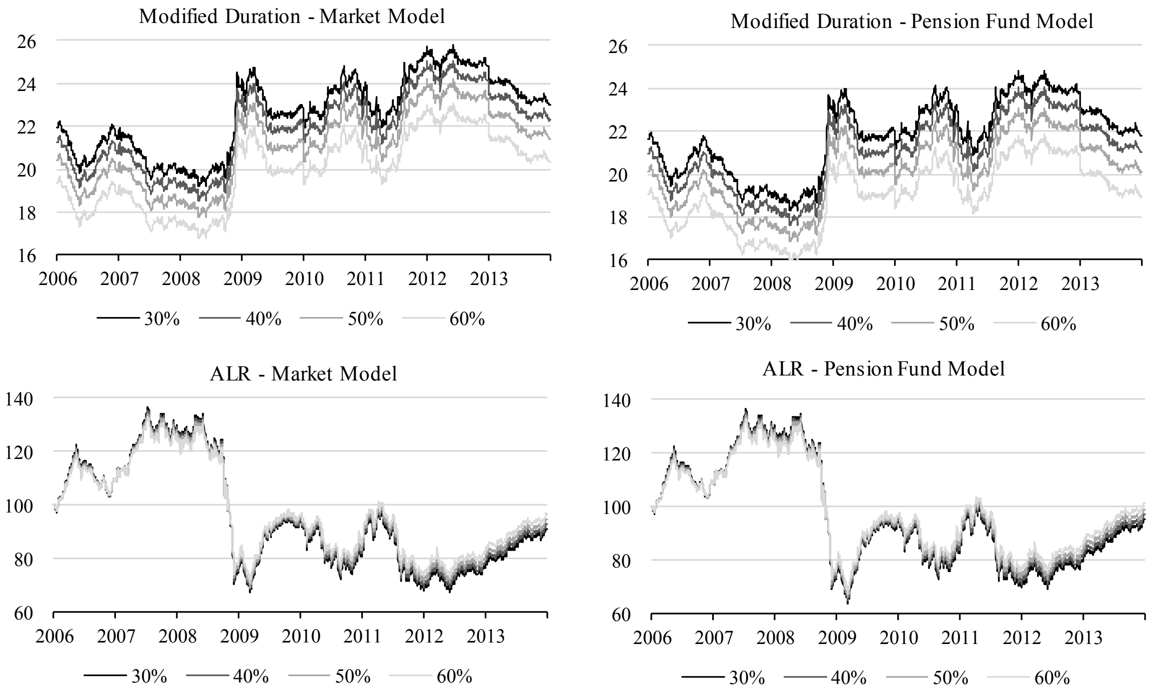
Figure 8: Conversion rate robustness check



Notes: The figure shows the different results dependent on the assumptions with respect to the conversion rate. The graphs illustrate the model for assumed average conversion rates of 7.1% (standard model), 6.7% (average blended conversion rate 2006-2013) and 5.6% (minimum blended conversion rate 2006-2013). The graphs in the first row show the movement in the replicating portfolio's modified duration with time. The second row shows the ALR – i.e., the asset performance measured with respect to the liability benchmark.

Based on Bütler and Staubli (2010), we assumed a capital option percentage (cash-out rate) of 30%. Since collective pension funds exhibit higher cash-out rates ranging from 50% to 60%, we perform robustness checks on this parameter by increasing it stepwise to 40%, 50% and 60%. Although the pension fund analyzed in the Pension Fund Model is an autonomous fund, we apply the higher cash-out rates to allow for comparison between the two calibrations. Figure 9 shows the results with respect to the modified duration and the ALR. The graphs highlight that, with increasing cash-out rates, the duration of the liabilities decreases substantially. Similar to the robustness check with respect to lower conversion rates, higher cash-out rates lead to an ALR that exhibits a slightly less volatile development. However, although the effect is observable, it does not impact the conclusions drawn in this study.

Figure 9: Capital option percentage (cash-out rate) robustness check



Notes: The figure shows the different results dependent on the assumptions with respect to the capital option percentage (cash-out rate). The graphs illustrate the model for assumed average cash-out rates of 30% (standard model), 40%, 50% and 60%. The graphs in the first row show the movement in the replicating portfolio's modified duration with time. The second row shows the ALR – i.e., the asset performance measured with respect to the liability benchmark.

4.5. Yearly ALR analysis

Table 5 finally shows the yearly performance and risk analysis of the investment portfolio and the liability benchmark as well as the resulting ALR time series. The risk analysis shows the yearly standard deviation and 99% daily value at risk. It clearly highlights the substantial influence of including the liability side as a benchmark in the analysis both on the return and on the risk side. In 6 out of the 8 years analyzed, the liability benchmark and the asset performance moved in opposite directions. This stems from the fact that historically, interest rates most often decreased when financial markets performed poorly (and vice versa). Pension funds therefore must be aware that during financial market downturns, they should not only be concerned about the negative effect on the asset side, but also about the disadvantageous development with respect to the liabilities. Furthermore, the risk analysis illustrates that the liability benchmark is more volatile and has a higher downside risk than the asset performance. This characteristic is caused by the interest rate volatility coupled with the high duration of the liabilities. Liabilities with an average duration of 20–25 years (as in our model) move strongly even when interest rates change only slightly.

The Pension Fund Model exhibits a substantially lower ratio of active participants towards passive participants – indicating the higher proportion of benefit recipients. A higher proportion of passive participants results in a reduced average duration of the pension liabilities. A lower duration finally leads to the fact that the Pension Fund Model exhibits lower volatility and lower downside risk in the liability benchmark than the Market Model. On the other hand, the Pension Fund Model is based on a slightly riskier asset allocation (due to a higher equity allocation), which results in higher volatility and downside risk of the asset performance. The overall effect on the volatility and downside risk of the ALR is therefore mixed.

When looking at the return measures of 2008, the impact of the financial crisis on both the asset performance as well as the liability benchmark can be observed. According to the model, the average asset performance of Swiss pension funds in the crash year amounted to -12.2%. However, given the parallel decrease in interest rate, the liability market value increased by 42.5%. Measuring the relative performance of the assets with respect to the liability benchmark then results in an ALR of -54.7% - which clearly illustrates the underestimation of the effect of the recent financial crisis on the pension funds' financial situation.

Based on the results discussed in this chapter, we see the ALR as a comprehensive performance measure, taking a mark-to-market perspective for the entire balance sheet. Current performance measures focus entirely on the asset performance. However, we illustrate that the usage of the liability side as benchmark adds additional insight for the performance and risk analysis. This is in particular true for pension funds and other financial institutions having highly long-term liabilities.

Table 5: Yearly ALR analysis

	Annualized return		Volatility		99% daily VaR	
	MM (%)	PFM (%)	MM (%)	PFM (%)	MM (%)	PFM (%)
2006						
Liability benchmark	-4.2	-4.1	10.0	9.9	-1.4	-1.3
Asset performance	6.0	5.8	3.1	2.9	-0.6	-0.5
ALR	10.2	9.9	10.0	10.0	-1.6	-1.6
2007						
Liability benchmark	-15.9	-15.2	9.5	9.1	-1.5	-1.4
Asset performance	0.5	1.7	3.8	3.8	-0.6	-0.7
ALR	16.3	16.8	11.0	10.7	-1.5	-1.5
2008						
Liability benchmark	42.5	40.5	19.2	18.3	-2.5	-2.5
Asset performance	-12.2	-15.6	7.6	9.6	-1.4	-1.8
ALR	-54.7	-56.1	21.4	22.0	-4.1	-4.0
2009						
Liability benchmark	-11.6	-11.1	14.4	13.8	-2.5	-2.4
Asset performance	11.1	14.7	4.8	7.9	-0.8	-1.4
ALR	22.7	25.8	16.0	17.9	-2.8	-2.9
2010						
Liability benchmark	17.7	17.0	15.1	14.6	-2.5	-2.4
Asset performance	4.6	6.1	4.1	5.5	-0.8	-1.0
ALR	-13.1	-10.9	16.8	17.5	-3.1	-3.1
2011						
Liability benchmark	14.1	13.4	18.4	17.7	-2.2	-2.1
Asset performance	0.8	0.3	5.5	7.0	-1.0	-1.3
ALR	-13.3	-13.1	20.7	21.1	-3.8	-4.0
2012						
Liability benchmark	-5.5	-5.4	14.8	14.2	-3.4	-3.3
Asset performance	7.0	8.4	3.2	4.1	-0.4	-0.5
ALR	12.5	13.7	15.7	15.5	-2.0	-2.1
2013						
Liability benchmark	-11.3	-10.6	8.8	8.3	-1.6	-1.6
Asset performance	6.2	7.6	3.6	4.1	-0.6	-0.7
ALR	17.5	18.2	8.8	8.7	-1.4	-1.4
Full period						
Liability benchmark	1.7	1.7	14.3	13.7	-2.2	-2.1
Asset performance	2.8	3.2	4.7	6.0	-0.9	-1.2
ALR	-4.2	-3.7	15.7	16.2	-2.8	-2.9

Notes: The table shows the annual return, the annualized volatility and the 99% daily value at risk of the liability benchmark and the asset performance as well as the resulting ALR time series for the Market Model (MM) and the Pension Fund Model (PFM). The annualized return of the ALR is calculated based on the yearly returns of the liability and the asset benchmark. The full period annualized returns for the liability benchmark, the asset performance and the ALR are calculated based on the geometric average of the respective yearly returns from 2006 to 2013. The value at risk is calculated based on the historical time series. A year is assumed to have 252 trading days.

5. Conclusion

We illustrated how to build a replicating portfolio for the liabilities of a pension fund and an entire pension market and highlighted its merits when using it as a benchmark for referencing the asset performance. In particular, due to the drop in yields since the recent financial crisis, the liability benchmark for Swiss pension funds has exhibited a substantial increase in value. Combining the liability and the asset performance illustrated that the recovery from the recent financial crisis took much longer than one would anticipate when looking at the asset side only.

We strongly advocate to using a comprehensive performance measure such as the ALR in two areas: Firstly when analyzing the performance of entire pension fund markets and secondly as operational tool for pension funds. Decisions on the asset side, such as the construction of the investment portfolio, can be improved when being in the full knowledge with regard to the risk factors on both sides of the balance sheet. In particular, only when looking at a comprehensive result, such as provided by the ALR, we can see the effect that a liability matching investment strategy might have.

The ALR Model is meant to be a starting point for further analyses in the field of ALM for pension funds. We see added value in a broad range of topics. The ALR Model can be extended in its ability to serve as performance measurement tool. It can be refined even more to a specific fund by calibration with internal information (for example, by using the actual age distribution) and more frequent data points (for example, quarterly reports).

Another stream of literature being targeted with the ALR Model is the area of portfolio rebalancing. At the moment, mainly value-based rebalancing strategies can be observed in the market. Some academic work is currently being done in the field of risk contribution rebalancing strategies (see Kohler & Wittig, 2014). A further extension targeted with the ALR Model is the implementation of an Asset-Liability-Rebalancing approach.

Furthermore, the model can be used as market model to analyze various pension markets around the world. By this means, we are able to highlight the development of the pension promises over the recent years and to calculate the large increase in the liability value due to the recent interest rate fall (see Novy-Marx & Rauh, 2011).

We also see potential in further studies surrounding the discount rates applied, given their huge impact on the value of the liabilities. It might be worthwhile to discuss whether applying the risk-free rate to pension payments is justifiable or whether an alternative approach would be warranted.

References

Boender, G. (1997). A hybrid simulation / optimisation scenario model for asset / liability management. *European Journal of Operational Research, 99*(1), 126-135.

Bogentoft, E., Romeijn, H.E. & Uryasev, S. (2001). Asset/Liability Management for Pension Funds Using CVaR Constraints. *The Journal of Risk Finance, 3*(1), 57-71.

Bütler, M. & Staubli, S. (2010). Payouts in Switzerland: Explaining Developments in Annuization. *Pension Research Council Working Paper*, 2010-23.

Chen, P., Yang, H. & Yin, G. (2008). Markowitz's mean-variance asset-liability management with regime switching: A continuous-time model. *Insurance: Mathematics and Economics, 43*(3)*,* 456-465.

Clark, G. (2000). *Pension Fund Capitalism.* New York: Oxford University Press.

Cronqvist, H. & Fahlenbrach, R. (2009). Large Shareholders and Corporate Policies. *The Review of Financial Studies, 22*(10), 3941-3976.

Dixon, A.D. (2008). The Rise of Pension Fund Capitalism in Europe: An Unseen Revolution? *New Political Economy, 13*(3), 249-270.

Drucker, P. (1976). *The Unseen Revolution: How Pension Fund Socialism Came to America*. New York: HarperCollings.

Kohler, A. & Wittig, H. (2014). Rethinking Portfolio Rebalancing: Introducing Risk Contribution Rebalancing as an Alternative Approach to Traditional Value-Based Rebalancing Strategies. *The Journal of Portfolio Management, 40*(3), 34-46.

Kouwenberg, R. (2001). Scenario generation and stochastic programming models for asset liability management. *European Journal of Operational Research, 134*(2)*,* 279-292.

Nelson, C.R. & Siegel, A.F. (1987). Parsimonious Modeling of Yield Curves. *The Journal of Business, 60*(4), 473-489.

Novy-Marx, R. & Rauh, J. (2011). Public Pension Promises: How Big Are They and What Are They Worth? *The Journal of Finance, 66*(4), 1211-1249.

Nyholm, K. (2008). *Strategic asset allocation in fixed-income markets*. West Sussex: John Wiley & Sons Ltd.

Söderlind, P. & Svensson, L. (1997). New Techniques to Extract Market Expectations from Financial Instruments. *Journal of Monetary Economics, 40*(2), 383-429.

Swisscanto. (2014). *Studie "Schweizer Pensionskassen"*. Available online at <http://www.swisscanto.ch/ch/de/berufliche-vorsorge/publikationen/pkstudie> [accessed on 17 July 2014].

Tower Watson. (2013). *Global Pension Assets Study 2013.* New York: Tower Watson. Available online at <*http://www.towerswatson.com/en-AU/Insights/IC-Types/Survey-Research-Results/2013/01/Global-Pensions-Asset-Study-2013*> [accessed on 12 November 2013].

Winklevoss, H.E. (1982). Plasm: Pension Liability and Asset Simulation Model. *The Journal of Finance, 37*(2), 585-594.

Ziemba, W.T. & Mulvey, J.M. (1998). *Worldwide Asset and Liability Modeling*. Cambridge: Cambridge University Press.

Part II
Fundamental Indexing in Global Bond Markets – the Risk Exposure Explains it All

Lidia Bolla[1]

Publication status: Revised & resubmitted (*Financial Analyst Journal*)

Abstract

Along with the continuing and unabated growth in index linked investing, also the criticism towards the predominant market capitalization weighting approach increases. We investigate the fundamental indexing methodology – an alternative index weighting approach – by applying it to the global government bond markets and investigate its exposure towards several risk factors that have not been considered in previous research. Fundamental indexing is said to outperform market capitalization weighted indices due to a performance drag in the market capitalization weighting methodology. The study at hand confirms the outperformance of the fundamental indexing approaches compared to a market value weighted index in the long term. However, our results show statistically significant and economically relevant exposures of the fundamentally weighted indices towards the risk factors term and duration risk, default risk, convexity risk, liquidity risk as well as carry trade risk. The increased risk exposure is able to explain the outperformance of the fundamental index weighting methodology in government bond markets.

[1] Lidia Bolla, M.A. HSG, CFA, is Managing Partner at Algofin AG, Webergasse 15, 9000 St. Gallen, Switzerland, lidia.bolla@algofin.ch.

1. Introduction

In the recent decades, indexed investment strategies have been on the rise. In particular, institutional investors increasingly apply a passive approach to investing. The move into passive strategies was supported by several studies showing an outperformance of passive strategies on a net return basis (cf. Malkiel, 2003). Given that most of the major market indices used in passive investing apply a market capitalization weighting approach, it follows that also the vast majority of passively invested portfolios are market value weighted. However, with the rise of passive investing, also the criticism towards this predominant weighting approach increased. Haugen and Baker (1991) showed at an early stage inefficiencies in capital weighted equity portfolios. Siegel (2006) introduced the term "Noisy Market Hypothesis", which describes the argument that security prices are subject to mispricing and thereby overvalued stocks tend to have lower returns, whereas undervalued stocks tend to have higher returns in the future. Following this logic, market value weighted indices are prone to overweight overvalued securities and underweight undervalued securities, which leads to a performance drag. This theory was also illustrated and further supported in research conducted by Treynor (2005) and Hsu (2006).

Following the criticism towards market capitalization weighting, new alternatives for passive portfolio construction have evolved. Fundamental indexing is one of the approaches that has been developed to overcome the described issues in market value weighted indices. Fundamental indexing approaches seem to deliver superior returns – however, several studies attribute the outperformance to a different risk factor exposure. The paper at hand analyzes the fundamental indexing approach in government bond markets on a worldwide scope and confirms the outperformance of several fundamental indexing approaches. However, it is also illustrated that the outperformance can clearly be attributed to a deviating risk factor exposure. In particular, we find an increased term, duration, default, convexity, liquidity and carry trade risk exposure. Opposing previous studies analyzing fixed income fundamental indexing, the results therefore provide strong evidence against the Noisy Market Hypothesis and support the argument that the outperformance in fundamental indexing can be attributed to a tilt in the risk factor exposure.

Within the string of literature on alternatives for passive portfolio construction, first and foremost is Arnott, Hsu and Moore (2005), who introduced the fundamental indexing approach. They weight US equities by fundamental factors (equity book value, gross sales, gross dividends, gross revenue and total employment) and find an average portfolio outperformance of 1.97% p.a. over a time period of 43 years. Arnott and West (2006) extend the research to regions outside the US and find similar results for the stock markets of 23 developed countries. Hemminki and Puttonen (2008) and Glabadanidis, Obaydin and Zurbruegg (2012) confirm the results found previously and conclude that the outperformance is in particular substantial in times of average stock market volatility. Hsu, Li and Kalesnik (2010) finally transfer the idea to the listed real estate market and find a yearly outperformance of 4.0% for the US market and 2.9% for non-US markets against the respective capital weighted benchmark.

Several authors question the findings in the area of fundamental indexing. Chow, Hsu, Kaelsnik and Little (2011) as well as Amenc, Goltz and Le Sourd (2009) confirm the results found previously – however, they attribute the outperformance to a value tilt in the fundamentally weighted equity portfolios. They conclude that fundamental indexing does not generate abnormal returns when regressed on Fama and French (1992) or Carhart (1997) risk factors. Perold (2007) and Kaplan (2008) criticize the theoretical foundation of fundamental indexing and the corresponding Noisy Market Hypothesis and argue that capital weighted indices do not generally exhibit a performance drag.

In contrast to the broad literature in equity fundamental indexing, there is a significant lack of research with respect to fundamental indexing approaches in fixed income markets. To the best of our knowledge, Arnott, Hsu, Li and Shepherd (2010) and Shepherd (2011) are the only authors so far who extend the fundamental indexing idea to bonds, whereby they analyze the markets for US corporate bonds, US high yield bonds and emerging market government bonds. In a similar approach to equity fundamental indexing, Arnott et al. use the factors cash flow, dividends, book value of assets (instead of equities), sales and face value of the debt issue in the analysis of US bonds. The approach with respect to emerging market bonds differs – here, the authors consider population, the square root of the land area, GDP and energy consumption as fundamentals. Arnott et al. find higher returns, lower volatilities and consequently improved Sharpe Ratios for all three markets. They find an average annual outperformance of fundamentally indexed US corporate bonds, US high yield bonds and emerging market bonds of 0.42%, 2.60% and 1.43% respectively. Arnott et al. see their study on the fixed income market as an out-of-sample test to support their previous research in equity markets. Given that value tilts are no major risk and return source in fixed income markets, finding an outperformance of a fundamental indexing strategy in those markets aims at providing counter-arguments towards the critics in the research of fundamental indexing. In another study on US corporate bonds, Shepherd (2011) confirms that price corrections are the main driver of the outperformance of fundamental indexing strategies and thus supports the Noisy Market Hypothesis in fixed income markets. Based on those research results, Citigroup recently launched the Citi RAFI Bond Index Series. Among others, the index series provides fundamentally weighted indices for developed and emerging market government bonds.

We believe that our work contributes to the existing literature by filling the crucial gaps in the fundamental indexing research with respect to the fixed income asset class. We study fundamental indexing strategies for government bond markets of developed countries. Thereby, we aim at conducting a broad analysis and consequently choose a worldwide scope by including countries from North and Middle America, Europe, Africa and the Asia Pacific region in the study. Adding to the literature in this area should in particular broaden the research by Arnott et al. (2010). In addition to the academic contribution and given the growth in passive investment strategies as well as the recently launched index series in the field of fixed income fundamental indexing, we also see a significant practical relevance in conducting this research.

The remainder of the study is structured as follows. Section 2 provides an overview of the data used and the methodology applied. Section 3 shows the performance statistics for the full observation period as well as several subperiods, whereas Section

4 discusses the multifactor risk regression analyses to evaluate the different risk factor exposures. Finally, we conclude in Section 5.[2]

2. Data and methodology

2.1. Return indices

We construct fundamental indices for government bonds based on the market value weighted Citigroup World Government Bond Index (CG WGBI) and the corresponding country indices. Table 1 provides an overview of the countries selected for the analysis. We choose a worldwide scope and run the analysis with 26 countries from North and Middle America, Europe, Africa and the Asia Pacific region. The US government is the biggest issuer in the market, followed by the Japanese and several European governments. The time period analyzed in this study ranges from January 1991[3] to December 2014, whereby the analysis is based on monthly data.

With respect to the country selection, the study does not try to exactly replicate the CG WGBI. The inclusion date of a specific country is not based on the inclusion date within the CG WGBI but rather on the index launch date of the country index. Countries that have been excluded from the CG WGBI due to a rating downgrade remain included in our analysis. This approach is chosen in order to maximize the data set and minimize the turnover within the index. As benchmark for the fundamentally weighted indices, we construct a market value weighted index with an

[2] The term "fundamental indexing" was originally coined by Arnott et al. (2005) for their alternative indexing approach in equity markets due to their reliance on fundamental company factors. When applying the approach to fixed income markets, in particular government bonds, the authors sometimes refer to the approach by the broader term "valuation-indifferent weighting" – since country characteristics instead of company fundamentals are used as weighting mechanism. However, also other alternative weighting approaches, such as an equal weighting strategy, can be classified as a valuation-indifferent weighting scheme but would not be classified as fundamental indexing approach. For the sake of comprehensibility and readability, we will therefore use the term fundamental indexing also with respect to fixed income markets and apply the term valuation-indifferent weighting in its broader meaning.

[3] The observation period is restricted to start in January 1991 due to the availability of the global equity risk factor dataset provided by Kenneth R. French.

equivalent country selection approach. By using Citigroup's country indices, we benefit from the inclusion and exclusion criteria applied to the individual bonds.[4]

Table 1: Overview country indices

	Citigroup index launch date	Return p.a. since launch	Standard deviation since launch	Sharpe Ratio since launch	Market value % 31.12.2014
Australia	29.12.1989	8.7%	11.8%	0.47	1.3%
Austria	30.10.1992	6.2%	10.3%	0.33	1.3%
Belgium	31.01.1991	6.7%	10.8%	0.35	2.1%
Canada	29.12.1989	7.3%	8.9%	0.47	1.8%
Denmark	29.12.1989	7.6%	10.4%	0.43	0.6%
Finland	31.01.1995	6.3%	10.3%	0.35	0.5%
France	29.12.1989	7.4%	10.5%	0.41	7.8%
Germany	29.12.1989	6.5%	10.5%	0.33	6.5%
Greece	30.06.2000	-0.4%	28.7%	n/a	0.0%
Ireland	30.10.1992	7.3%	12.8%	0.35	0.7%
Italy	29.12.1989	7.7%	12.4%	0.37	7.8%
Japan	29.12.1989	4.6%	11.5%	0.13	22.8%
Malaysia	31.07.2007	3.4%	8.6%	0.34	0.4%
Mexico	30.01.2004	6.2%	13.6%	0.35	0.9%
Netherlands	29.12.1989	6.8%	10.5%	0.35	2.1%
New Zealand	30.10.1992	8.9%	12.5%	0.48	0.2%
Norway	31.01.1995	5.4%	11.1%	0.25	0.2%
Poland	31.01.2000	10.0%	16.3%	0.50	0.5%
Portugal	31.01.1995	7.2%	14.2%	0.32	0.6%
Singapore	30.09.2004	5.4%	7.3%	0.54	0.3%
South Africa	29.04.2011	-6.1%	18.9%	n/a	0.4%
Spain	31.01.1991	6.4%	12.2%	0.28	4.2%
Sweden	31.01.1991	5.9%	11.7%	0.26	0.4%
Switzerland	29.12.1989	6.6%	11.5%	0.30	0.3%
United Kingdom	29.12.1989	8.0%	10.0%	0.49	6.4%
United States	29.12.1989	6.2%	4.4%	0.71	30.0%

Notes: The table provides an overview on the country indices in the CG WGBI. The data refers to the period of data availability and not the inclusion of the country in the WGBI. The statistics are based on USD returns.

[4] The bonds for example require a minimum remaining life of one year and a specified minimum issue size depending on the country. Please refer to the Citigroup index construction methodology for a detailed description of the index criteria. For the sake of brevity, we abstain from showing them in detail here.

2.2. Fundamental factors

For the sake of comparability, we choose the same four fundamental factors for the fundamental weighting approach as Arnott et al. (2010) with respect to government bonds: (1) gross domestic product (GDP) in USD as a proxy for the size of a country's economy, (2) size of the population as a proxy for the labor force's size, (3) square root of the land area as a proxy for the country's resource richness and (4) energy usage as a proxy for technological progress. All factor data is obtained from the World Bank database[5] and available on a yearly frequency for the years 1960 to 2013.[6]

As will be discussed in the next section, the fundamental weighting scheme is based on five year rolling averages of the fundamental factors. Given our observation period from 1991 to 2014, we consequently use fundamental factor data from the years 1986 to 2013. The factor data over the relevant period is summarized in Table 2. By comparing it to Table 1, it can be concluded that in particular the factor land area leads to a substantial deviation from the market value weighting approach by shifting the weights towards countries such as Australia and Canada. On the other hand, the factors GDP and energy usage increase the weighting factor of the US even more.

2.3. Methodology

We create five fundamentally weighted fixed income indices. First, we use each of the four fundamental factors on a standalone basis and second, we combine the factors to a composite index. To construct the composite index, all four fundamental factors are weighted equally. As benchmark to measure the performance of the five fundamentally weighted indices, we calculate an equivalent market value weighted index. The equivalent market value weighted index is based on the same set of countries as the fundamentally weighted indices, but uses the market value of the issuer countries' bonds as weighting factor. Furthermore, an equally weighted index,

[5] http://data.worldbank.org

[6] Due to gaps in the dataset, the data for energy usage has to be approximated for the year 2013 and partially for the year 2012.

which equally weights the issuer countries of the bond universe, is constructed as an additional valuation-indifferent index. If the Noisy Market Hypothesis holds, the equally weighted index should as well outperform the market value weighted index, given that such naïve weighting scheme would also eliminate the suggested performance drag potentially inherent in the market value weighting methodology.

Table 2: Overview factor data

	GDP		Population		Land area		Energy usage	
	USD bn	%	Mio.	%	sqrt(sq. km)	%	mtoe	%
Australia	595	2%	19	2%	2'772	14%	99	2%
Austria	258	1%	8	1%	287	1%	28	1%
Belgium	314	1%	10	1%	123	1%	53	1%
Canada	929	3%	31	3%	3'016	15%	231	5%
Denmark	210	1%	5	1%	206	1%	18	0%
Finland	166	1%	5	0%	552	3%	31	1%
France	1'792	6%	61	6%	740	4%	237	5%
Germany	2'467	9%	81	8%	591	3%	327	7%
Greece	179	1%	11	1%	359	2%	24	1%
Ireland	130	0%	4	0%	262	1%	12	0%
Italy	1'484	5%	58	5%	542	3%	156	3%
Japan	4'297	15%	126	12%	604	3%	459	10%
Malaysia	124	0%	23	2%	573	3%	41	1%
Mexico	647	2%	102	10%	1'394	7%	142	3%
Netherlands	528	2%	16	1%	184	1%	70	2%
New Zealand	83	0%	4	0%	513	3%	15	0%
Norway	235	1%	5	0%	586	3%	24	1%
Poland	226	1%	38	4%	553	3%	98	2%
Portugal	146	1%	10	1%	302	1%	20	0%
Singapore	116	0%	4	0%	26	0%	18	0%
South Africa	192	1%	43	4%	1'101	5%	104	2%
Spain	852	3%	42	4%	707	3%	108	2%
Sweden	330	1%	9	1%	640	3%	48	1%
Switzerland	367	1%	7	1%	199	1%	24	1%
United Kingdom	1'716	6%	59	6%	492	2%	205	4%
United States	10'215	36%	279	26%	3'026	15%	2'046	44%
Total	**28'599**	**100%**	**1'060**	**100%**	**20'351**	**100%**	**4'640**	**100%**

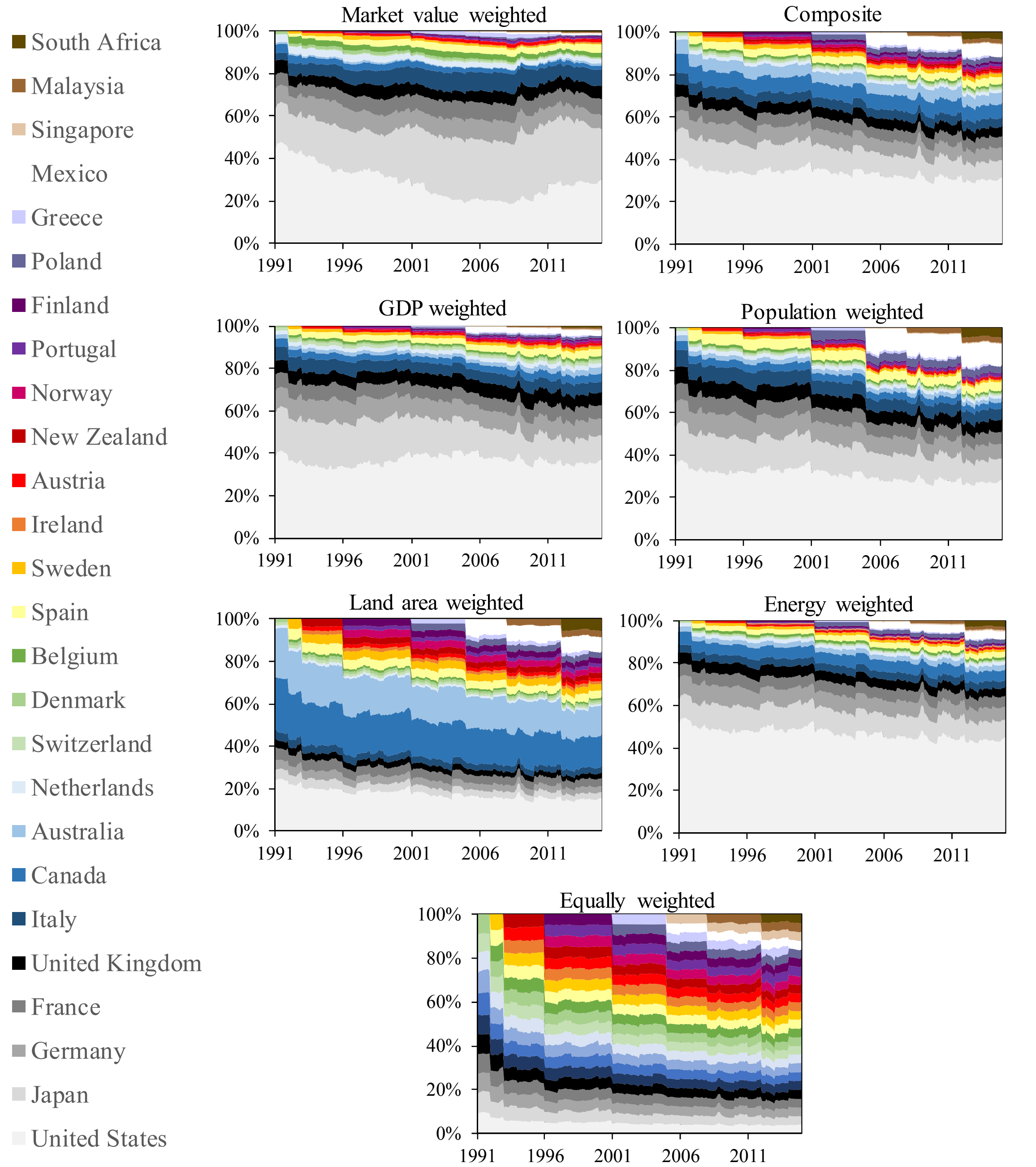
Notes: The table shows the averages of the fundamental factors and the corresponding average percentage weighting over the years 1986 to 2013. GDP is shown in billion USD, population in million, land area in square root of square kilometers and energy usage in megatons of oil equivalent (mtoe).

The indices are rebalanced with a yearly frequency on January 1 of every year. Since the fundamental factor data is obtained on a yearly basis, the implementation of a higher rebalancing frequency is not constructive. We use five year rolling averages of each country's fundamental factors for building the index weights. This approach aims at creating stable indices and thus reducing the yearly rebalancing turnover. We base the analysis on USD returns and therefore show the indices in an unhedged setting. Furthermore, we include transaction costs in the analysis for all indices by assuming a flat fee of 10 bps for every purchase and selling transaction.

We perform a range of robustness checks to assess the significance of the methodology applied. First, we perform the entire analysis using hedged versions of the indices. The hedged indices are constructed by calculating local currency returns and taking into account the interest rate differentials as hedging costs. The respective results are shown in Section 4. In addition, we amend the size of the rolling window for building the fundamental factor averages. We find that our results remain robust independent of the rolling window size. Last, we amend the rebalancing date. The performance of the indices is measured in a standard back testing approach and we assume that the factor information of the past five years is already available on January 1 of the subsequent year. Whereas this setting is usually unproblematic for the factor land area, it might be debatable for the other factors, where the information is usually not available in such a short time period after the end of the respective year. We perform robustness checks by moving the rebalancing dates by up to eleven months and receive similar results. Although some of the factors, in particular definitive GDP numbers, are only available with an even longer time lag, we still think that the index construction is feasible. First, by relying on estimates of the factor data, such as GDP estimates, the most current factor information can be approximated. Second, by using a rolling estimation window of five years and due to the low fluctuation in the factor weightings, deviations between estimates and actual values do not significantly influence the index construction.[7]

[7] The robustness checks with respect to the rolling window size and the rebalancing date show that the conclusions drawn in the study are not altered when amending those assumptions. For the sake of brevity, we therefore abstain from presenting those additional results in detail.

Figure 1: Country weights



Notes: The figure shows the country weights of the market value weighted index (benchmark), all four fundamentally weighted standalone indices (GDP, population, land area, energy), the composite index that equally weights the four fundamental factors and the equally weighted index that equally weights the issuer countries.

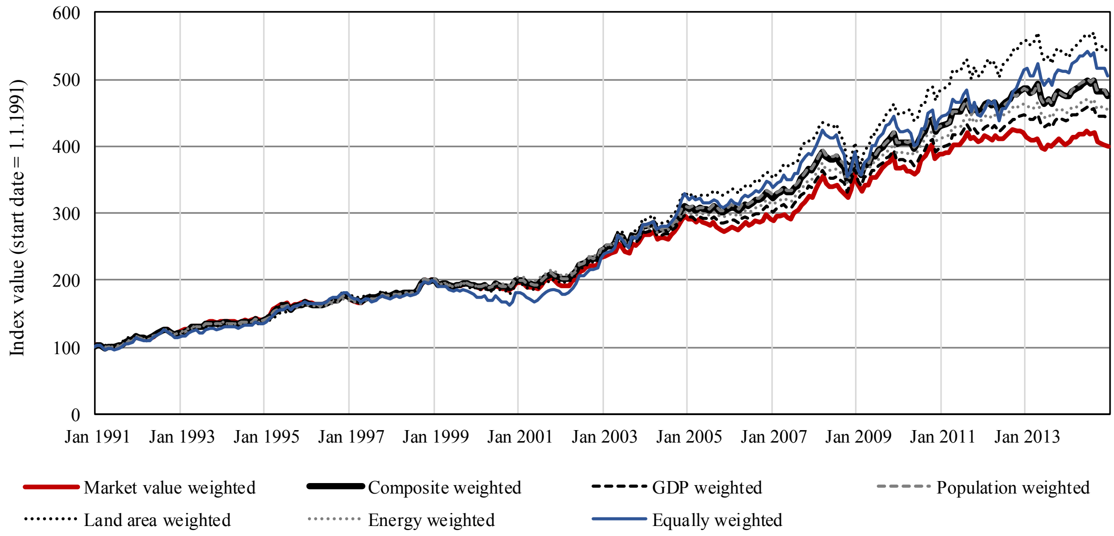
The country indices have been launched at different dates. We start the analysis in January 1991 with a subset containing those eleven country indices that have been launched up to that point and include the other countries at the rebalancing date, on which the first data points are available. All the indices, including the fundamentally weighted indices, the market value weighted index as well as the equally weighted index, do have the same set of countries included at every point in time. Figure 1 shows the country weightings of all indices over the time period analyzed. Since countries are included at the rebalancing date on which the first data points are available, the indices steadily grow with respect to the number of countries included. Among the fundamentally weighted indices, the land area weighted index is characterized by the largest deviation in country allocations. Countries that have only been classified as developed countries during the observation period, such as Mexico or Malaysia, do not yet exhibit large market values and are therefore only considered with a small weight in the market value weighted index. However, due to the relatively large population and land area, in particular Mexico obtains a higher share in some of the fundamentally weighted indices.

3. Performance statistics

3.1. Full observation period

The five fundamentally weighted government bond indices, the market value equivalent index as well as the equally weighted index are calculated for the time period January 1991 to December 2014. The period analyzed therefore covers 24 years entailing high and low interest rate environments, bull and bear markets as well as severe financial market crises. The results show an outperformance of all fundamentally weighted indices and the equally weighted index compared to the market value weighted index. Figure 2 illustrates the development of the indices graphically, while Table 3 lists the performance statistics.

Figure 2: Index plots



Notes: The figure shows the index development of the market value weighted index (benchmark), all four fundamentally weighted standalone indices (GDP, population, land area, energy), the composite index that equally weights the four fundamental factors and the equally weighted index that equally weights the issuer countries. The index start date is on January 1, 1991 with an index value of 100.

Table 3: Performance statistics

	Benchmark	Single factors				Multi factors	
	Market value weighted	GDP weighted	Population weighted	Land area weighted	Energy weighted	Composite weighted	Equally weighted
Index value (end)	399.66	439.55	475.76	536.01	454.67	475.40	505.35
Return p.a.	5.78%	6.17%	6.50%	7.00%	6.31%	6.50%	6.75%
Excess return p.a.		0.40 pps	0.73 pps	1.22 pps	0.54 pps	0.72 pps	0.98 pps
Volatility p.a.	6.62%	6.24%	6.63%	7.40%	5.59%	6.30%	8.91%
Sharpe Ratio	0.47	0.56	0.58	0.59	0.65	0.61	0.46
Tracking error		1.35%	2.02%	4.19%	1.94%	2.05%	4.34%

Notes: The table shows the index statistics of the market value weighted index (benchmark), all four fundamentally weighted standalone indices (GDP, population, land area, energy), the composite index that equally weights the four fundamental factors and the equally weighted index that equally weights the issuer countries. The period analyzed ranges from January 1991 to December 2014. Excess returns and tracking errors are calculated with respect to the market value weighted index.

Over the period analyzed, the market value weighted benchmark shows an average annualized return of 5.78%. The GDP weighted index shows an average yearly outperformance of 0.40 pps, the population weighted index 0.73 pps, the energy weighted index 0.54 pps and the land area weighted index even 1.22 pps. The composite index shows an average yearly outperformance of 0.72 pps and also the equally weighted index is able to outperform the market value weighted index by 0.98 pps.

The results with respect to the volatility of the valuation-indifferent indices as opposed to the volatility of the market value weighted index are mixed. The volatility is reduced for the GDP weighted, the energy weighted as well as the composite weighted index, whereas the other valuation-indifferent indices show a higher volatility measure than the market value weighted index. However, the risk return perspective measured by the Sharpe Ratio is still positive: the outperformance of the fundamentally weighted indices is considerable enough to produce substantially higher Sharpe Ratios for all five fundamentally weighted indices if compared to the market value weighted index. The equally weighted index exhibits a slightly lower Sharpe Ratio than the benchmark. The tracking errors indicate the degree of similarity with respect to the country weighting of the valuation-indifferent indices and the market value weighted index. The GDP weighted index shows the lowest tracking error and therefore the closest resemblance to the market value weighting. As already stated earlier, the land area weighting leads to a substantial deviation from the market value weighting approach, which is also reflected in a relatively large tracking error.

To test the significance of the outperformance, we regress – on a monthly basis – the fundamentally and equally weighted index returns minus the risk free rates on the market value weighted index returns minus the risk free rates. We implement the regression as an ordinary least squares regression including a variance-covariance estimation based on Newey and West (1987). The Newey and West variance-covariance estimation leads to a more robust regression output by taking potential autocorrelation and heteroscedasticity of the regression residuals into account. The results are shown in Table 4. The alphas of the fundamentally weighted fixed income indices are positive and in most instances statistically significant. We find an annualized alpha for the composite index of 1.01% and annualized alphas ranging from 0.62% to 1.45% for the standalone fundamentally weighted indices. The equally weighted index also shows a positive annualized alpha of 0.40%, although with no statistical significance.

Table 4: Regression output

	Single factors				Multi factors	Equally weighted
	GDP weighted	Population weighted	Land area weighted	Energy weighted	Composite weighted	
Annualized alpha	0.62%**	0.86%**	1.45%	1.10%***	1.01%**	0.40%
	(0.0112)	(0.0444)	(0.1013)	(0.0002)	(0.0117)	(0.6851)
Beta	0.92	0.96	0.93	0.81	0.91	1.19
Adj. R square	95.99%	90.96%	68.37%	92.81%	90.43%	78.38%

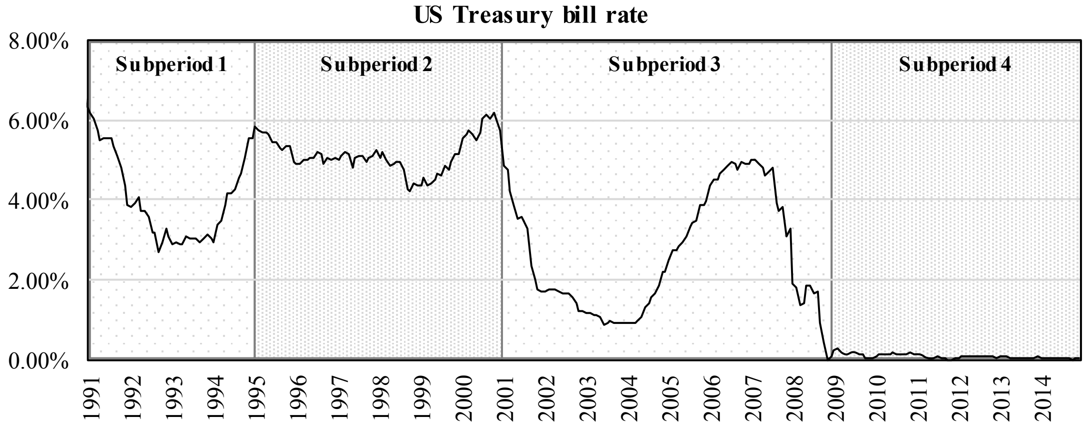
Notes: ***/**/* denotes significance at the 1% / 5% / 10% level. The table shows the regression results of all four fundamentally weighted standalone indices (GDP, population, land area, energy), the composite index that equally weights the four fundamental factors and the equally weighted index that equally weights the issuer countries. The monthly index returns minus the risk free rate are regressed on the monthly market value weighted index returns minus the risk free rate. The OLS regressions include a variance-covariance estimation based on Newey and West (1987) and are based on monthly data points. The regressions analyze the time period from January 1991 to December 2014 and use 288 data points for each setting. Values in brackets represent the p-values of alpha.

We can therefore conclude that the fundamental indexing approach leads to a statistically and economically significant higher performance than a market value weighted index when applied to the government bond market of developed countries. The outperformance might be explained by two different reasons: first, the Noisy Market Hypothesis holds and the outperformance results from a performance drag in the market value weighting methodology or, second, the fundamental indices exhibit a different risk factor exposure and therefore show a higher compensation of such elevated risk exposure. Before we turn to the risk factor analysis, we will first test whether the outperformance also holds for different subperiods.

3.2. Subperiod analysis

We divide the observation period into four subperiods, whereby we try to capture different interest rate environments. Figure 3 shows the development of the US Treasury bill rate since 1991. The first subperiod captures the years 1991 to 1994 and covers the end of the savings and loan crisis in the US. The second subperiod, ranging from 1995 to 2000, is characterized by a relatively stable, high interest rate environment. The third subperiod covers the years 2001 to 2008 and therefore entails the dot-com bubble as well as the financial crisis. The last subperiod ranges from 2009 to 2014 and covers the subsequent low interest rate environment.

Figure 3: Subperiods



Notes: The figure shows the separation of the observation period by creating different subperiods of varying interest rate environments measured with respect to the US Treasury bill rate. The first subperiod ranges from 1991 to 1994, the second subperiod ranges from 1995 to 2000, the third subperiod ranges from 2001 to 2008 and the fourth subperiod ranges from 2009 to 2014.

The return statistics as well as the regression results for the four subperiods are shown in Table 5. Looking at the excess returns, we see that the outperformance found previously can be seen for most, but not all subperiods. For the first subperiod, which covers the end of the savings and loan crisis in the US, we find negative excess returns for all valuation-indifferent indices except the GDP weighted index. The subsequent subperiods mostly show positive excess returns, whereby the last subperiod, characterized by the low interest rate environment, shows the highest positive excess returns. The results with respect to the Sharpe Ratios are similar to the return analysis. Except for the first subperiod, all fundamentally weighted indices generally yield a superior Sharpe Ratio than the market value weighted index. The equally weighted index yields a risk-adjusted outperformance in two out of four subperiods.

We also perform a single factor OLS regression, whereby the monthly valuation-indifferent index returns minus the risk free rate are regressed on the monthly market value weighted index returns minus the risk free rate. The underperformance of the valuation-indifferent indices in the first subperiod is reflected by negative alphas in the regression output (lowest panel of Table 5), yet the negative alphas mostly lack statistical significance. The outperformance of the fundamentally weighted indices in the remaining three subperiods is also confirmed, however, we only find a statistical significance in a few instances. The equally weighted index yields a positive alpha in the last two subperiods, although with no statistical significance.

Table 5: Subperiod analysis

		Benchmark	Single factors				Multi factors	
		Market value weighted	GDP weighted	Population weighted	Land area weighted	Energy weighted	Composite weighted	Equally weighted
Return p.a.	1: 31.12.1990-31.12.1994	8.59%	8.66%	8.25%	7.65%	7.93%	8.15%	7.63%
	2: 31.12.1994-31.12.2000	5.46%	5.92%	6.07%	6.00%	6.58%	6.15%	4.75%
	3: 31.12.2000-31.12.2008	7.57%	7.44%	8.20%	9.14%	7.73%	8.11%	9.69%
	4: 31.12.2008-31.12.2014	1.82%	3.08%	3.51%	4.70%	3.09%	3.60%	4.26%
Excess return p.a.	1: 31.12.1990-31.12.1994		0.07 pps	-0.35 pps	-0.94 pps	-0.67 pps	-0.44 pps	-0.97 pps
	2: 31.12.1994-31.12.2000		0.46 pps	0.61 pps	0.54 pps	1.12 pps	0.69 pps	-0.71 pps
	3: 31.12.2000-31.12.2008		-0.13 pps	0.63 pps	1.57 pps	0.16 pps	0.54 pps	2.12 pps
	4: 31.12.2008-31.12.2014		1.26 pps	1.68 pps	2.88 pps	1.27 pps	1.78 pps	2.44 pps
Volatility p.a.	1: 31.12.1990-31.12.1994	5.96%	6.30%	6.61%	5.99%	5.51%	5.91%	8.41%
	2: 31.12.1994-31.12.2000	6.25%	6.11%	5.98%	5.96%	5.00%	5.58%	7.78%
	3: 31.12.2000-31.12.2008	7.30%	6.48%	6.81%	8.01%	6.09%	6.70%	9.20%
	4: 31.12.2008-31.12.2014	6.40%	6.03%	7.07%	8.67%	5.52%	6.71%	9.94%
Sharpe Ratio	1: 31.12.1990-31.12.1994	0.81	0.78	0.68	0.65	0.76	0.74	0.46
	2: 31.12.1994-31.12.2000	0.08	0.16	0.19	0.18	0.33	0.22	-0.03
	3: 31.12.2000-31.12.2008	0.70	0.77	0.85	0.84	0.87	0.85	0.79
	4: 31.12.2008-31.12.2014	0.27	0.50	0.48	0.53	0.54	0.52	0.42
Annualized alpha	1: 31.12.1990-31.12.1994		-0.19%	-0.82%*	-0.01%	-0.25%	-0.32%	-2.56%
	2: 31.12.1994-31.12.2000		0.47%**	0.63%**	0.64%	1.23%**	0.75%	-0.77%
	3: 31.12.2000-31.12.2008		0.51%	1.17%	1.88%	1.14%**	1.16%	1.39%
	4: 31.12.2008-31.12.2014		1.44%**	1.70%	2.69%	1.59%**	1.86%*	2.01%

Notes: ***/**/* denotes significance at the 1% / 5% / 10% level. The table shows the index statistics for four subperiods of the market value weighted index (benchmark), all four fundamentally weighted standalone indices (GDP, population, land area, energy), the composite index that equally weights the four fundamental factors and the equally weighted index that equally weights the issuer countries. Excess returns and annualized alphas are calculated with respect to the market value weighted index. The calculations are based on 48, 72, 96 and 72 data points for the subperiods 1, 2, 3 and 4.

The subperiod analysis therefore shows that the outperformance of the fundamentally weighted indices as well as the equally weighted index found over the entire observation period cannot be confirmed for all subperiods. Rather, the results suggest that valuation-indifferent strategies do not outperform a market value weighted index in certain interest rate environments. This tends to support the hypothesis that fundamentally weighted strategies yield a deviating performance due to their different risk factor exposure when compared to market value weighted strategies.

4. Risk factor analysis

4.1. Risk factor exposure

We test the hypothesis that the outperformance of the fundamentally indexed strategies, although valid, might not be due to the Noisy Market Hypothesis, but rather based on a difference in risk exposure. Whereas the outperformance of fundamentally weighted equity indices was criticized to have its roots in a value tilt, the outperformance of the fundamentally weighted fixed income indices might suffer a similar tilt in fixed income risk exposures.

Table 6 gives an overview about the average bond risk factors of the indices. Whereas the market value weighted index exhibits an average modified duration of 5.63 over the period observed, all fundamentally weighted indices as well as the equally weighted index show a lower duration value. Furthermore, the table shows a rating code, whereby 1 stands for an AAA rating with an increase of 1 point per notch (i.e., 2 for an AA+ rating, 3 for an AA rating, etc.). The rating analysis is based on the long-term foreign currency country rating by Fitch. Given that we only include government bonds, the average rating of all indices is relatively high. Last, the table shows a convexity measure, which illustrates the sensitivity of the duration to a change in interest rates. Convexity is approximated by the 12 months rolling average of the monthly change in duration over the monthly change in yield. All fundamentally weighted indices as well as the equally weighted index show higher convexity exposures than the market value weighted index.

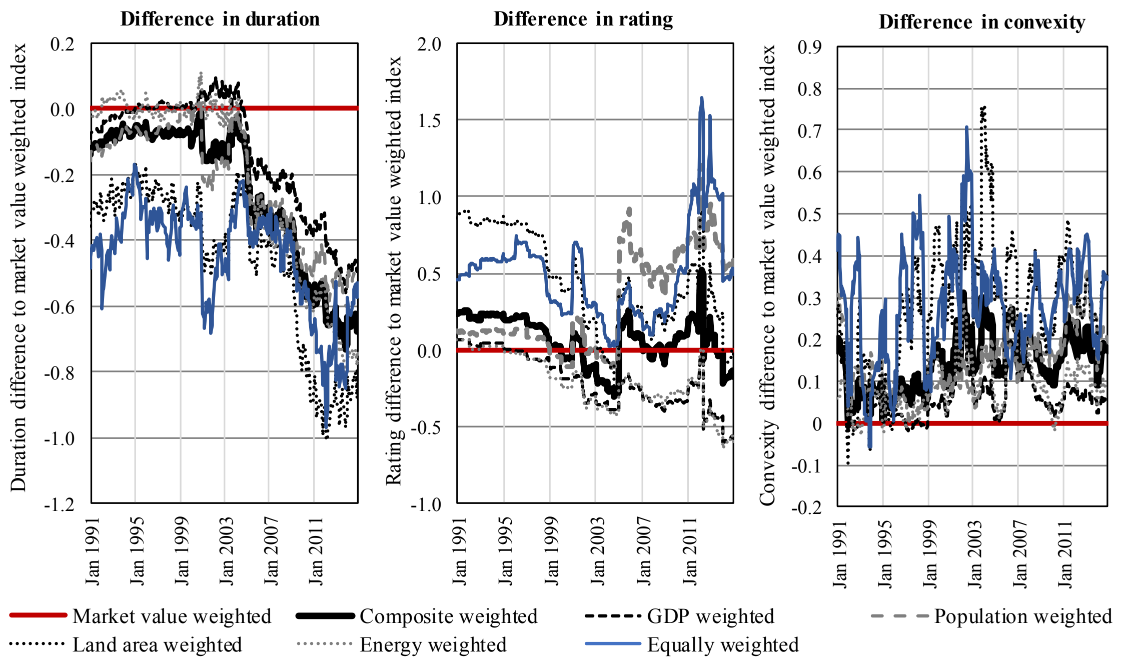
Figure 4 shows the difference in bond risk factors of the valuation-indifferent indices and the market value weighted index (red zero-line) over the observation period. Among others, the figure illustrates that the difference in duration increased with time and that the convexity of the valuation-indifferent indices exceeded the convexity of the market value weighted index for the entire observation period.

Table 6: Average bond risk factors

	Benchmark	Single factors				Multi factors	
	Market value weighted	GDP weighted	Population weighted	Land area weighted	Energy weighted	Composite weighted	Equally weighted
Average duration	5.63	5.50	5.41	5.18	5.42	5.38	5.18
Average rating (1=AAA)	1.91	1.71	2.22	2.36	1.71	1.99	2.41
Average convexity	0.61	0.67	0.75	0.89	0.70	0.75	0.89

Notes: The table shows the average bond risk factors of the indices. Duration is measured as the average modified duration over the observation period. The average rating code is calculated by assigning number codes to the Fitch country rating, whereby 1 stands for an AAA rating, 2 for a AA+ rating, etc. (1 point difference between each rating notch). Convexity is approximated by the 12 months rolling average of the monthly change in duration over the monthly change in yield.

Figure 4: Bond risk factors – difference to market value weighted index



Notes: The figure shows the development of the difference in bond risk factors of the valuation-indifferent indices and the market value weighted index. The market value weighted index (benchmark) is illustrated by the red zero-line.

4.2. Initial risk factor regression

We test whether the abnormal returns of the fundamentally weighted indices remain positive and significant if we account for the risk factor exposure of the different indices. We implement two different risk factor regressions. First – as an initial risk factor regression – we perform the analysis that was conducted by Arnott et al. (2010). We use the Fama and French (1992) equity risk factors for the market return, the size return (SMB, small minus big) and valuation return (HML, high minus low), which are argued to be potential risk factors for both equities and bonds. The Fama and French equity risk factors are obtained from the global dataset provided by Kenneth R. French.[8] Based on Fama and French (1993) and analogous to Arnott et al. (2010), we will additionally extend the three factor model with the two bond specific risk factors term risk (TERM), which accounts for the difference in long-term and short-term government bond returns, and default risk (DEFAULT), which captures the difference between the return on corporate and government bonds. Although the fundamental indices tested in the study at hand contain government bonds only, default risk might be a major driver of return given the worldwide scope and the inclusion of lower rated countries. The bond risk factors are calculated using global short- and long-term government and corporate bond returns from Datastream. Below formula shows the described initial multifactor regression approach, whereby r_{fw} captures the return of the valuation-indifferent indices.

$$r_{fw} = \alpha + r_f + \beta_1\left(r_{mkt} - r_f\right) + \beta_2 SMB + \beta_3 HML + \beta_4 TERM + \beta_5 DEFAULT + \varepsilon \tag{1}$$

Using the three equity factors as well as the two bond factors by Fama and French corresponds to the analysis conducted by Arnott et al. (2010), who found abnormal returns for fundamentally weighted US corporate and emerging government bond markets. Table 7 shows our corresponding results. Analogous to Arnott et al., even when adjusted for the described risk factors, we find higher annualized alphas for the fundamentally weighted indices than for the market value weighted index. As expected, in particular the bond risk factors term risk and default risk show a high statistical significance. However, we also perform a paired t-test to compare the difference between the alphas of the fundamentally weighted indices and the market value weighted index – Table 7 shows the corresponding p-values in the last row. The high p-values indicate that the divergence in alphas between the valuation-indifferent

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

indices and the market value weighted index is statistically not different from zero. Hence, the results of our initial risk factor regression on the one hand confirm the outperformance also found by Arnott et al. for the US corporate and emerging government bond markets, on the other hand question the statistical significance of the observed outperformance for the developed government bond markets analyzed in the study at hand.

Table 7: Initial risk factor regression

	Benchmark	Single factors				Multi factors	
	Market value weighted	GDP weighted	Population weighted	Land area weighted	Energy weighted	Composite weighted	Equally weighted
Annualized alpha	1.03%	1.35%	1.47%*	1.24%	1.29%*	1.36%*	1.42%
	(0.2879)	(0.1073)	(0.0772)	(0.1995)	(0.0725)	(0.0890)	(0.2142)
Market return	-9.17%***	-6.74%***	-4.01%**	6.56%***	-4.99%***	-2.48%	-2.10%
	(0.0000)	(0.0002)	(0.0359)	(0.0030)	(0.0019)	(0.1619)	(0.4267)
SMB	-4.75%	-5.01%	-4.42%	3.55%	-3.79%	-2.63%	-2.44%
	(0.1987)	(0.1446)	(0.1796)	(0.2422)	(0.1495)	(0.3669)	(0.6032)
HML	-1.42%	-0.41%	1.62%	5.13%*	0.10%	1.51%	6.53%*
	(0.6274)	(0.8683)	(0.5377)	(0.0627)	(0.9637)	(0.5292)	(0.0867)
TERM	52.48%***	51.07%***	50.08%***	51.31%***	54.64%***	51.71%***	46.14%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
DEFAULT	95.61%***	90.50%***	96.68%***	92.94%***	75.68%***	89.11%***	134.03%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Adj. R square	66.15%	70.28%	72.14%	72.76%	74.72%	74.47%	70.39%
Paired t-test p-value	n/a	(0.2397)	(0.2417)	(0.7704)	(0.4620)	(0.3944)	(0.5549)

Notes: ***/**/* denotes significance at the 1% / 5% / 10% level. The table shows the multifactor regression results of the regression setting similar to Arnott et al. (2010). The monthly index returns minus the risk free rate are regressed on several risk factors: (1) the Fama and French equity market excess returns, (2) the Fama and French equity risk factor SMB (size), (3) the Fama and French equity risk factor HML (book to market), (4) the bond risk factor TERM and (5) the bond risk factor DEFAULT. The paired t-test investigates whether the difference between the abnormal return (alpha) of the indices (fundamentally and equally weighted indices) and the benchmark (market value weighted index) is significantly different from zero. The OLS regressions include a variance-covariance estimation based on Newey and West (1987) and are based on monthly data points. The regressions analyze the time period from January 1991 to December 2014 and use 288 data points for each setting. Values in brackets represent p-values.

4.3. Extended risk factor regression

We implement a second regression setting, whereby we extend the risk factor universe to receive additional insights into the risk factor exposure of the different indices. We continue to consider the Fama and French equity risk factors SMB and

HML as well as the bond risk factors term and default risk, but additionally include the following risk factors that have not been considered in previous research:

- Excess market value weighted government bond index returns
- Duration risk
- Convexity risk
- Liquidity risk
- Carry trade risk

First, we replace the Fama and French excess equity market return by the government bond market value weighted index returns minus the risk free rate as market return. The resulting regression alpha can therefore directly be interpreted as abnormal return, i.e., as over- or underperformance of the valuation-indifferent indices with respect to the market value weighted benchmark. Thus, the exposure towards the remaining explanatory variables also needs to be interpreted as risk factor exposure additional to the risk factor exposure in the market value weighted index.

Second, we complement the bond risk factor TERM with an additional risk factor for duration risk. The bond risk factor TERM reflects the fact that long-term bonds generally feature higher interest rates than short-term bonds since duration risk increases with longer bond terms. We take an additional perspective on duration risk by considering that countries with high duration bonds might have a different yield level than countries with low duration bonds. In fact, our analysis shows that countries with a high average duration show a lower yield level than countries with a low average duration. We believe that the explanation for this connection can be found in inverting the relationship: countries with a low interest rate level generally issue longer-term bonds, whereas countries with a high interest rate environment issue shorter-term bonds. As for the comparison of index methodologies, we would therefore expect those indices, which show a higher exposure towards countries issuing high duration bonds, to underperform. The previous Table 6 illustrated that the market value weighted index exhibits the highest average duration. The outperformance of the fundamentally weighted indices might therefore further be explained by its increased allocation to low duration countries, which exhibit higher yields. To test this theory, we separate the countries into two portfolios, whereby the first portfolio contains the bonds of those countries with a low average duration level and the second portfolio entails those countries with a high average duration level. The portfolios are rebalanced every month. Finally, we build the duration risk factor (DURATION) by subtracting the return of the second portfolio (countries with high duration) from the return of the first portfolio (countries with low duration).

Third, we extend the bond risk factors by including convexity risk (CONVEXITY). Bonds with high convexity risk should generally experience higher returns, owing to the lower interest rate sensitivity in an increasing interest rate environment and higher interest rate sensitivity in a decreasing interest rate environment. We therefore divide the index country universe into two different portfolios – the first portfolio contains countries with bonds featuring high convexity risk, while the second portfolio combines those countries with bonds featuring low convexity risk. The portfolios are rebalanced on a monthly basis and their return is calculated by equally weighting the returns of the constituent countries. The regression risk factor CONVEXITY is then calculated by deducting the returns of the low convexity portfolio from the return of the high convexity portfolio.

Fourth, we extend the risk factor analysis by testing the abnormal returns for liquidity risk (LIQ). Given the high interdependence of liquidity and volatility, we approximate liquidity risk with changes in the VIX index. Please refer to the research conducted by Nagel (2012), Brunnermeier and Pedersen (2009) as well as Adrian and Shin (2010) for a detailed discussion on the relationship. Data on the VIX index is obtained from the Chicago Board Options Exchange (CBOE).

Last, we include a carry trade risk factor (CARRY). Thereby, we consider the currency pairs of all countries that are part of the analysis with respect to the USD. The carry trade return risk factor is calculated by separating the currencies into two portfolios, whereby the first portfolio contains the currencies with large interest rate differentials towards the USD and the second portfolio entails those currencies with low interest rate differentials towards the USD. The portfolios are rebalanced every month. Following Hu, Pan and Wang (2013), the return for each currency pair is

$$r_{t+1} = i_t^* - i_t + s_t - s_{t+1} = i_t^* - i_t - \Delta s_{t+1} \tag{2}$$

where i_t^* is the foreign risk free rate, i_t the US risk free rate and s_t the log of the spot foreign exchange rate of the foreign currency to the USD at time t. The portfolio return is calculated by equal weighting the returns of the currencies within each portfolio. Finally, we build the carry trade return risk factor (CARRY) by subtracting the return of the second portfolio (currencies with low interest rate differentials) from the return of the first portfolio (currencies with high interest rate differentials).

Below formula shows the multifactor regression approach, whereby r_{fw} captures the return of the valuation-indifferent indices and r_{mv} the return of the market value weighted index.[9] The risk factors for duration, convexity, liquidity as well as carry trade risk represent the newly introduced risk factors that have not been considered in previous research and intend to add further insights with respect to the sources of outperformance of fundamentally weighted fixed income indices.

$$\begin{aligned} r_{fw} = \alpha + r_f + \beta_1(r_{mv} - r_f) + \beta_2 SMB + \beta_3 HML + \beta_4 TERM + \beta_5 \text{DURATION} + \\ \beta_6 DEFAULT + \beta_7 \text{CONVEXITY} + \beta_8 LIQ + \beta_9 CARRY + \varepsilon \end{aligned} \tag{3}$$

Table 8 shows the risk factor regression results for the fundamentally weighted composite index. The left panel illustrates the results for the standard settings, i.e., the analyses based on unhedged index returns. As already seen in the initial risk factor regression, the equity risk factors SMB and HML do not show significant exposures. The standard bond risk factors term risk and default risk again show statistically significant and economically relevant beta values. If we compare the beta values of those two bond risk factors in Table 8 (extended risk factor regression) to Table 7 (initial risk factor regression), we can observe a reduction in their size. This is caused by the fact that a share of the return of the composite index that is due to term and default risk is already captured in the explanatory variable r_{mv} (market value weighted index returns) – namely, the term and default risk exposure that corresponds

[9] We test the multifactor regression approach for potential multicollinearity between the explanatory variables by calculating the pairwise correlations as well as the variance inflation factor (VIF) for each variable. We find that the variables r_{mv} and DEFAULT exhibit the highest pairwise correlation (0.65). However, we find no evidence for multicollinearity (average VIF of 1.8, maximum VIF of 3.4).

to the term and default risk exposure of the market value weighted bond index. As noted earlier, the risk factor exposure of the extended regression setting in Table 8 only captures the risk factor exposure additional to the risk factor exposure in the market value weighted index. Regression setting 1, which includes the bond risk factors that have been considered in previous studies (TERM, DEFAULT), yields a statistically significant annualized alpha – and therefore an outperformance of the composite index with respect to the market value weighted bond index – of 90 bps.

Table 8: Extended risk factor regression – composite index

Composite	Unhedged returns					Hedged returns				
Regression setting	1	2	3	4	5	1	2	3	4	5
Annualized alpha	0.90%***	0.50%**	0.44%*	0.42%*	0.24%	-0.13%	-0.31%**	-0.36%***	-0.35%***	-0.34%**
	(0.0023)	(0.0405)	(0.0606)	(0.0702)	(0.3112)	(0.2419)	(0.0109)	(0.0046)	(0.0050)	(0.0109)
Market return	69.0%***	71.5%***	72.8%***	74.5%***	78.8%***	103.2%***	99.8%***	99.9%***	99.7%***	99.5%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SMB	-0.3%	-0.7%	-0.6%	-0.1%	-0.7%	0.6%	0.6%	0.5%	0.4%	0.5%
	(0.8340)	(0.5668)	(0.6012)	(0.9173)	(0.5877)	(0.1338)	(0.1865)	(0.2565)	(0.3213)	(0.2908)
HML	1.2%	0.7%	1.0%	1.4%	1.2%	0.0%	-0.2%	-0.2%	-0.2%	-0.2%
	(0.2788)	(0.4989)	(0.2923)	(0.1470)	(0.1419)	(0.9476)	(0.5860)	(0.5659)	(0.4764)	(0.4950)
TERM	14.6%***	16.4%***	15.8%***	15.1%***	11.9%***	3.2%*	6.6%***	6.6%***	6.7%***	6.8%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0583)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
DURATION		23.4%***	19.0%***	17.9%***	14.2%***		12.3%***	11.4%***	11.6%***	11.6%***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DEFAULT	29.8%***	24.3%***	21.7%***	18.7%***	15.0%***	1.3%*	1.0%	0.8%	1.0%	1.0%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0897)	(0.1494)	(0.2468)	(0.1498)	(0.1279)
CONVEXITY			13.2%***	12.7%***	7.7%**			6.0%**	6.1%**	6.1%**
			(0.0004)	(0.0002)	(0.0267)			(0.0378)	(0.0341)	(0.0340)
LIQ				-0.5%***	-0.2%				0.1%	0.0%
				(0.0001)	(0.1248)				(0.4138)	(0.5759)
CARRY					11.7%***					-0.4%
					(0.0011)					(0.5109)
Adj. R square	93.42%	94.94%	95.37%	95.53%	96.09%	96.51%	96.97%	97.05%	97.05%	97.05%

Notes: ***/**/* denotes significance at the 1% / 5% / 10% level. The table shows the extended multifactor regression results of the composite index. The monthly index returns minus the risk free rate are regressed on several risk factors: (1) the monthly market value weighted government bond index returns minus the risk free rate ("Market return"), (2) the Fama and French equity risk factor SMB (size), (3) the Fama and French equity risk factor HML (book to market), (4) the bond risk factor TERM, (5) the country duration risk factor DURATION, (6) the bond risk factor DEFAULT, (7) the bond risk factor CONVEXITY, (8) liquidity risk (LIQ, approximated by the VIX index) and (9) carry trade risk (CARRY). The OLS regressions include a variance-covariance estimation based on Newey and West (1987) and are based on monthly data points. The regressions analyze the time period from January 1991 to December 2014 and use 288 data points for each setting. Values in brackets represent p-values.

The fundamentally weighted composite index also shows a highly significant exposure towards the newly introduced bond risk factors duration (introduced in regression setting 2) and convexity (introduced in regression setting 3). By including the new bond risk factors duration and convexity, the annualized alpha is reduced to 44 bps. The higher exposure towards those newly introduced risk factors is therefore able to explain an additional part of the outperformance of the fundamentally weighted index.

The regression analysis is further extended by including the liquidity and carry trade risk factors (regression settings 4 and 5). The index returns show a partly statistically significant exposure towards liquidity risk (LIQ), although the economic impact of the risk factor is rather low. However, the fundamentally weighted strategy shows a substantial exposure towards the carry trade risk factor (CARRY). Not only is the carry trade risk factor highly statistically significant, but it is also able to explain the remainder of the abnormal returns. By including the additional risk factors liquidity risk and carry trade risk, the annualized alpha shrinks to 24 bps and loses its statistical significance.

The extension of the risk factor universe consequently leads to the conclusion that the abnormal returns found previously can in particular be attributed to a higher term, duration, default, convexity and carry trade risk exposure of the fundamentally weighted composite index. The explanatory power of the models, measured by the adjusted R^2, is illustrated in the last row of Table 8. The explanatory power is increasing continuously with the inclusion of the new risk factors. Obviously, the largest amount of the models' explanatory power stems from the market return. However, we can quantify the added value of the other explanatory variables by comparing the adjusted R^2 of the extended risk factor regression to the adjusted R^2 of the single factor regression in Table 4, where the market return represents the only explanatory variable. For the fundamentally weighted composite index, the inclusion of the risk factors increases the explanatory power from 90.43% to 96.09%. The investigated risk factors therefore substantially improve our understanding of the sources of outperformance in the fundamental indexing methodology.

The right panel of Table 8 lists the results of the robustness check with respect to the hedged version of the fundamentally weighted composite index. This additional analysis is based on hedged returns, whereby we use local currency returns and take the interest rate differentials as hedging costs into account. By looking at hedged returns, we exclude any foreign exchange effects. This is reflected in the results by the fact that the significant exposure towards carry trade risk vanishes. The default risk exposure – although still positive – shows a reduced statistical significance. The risk factors term, duration and convexity remain significant risk factors in explaining the returns of the fundamentally weighted composite index. As opposed to the unhedged environment, the abnormal returns in the hedged environment are negative. Furthermore, we can even observe a statistically significant underperformance of the composite strategy when including the full set of risk factors. The robustness check on the hedged returns therefore further opposes the argument that the fundamentally weighted indices are able to systematically outperform the market value weighted index.

Tables 9 to 13 show the risk factor regression results for the fundamentally weighted standalone indices and the equally weighted index. The results found previously can be confirmed for all standalone weighting methodologies. In the unhedged environment, the abnormal positive returns found previously can be fully explained by the analyzed risk factors. None of the standalone indices shows any statistically significant abnormal return after accounting for the differences in risk exposure. The land area weighted index, which exhibits the largest deviation in country allocation of the fundamentally weighted indices, exhibits the largest exposures towards the risk factors duration and default. The GDP weighted index as well as the energy weighted index, which show the highest average allocation to the US, exhibit the lowest exposure towards the risk factor default. In addition to the fundamentally weighted indices, also the equally weighted index does not show abnormal returns unexplainable by the risk factor exposure. For all indices, in particular the newly introduced bond risk factors duration, convexity as well as carry trade risk seem to be responsible for a substantial amount of the outperformance. The inclusion of the risk factors increases the explanatory power of the model for the GDP weighted index by 0.95 pps, for the population weighted index by 5.01 pps, for the land area weighted index by 19.34 pps, for the energy weighted index by 3.74 pps and for the equally weighted index by 12.74 pps. In particular for those indices, which show high deviations from the market value weighting (e.g., land area weighted and equally weighted indices), the investigated risk factor universe is able to explain a substantial additional part of the performance.

The robustness check for hedged returns of the fundamentally weighted standalone indices and the equally weighted index confirms the results found previously: The abnormal returns are consistently negative, however, we only find a statistical significance of the negative abnormal returns for the population weighted, the land area weighted and the equally weighted indices.

In the study at hand we are questioning whether the outperformance found for fundamentally weighted indices might be explained by the Noisy Market Hypothesis or different risk factor exposures. The results found in this study question the Noisy Market Hypothesis and the argument that the outperformance results from a performance drag in the market value weighting methodology. Rather, we find statistically significant and economically relevant evidence that the fundamentally weighted government bond indices exhibit a different risk exposure and therefore show a higher compensation of such elevated risk exposure. The fact that we find analogous results for the equally weighted index, which represents an additional valuation-indifferent weighting methodology, further supports the argument that the Noisy Market Hypothesis does not hold. Arnott et al. (2010) see their study on the fixed income market as an out-of-sample test to support their previous research in equity markets. Following this argument, our results tend to support the critics of the fundamental indexing approach in equity markets, which argue that also the equity outperformance in fundamental indexing can be explained by a risk factor tilt.

Table 9: Extended risk factor regression – GDP weighted index

GDP	Unhedged returns					Hedged returns				
Regression setting	1	2	3	4	5	1	2	3	4	5
Annualized alpha	0.55%***	0.40%*	0.38%*	0.38%*	0.29%	-0.11%	-0.17%	-0.19%	-0.18%	-0.16%
	(0.0090)	(0.0538)	(0.0703)	(0.0699)	(0.1798)	(0.3285)	(0.1365)	(0.1158)	(0.1178)	(0.1874)
Market return	82.5%***	83.5%***	84.0%***	84.0%***	85.9%***	103.2%***	101.9%***	101.9%***	101.1%***	100.8%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SMB	-1.3%	-1.5%	-1.4%	-1.4%	-1.6%	0.8%**	0.8%*	0.7%*	0.6%	0.6%
	(0.2270)	(0.1577)	(0.1681)	(0.1682)	(0.1313)	(0.0407)	(0.0534)	(0.0608)	(0.1406)	(0.1054)
HML	0.5%	0.3%	0.4%	0.4%	0.3%	0.1%	0.0%	0.0%	-0.1%	-0.1%
	(0.5847)	(0.7530)	(0.6445)	(0.6412)	(0.6981)	(0.7472)	(0.8829)	(0.8918)	(0.7128)	(0.7527)
TERM	7.6%***	8.3%***	8.0%***	8.0%***	6.6%***	3.1%**	4.4%**	4.4%**	4.7%**	4.9%***
	(0.0006)	(0.0001)	(0.0002)	(0.0002)	(0.0009)	(0.0490)	(0.0143)	(0.0160)	(0.0112)	(0.0087)
DURATION		8.9%***	7.2%**	7.2%**	5.5%*		4.8%***	4.5%**	5.3%***	5.3%***
		(0.0041)	(0.0233)	(0.0214)	(0.0840)		(0.0043)	(0.0104)	(0.0014)	(0.0013)
DEFAULT	13.0%***	11.0%***	10.0%***	9.9%***	8.2%***	0.1%	0.0%	-0.1%	0.5%	0.6%
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0085)	(0.8808)	(0.9503)	(0.8546)	(0.3311)	(0.2612)
CONVEXITY			5.0%*	5.0%*	2.8%			1.9%	2.1%	2.3%
			(0.0603)	(0.0635)	(0.3783)			(0.4188)	(0.3225)	(0.2926)
LIQ				0.0%	0.1%				0.2%***	0.2%***
				(0.9523)	(0.3542)				(0.0010)	(0.0059)
CARRY					5.1%*					-0.8%
					(0.0995)					(0.1829)
Adj. R square	96.59%	96.80%	96.85%	96.84%	96.94%	97.68%	97.74%	97.74%	97.85%	97.85%

Notes: Please refer to Table 8 for a detailed description of the variables.

Table 10: Extended risk factor regression – population weighted index

Population	Unhedged returns					Hedged returns				
Regression setting	1	2	3	4	5	1	2	3	4	5
Annualized alpha	0.88%***	0.46%*	0.38%	0.37%	0.20%	-0.06%	-0.27%**	-0.36%***	-0.36%***	-0.39%***
	(0.0061)	(0.0800)	(0.1369)	(0.1521)	(0.4691)	(0.5984)	(0.0192)	(0.0022)	(0.0023)	(0.0016)
Market return	77.2%***	79.9%***	81.6%***	82.7%***	86.5%***	105.5%***	101.5%***	101.7%***	101.8%***	102.2%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SMB	-1.5%	-1.9%	-1.8%	-1.5%	-2.0%	0.6%	0.5%	0.4%	0.4%	0.3%
	(0.3358)	(0.1613)	(0.1758)	(0.2520)	(0.1617)	(0.1432)	(0.1654)	(0.3049)	(0.2762)	(0.3883)
HML	1.7%	1.1%	1.5%	1.8%*	1.6%*	0.2%	0.0%	0.0%	0.0%	0.0%
	(0.1625)	(0.3155)	(0.1185)	(0.0808)	(0.0689)	(0.6384)	(0.9754)	(0.9788)	(0.9759)	(0.9710)
TERM	8.8%***	10.8%***	10.0%***	9.5%***	6.7%***	0.0%	4.1%***	4.0%***	4.0%***	3.8%**
	(0.0067)	(0.0001)	(0.0001)	(0.0001)	(0.0027)	(0.9982)	(0.0082)	(0.0078)	(0.0086)	(0.0123)
DURATION		24.7%***	18.8%***	18.1%***	14.8%***		14.8%***	13.1%***	13.0%***	13.1%***
		(0.0000)	(0.0000)	(0.0000)	(0.0007)		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DEFAULT	28.2%***	22.4%***	18.8%***	17.0%***	13.6%***	2.0%**	1.6%**	1.2%**	1.2%*	1.1%*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0173)	(0.0162)	(0.0404)	(0.0710)	(0.0872)
CONVEXITY			17.9%***	17.6%***	13.2%***			11.0%***	11.0%***	10.8%***
			(0.0000)	(0.0000)	(0.0002)			(0.0000)	(0.0000)	(0.0000)
LIQ				-0.3%**	-0.1%				0.0%	0.0%
				(0.0411)	(0.7154)				(0.7040)	(0.8639)
CARRY					10.3%***					0.9%
					(0.0036)					(0.2163)
Adj. R square	93.29%	94.83%	95.54%	95.59%	95.97%	96.05%	96.75%	97.10%	97.09%	97.10%

Notes: Please refer to Table 8 for a detailed description of the variables.

Table 11: Extended risk factor regression – land area weighted index

Land area	Unhedged returns					Hedged returns				
Regression setting	1	2	3	4	5	1	2	3	4	5
Annualized alpha	1.46%**	0.61%	0.52%	0.46%	0.05%	-0.12%	-0.47%**	-0.54%**	-0.54%**	-0.54%**
	(0.0281)	(0.2813)	(0.3295)	(0.3788)	(0.9240)	(0.5738)	(0.0211)	(0.0151)	(0.0129)	(0.0156)
Market return	49.1%***	54.7%***	56.4%***	62.1%***	71.5%***	105.3%***	98.4%***	98.6%***	99.3%***	99.3%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SMB	3.2%	2.3%	2.5%	4.0%**	2.8%	0.8%	0.6%	0.5%	0.6%	0.6%
	(0.2072)	(0.3289)	(0.2639)	(0.0384)	(0.1888)	(0.3398)	(0.4416)	(0.5285)	(0.4152)	(0.4111)
HML	2.2%	1.0%	1.5%	2.8%	2.4%	-0.3%	-0.6%	-0.6%	-0.5%	-0.5%
	(0.3375)	(0.5897)	(0.4332)	(0.1275)	(0.1586)	(0.6983)	(0.3414)	(0.3218)	(0.4600)	(0.4542)
TERM	22.8%***	26.9%***	26.0%***	23.5%***	16.5%***	1.5%	8.5%***	8.4%***	8.1%***	8.1%***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0012)	(0.6388)	(0.0011)	(0.0010)	(0.0011)	(0.0012)
DURATION		50.3%***	43.9%***	40.6%***	32.3%***		25.0%***	23.8%***	23.1%***	23.1%***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DEFAULT	65.1%***	53.3%***	49.5%***	40.1%***	31.7%***	1.3%	0.6%	0.3%	-0.2%	-0.2%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3204)	(0.5930)	(0.7812)	(0.8619)	(0.8610)
CONVEXITY			19.3%**	17.8%**	6.8%			7.8%	7.6%	7.6%
			(0.0376)	(0.0335)	(0.4080)			(0.2704)	(0.2809)	(0.2898)
LIQ				-1.6%***	-1.0%***				-0.2%	-0.2%
				(0.0000)	(0.0026)				(0.2481)	(0.2672)
CARRY					25.8%***					0.0%
					(0.0001)					(0.9866)
Adj. R square	78.72%	83.82%	84.45%	85.74%	87.70%	87.70%	89.43%	89.55%	89.59%	89.56%

Notes: Please refer to Table 8 for a detailed description of the variables.

Table 12: Extended risk factor regression – energy weighted index

Energy	Unhedged returns					Hedged returns				
Regression setting	1	2	3	4	5	1	2	3	4	5
Annualized alpha	0.69%***	0.47%**	0.42%**	0.41%**	0.31%	-0.24%	-0.33%*	-0.36%**	-0.35%**	-0.30%
	(0.0014)	(0.0207)	(0.0366)	(0.0389)	(0.1115)	(0.1328)	(0.0581)	(0.0437)	(0.0493)	(0.1052)
Market return	65.3%***	66.7%***	67.7%***	68.3%***	70.6%***	98.9%***	97.2%***	97.3%***	96.5%***	95.8%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SMB	-0.9%	-1.2%	-1.1%	-0.9%	-1.2%	0.4%	0.4%	0.3%	0.2%	0.3%
	(0.4490)	(0.3245)	(0.3304)	(0.4091)	(0.2999)	(0.4552)	(0.5027)	(0.5568)	(0.7806)	(0.6420)
HML	0.7%	0.4%	0.6%	0.8%	0.7%	-0.2%	-0.3%	-0.3%	-0.5%	-0.4%
	(0.4389)	(0.6536)	(0.4511)	(0.3638)	(0.3873)	(0.6650)	(0.5464)	(0.5422)	(0.3261)	(0.3763)
TERM	20.1%***	21.2%***	20.7%***	20.4%***	18.7%***	8.1%***	9.8%***	9.8%***	10.1%***	10.5%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0001)	(0.0002)	(0.0001)	(0.0000)
DURATION		13.0%***	9.7%***	9.3%***	7.3%***		6.1%**	5.5%**	6.3%**	6.1%**
		(0.0000)	(0.0006)	(0.0006)	(0.0087)		(0.0149)	(0.0372)	(0.0164)	(0.0169)
DEFAULT	15.0%***	11.9%***	9.9%***	8.8%***	6.8%**	1.9%*	1.8%*	1.6%	2.3%**	2.4%***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0184)	(0.0629)	(0.0887)	(0.1150)	(0.0134)	(0.0056)
CONVEXITY			10.1%***	9.9%***	7.2%***			3.6%	3.8%	4.2%
			(0.0000)	(0.0000)	(0.0037)			(0.2607)	(0.2256)	(0.1983)
LIQ				-0.2%	0.0%				0.2%**	0.1%
				(0.1359)	(0.8246)				(0.0230)	(0.1222)
CARRY					6.3%***					-1.7%**
					(0.0094)					(0.0382)
Adj. R square	95.43%	96.03%	96.34%	96.36%	96.55%	95.52%	95.60%	95.62%	95.71%	95.75%

Notes: Please refer to Table 8 for a detailed description of the variables.

Table 13: Extended risk factor regression – equally weighted index

Equally W.	Unhedged returns					Hedged returns				
Regression setting	1	2	3	4	5	1	2	3	4	5
Annualized alpha	0.91%	0.00%	-0.09%	-0.10%	-0.38%	-0.09%	-0.58%**	-0.66%**	-0.67%**	-0.78%***
	(0.2030)	(0.9932)	(0.8692)	(0.8490)	(0.5220)	(0.7783)	(0.0400)	(0.0134)	(0.0129)	(0.0023)
Market return	88.7%***	94.5%***	96.3%***	97.6%***	104.0%***	117.7%***	108.2%***	108.5%***	109.1%***	110.7%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SMB	0.3%	-0.6%	-0.5%	-0.1%	-0.9%	0.8%	0.5%	0.4%	0.5%	0.3%
	(0.9239)	(0.8199)	(0.8572)	(0.9621)	(0.7490)	(0.4276)	(0.4831)	(0.6006)	(0.4639)	(0.7190)
HML	5.8%**	4.5%**	5.0%**	5.3%**	5.0%**	1.0%	0.6%	0.5%	0.7%	0.6%
	(0.0274)	(0.0468)	(0.0238)	(0.0209)	(0.0159)	(0.3559)	(0.5362)	(0.5392)	(0.4407)	(0.5092)
TERM	-1.9%	2.4%	1.5%	1.0%	-3.8%	-10.9%**	-1.3%	-1.4%	-1.7%	-2.5%
	(0.7402)	(0.6207)	(0.7530)	(0.8377)	(0.3589)	(0.0160)	(0.6482)	(0.6260)	(0.5498)	(0.3424)
DURATION		53.5%***	47.3%***	46.5%***	41.0%***		34.6%***	32.9%***	32.3%***	32.7%***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DEFAULT	59.7%***	47.2%***	43.4%***	41.2%***	35.6%***	-0.3%	-1.2%	-1.6%	-2.1%	-2.4%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8878)	(0.4190)	(0.2849)	(0.1853)	(0.1034)
CONVEXITY			18.6%***	18.3%***	10.9%			10.5%*	10.3%*	9.5%
			(0.0074)	(0.0085)	(0.2175)			(0.0795)	(0.0951)	(0.1312)
LIQ				-0.4%	0.0%				-0.1%	0.0%
				(0.2148)	(0.8996)				(0.1990)	(0.9439)
CARRY					17.3%**					3.7%***
					(0.0486)					(0.0065)
Adj. R square	86.12%	90.10%	90.51%	90.53%	91.11%	82.28%	86.02%	86.29%	86.31%	86.59%

Notes: Please refer to Table 8 for a detailed description of the variables.

5. Conclusion

Our study confirms the outperformance of several fundamental indexing approaches by applying the methodology to the government bond markets on a worldwide scope. Our findings, however, suggest that the outperformance of the fundamentally weighted strategies, although valid, are not due to the Noisy Market Hypothesis and a potential performance drag in market value weighted strategies, but rather based on a difference in risk exposure. First, we find evidence that the strategy does not deliver consistent superior results in all subperiods but rather is dependent on a specific time frame and interest rate environment. Second, the regression analyses reveal statistically significant and economically relevant loadings on several risk factors. We test the previously investigated bond risk factors term as well as default and extend the risk factor universe with the newly introduced explanatory variables duration, convexity, liquidity and carry trade risk. In particular, the exposures towards the risk factors that have not been considered in previous research are able to explain a substantial part of the abnormal returns of valuation-indifferent indices.

It is not our intention to prevent investors from using fundamentally weighted indices, the opposite is true: we believe that it is highly crucial to provide investors with alternatives to the predominant market value weighting approach in indexing – and fundamental indexing is an appealing alternative. In particular in fixed income markets, investors require substitutes for the market value weighted indices, due to the systematic shift – that is inherent in market value weighted fixed income indices – towards those countries and companies with an increasing volume of outstanding debt. However, based on our research results, we argue that there is no systematic performance difference between the market value weighting methodology and valuation-indifferent weighting schemes.

Given the growth in passive investment strategies, we see a significant practical relevance in conducting this study and future research in the field of alternative indexing methodologies. We believe that the growth in passive investing will continue unabated, making future studies on the causes of performance differences between indexing methodologies highly necessary.

References

Adrian, T. & Shin, H.S. (2010). Liquidity and leverage. *Journal of Financial Intermediation, 19*(3), 418-437.

Amenc, N., Goltz, F. & Le Sourd, V. (2009). The Performance of Characteristics-based Indices. *European Financial Management, 15*(2), 241-278.

Arnott, R.D., Hsu, J.C., Li, F. & Shepherd, S.D. (2010). Valuation-Indifferent Weighting for Bonds. *The Journal of Portfolio Management, 36*(3), 117-130.

Arnott, R.D., Hsu, J.C. & Moore, P. (2005). Fundamental Indexation. *Financial Analyst Journal, 61*(2), 83-99.

Arnott, R.D. & West, J.M. (2006). Fundamental Indexes™: Current and Future Applications. *ETFs and Indexing, 2006*(1), 111-121.

Brunnermeier, M.K. & Pedersen, L.H. (2009). Market Liquidity and Funding Liquidity. *Review of Financial Studies, 22*(6), 2201-2238.

Carhart, M.M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance, 52*(1), 57-82.

Chow, T., Hsu, J.C., Kaelsnik, V. & Little, B. (2011). A Survey of Alternative Equity Index Strategies. *Financial Analyst Journal, 67*(5), 37-57.

Fama, E.F. & French, K.R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance, 47*(2), 427-465.

Fama, E.F. & French, K.R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56.

Glabadanidis, P., Obaydin, I. & Zurbruegg, R. (2012). RAFI® Replication: Easier done than said? *Journal of Asset Management, 13*(3), 210-225.

Haugen, R.A. & Baker, N.L. (1991). The efficient market inefficiency of capitalization-weighted stock portfolios. *The Journal of Portfolio Management, 17*(3), 35-40.

Hemminki, J. & Puttonen, V. (2008). Fundamental indexation in Europe. *Journal of Asset Management, 8*(6), 401-405.

Hsu, J.C. (2006). Cap-Weighted Portfolios Are Sub-Optimal Portfolios. *Journal of Investment Management, 4*(3), 44-53.

Hsu, J.C., Li, F. & Kalesnik, V. (2010). Does Valuation-Indifferent Indexing Work for the Real Estate Market? *The Journal of Investing, 19*(3), 72-79.

Hu, G.X., Pan, J. & Wang, J. (2013). Noise as Information for Illiquidity. *The Journal of Finance, 68*(6), 2341-2382.

Kaplan, P.D. (2008). Why Fundamental Indexation Might – or Might Not – Work. *Financial Analyst Journal, 64*(1), 32-39.

Malkiel, B.G. (2003). Passive Investment Strategies and Efficient Markets. *European Financial Management*, *9*(1), 1-10.

Nagel, S. (2012). Evaporating Liquidity. *Review of Financial Studies, 25*(7), 2005-2039.

Newey, W.K. & West, K.D. (1987). A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica, 55*(3), 703-708.

Perold, A.F. (2007). Fundamentally Flawed Indexing. *Financial Analyst Journal, 63*(6), 31-37.

Shepherd, S.D. (2011). Fundamental Index® Fixed-Income Performance: It's All in the Price. *The Journal of Index Investing, 1*(4), 75-80.

Siegel, J.J. (2006, June 14). The ‘Noisy Market’ Hypothesis. The Wall Street Journal. Available online at <http://online.wsj.com/news/articles/SB115025119289879729> [accessed on 18 March 2014].

Treynor, J. (2005). Why Market-Valuation-Indifferent Indexing Works. *Financial Analyst Journal, 61*(5), 65-69.

Part III
Index Linked Investing – A Curse for the Stability of Financial Markets around the Globe?

Lidia Bolla[1], Alexander Kohler[2], Hagen Wittig[3]

Publication status: Accepted (*The Journal of Portfolio Management*)

Abstract

We analyze the development of various risk commonalities in Europe, the US as well as in emerging markets and find a substantial increase of co-movements in trading patterns, price returns and liquidity risk within equity markets. We test the hypothesis that index linked investing is a major driver for the increase in risk commonality. By aggregating the data in a cross-regional perspective, we capitalize on the different levels of indexation in the markets and find statistically significant and economically relevant evidence that the growth in index linked investing is related to the increased co-movement within equity markets. The results suggest a significant increase in market fragility around the globe, leading to an increased danger of more severe reactions to unanticipated events going forward. Portfolio managers are well advised to account for the increased proportion of index linked investing within their risk management tools, diversification approaches and active management strategies.

[1] Lidia Bolla, M.A. HSG, CFA, is Managing Partner at Algofin AG, Webergasse 15, 9000 St. Gallen, Switzerland, lidia.bolla@algofin.ch.

[2] Alexander Kohler, PhD, is Manager at Deloitte Consulting AG, General Guisan-Quai 38, 8022 Zurich, Switzerland, akohler@deloitte.ch.

[3] Hagen Wittig, M.A. HSG, CFA, is Managing Partner at Algofin AG, Webergasse 15, 9000 St. Gallen, Switzerland, hagen.wittig@algofin.ch.

1. Introduction

Since the launch of the first US index funds in the 1970s, markets have seen an exponential growth in index linked investment strategies. According to Sullivan and Xiong (2012), the share of passively managed investments in the US increased from below 10% in 1993 to over 34% in 2010. Both actively and passively managed fund assets have increased in volume over those 17 years – however, while actively managed assets exhibited an annual growth rate of 13%, passively managed assets grew by 26% a year. The trend towards index linked investing is also reflected in the growth of assets under management of exchange traded funds (ETF), which are predominantly classified as passive investment vehicles. Table 1 shows the growth rates of ETF's assets under management (AuM) by region, illustrating the substantial increase of index linked investing all around the world. Given that the European market for index linked investing lags behind the US and only emerged in the last two decades, the increase in ETF AuM from 2003 to 2013 was particularly high in Europe (34% p.a.).

Table 1: Growth in ETF assets under management by region

ETF AuM (in USD bn)	2003*	2013*	Total Growth (2003-2013)	Growth p.a. (2003-2013)
US	144.1	1'614.4	1020%	27%
Europe	20.5	396.6	1835%	34%
Asia Pacific	34.8	167.4	381%	17%
RoW	5.8	75.4	1200%	29%
World	**205.2**	**2'253.8**	**998%**	**27%**

Notes: The table shows the assets under management (AuM) of ETFs in USD bn, including all asset classes, as well as the total and annual growth rate for the period 2003 to 2013; *Source: Deutsche Bank Securities Inc. (2014)

The move into index linked strategies was supported – and possibly even triggered – by several academic studies, such as the research conducted by Sharpe (1966) and Jensen (1968) in early years or Malkiel (2003) in a more recent study, showing that active investing does not lead to higher risk-adjusted net returns than following a passive approach. Malkiel found an outperformance of index linked strategies for both equity and bond markets as well as for US and non-US markets.

Since index linked investment strategies ignore individual company characteristics except those relevant for the index weighting methodology (e.g., market capitalization), market transactions of indexed investment vehicles generally affect all stocks within the underlying index. Index linked investing therefore leads to a market environment where a market participant does not distinguish between single securities and either buys or sells the entire index universe. During bull markets, a large proportion of investors will increase their equity allocation. If they do so by investing in index linked products, they all buy the stocks of the entire index universe. In bear markets or a market crash, index linked investors reduce their equity allocation by selling all stocks of the index universe at a similar time. Consequently, index linked investing promotes a market environment where the decision on the purchase or sale of individual securities is mostly driven by overall market trends (e.g., investor sentiment) and not by security specific characteristics (e.g., profit warning of a certain company). A market environment that is characterized by a large proportion of index linked investing might therefore show an increased co-movement of the securities in the index universe and, accordingly, a reduction in diversification possibilities for investors. The paper at hand tests the hypothesis that the growing share of index linked investing around the world leads to such an increase in co-movements within equity markets.

The co-movement of financial assets can be estimated by analyzing the risk commonalities within a market. A higher co-movement and hence a higher risk commonality is for example reflected in higher correlations of price returns, similar changes in the trading volume of securities or a simultaneous liquidity reduction with respect to the underlying index constituents. In the study at hand, we examine a wide range of risk commonality measures with respect to trading patterns, price returns and liquidity risk and investigate whether the commonality development can be associated with the growth in index linked investing. The analysis is conducted on a worldwide scope and investigates equity markets in the Eurozone, in the UK, in Switzerland, in the US and in emerging markets. Our results show a substantial increase in the co-movement of stocks within all markets. Furthermore, we find statistically significant and economically relevant evidence that the growth in index linked investing is related to the substantial increase in risk commonalities. The analysis illustrates that for regions in an earlier stage in the evolution of index linked investing, large cap companies are more affected by the increase in index linked investing. For regions with more mature passive investing markets, the effect of index linked investing on the risk commonalities starts to spill over to smaller cap companies. Overall, the results tend to suggest a significant increase in market fragility around the globe, leading to an increased danger of more severe reactions to unanticipated events going forward. Portfolio managers consequently need to revise their risk management tools given that the historical correlation structures might underestimate the current and future risks in markets with large proportions of index linked investing. Furthermore, we argue that it might even be reasonable for portfolio managers to use the proportion of index linked investing as a criteria in diversification considerations.

The influence of index linked investing on financial markets and individual securities has been the subject of several studies. The existing body of literature can be broadly divided into two types of studies: (i) event studies, whereby index inclusions (exclusions) and their effect on the included (excluded) stock is being analyzed,[4] and (ii) market studies, whereby authors study the impact of the growth in index linked investing on the overall market. The study at hand can be assigned to the second – to date less investigated – stream. The research in this field has been coined mainly by Sullivan and Xiong (2012) as well as Kamara, Lou and Sadka (2008, 2010). Sullivan and Xiong (2012) study US equity markets over the last twenty years and discover increased commonalities in trading behavior and consequently a higher level of return and trading volume correlation due to the growth in index funds. The authors find that the cross-sectional dispersion in trading volume among stocks was reduced gradually along with the growth of index funds. Furthermore, Sullivan and Xiong observe a substantial decrease in the differences between the stocks' return betas over the recent years, resulting thus in reduced diversification possibilities within the

[4] See Petajisto (2011), Shleifer (1986), Beneish and Whaley (1996), Chan, Kot and Tang (2013) or Biktimirov and Li (2014) on the price impact of index inclusions and exclusions; see Barberis, Shleifer and Wurgler (2005) and Claessens and Yafeh (2013) on the market risk sensitivity impact of index inclusions.

market. In another study on US equity markets, Kamara, Lou and Sadka (2010) find that the return betas of large cap companies increased over the time period analyzed, while small cap companies experienced a reduction in the sensitivity to systematic risk. The authors argue that the growth in passive investment strategies and institutional investing is positively correlated with the development. Since large cap stocks are affected to a higher degree by index linked and institutional investing than small cap stocks, they are also able to explain the dispersion with respect to the company size. In a similar study and on an analogous data set, Kamara, Lou and Sadka (2008) observe a growing divergence with respect to the sensitivities of the stocks' liquidity to the overall market liquidity (liquidity beta). They find that the liquidity of small cap companies became less sensitive to the overall market liquidity, while the commonality in liquidity of large cap companies increased. According to the authors, the growth in passive and institutional investing is a major source for this development.

Those findings imply fundamental consequences for financial markets caused by the growth in index linked investing. However, the existing market studies are uniquely limited to the US. To the best of our knowledge, a study that analyzes and compares the development on a worldwide scope has not yet been conducted. We aim at filling this gap. Thereby, we are not only interested in transferring the research from the US to other markets, but also intend to aggregate the findings of the various markets in a cross-regional perspective. The comparison of different countries and regions provides us with a great advantage: passive investing is on the rise all around the world – however, all markets show a different level of indexation. Based on the existing research on US markets, we would expect different market characteristics for different levels of indexation.

2. Methodology

The following section provides an overview about the analyzed risk commonality measures with respect to trading patterns, price returns and liquidity risk as well as a description of the regression settings. The calculation of the risk commonality measures is based on the approaches by Sullivan and Xiong (2012) as well as Kamara, Lou and Sadka (2008, 2010). Please refer to the appendix for the formal description of the risk commonality measures.

2.1. Description of risk commonalities

For gaining insights into the development of the commonalities in trading patterns, we analyze, analogous to Sullivan and Xiong (2012), the cross-sectional dispersion of the change in trading volume (VΔDISP) and the average pairwise correlation of the change in trading volume (VΔCORR). Both variables are calculated based on the day-to-day logarithmic difference in trading volume. The cross-sectional dispersion of the change in trading volume (VΔDISP) is estimated by calculating the cross-sectional standard deviation of the volume changes for each time period, averaged over a rolling window of 36 months to provide a long-term estimate of the variable.[5] The average pairwise correlation of the change in trading volume (VΔCORR) estimates the pairwise correlations of the change in trading volume between the stocks in a market over a rolling window of 36 months, whereby the correlations are equally weighted to provide an average estimation of the pairwise correlation.

In order to study the development of the commonalities in price returns, we analyze the average pairwise correlations of the price returns (PCORR), calculated analogous to VΔCORR, and the variation in return betas. All variables are based on daily price returns. With respect to the return betas, commonality is tested by investigating whether the securities' returns are increasingly behaving in line with the overall market return. We therefore calculate the average absolute difference of the return betas – i.e., the sensitivity of the securities' returns to the market return – to 1. The variation in return beta ($ABS(\beta_{Ret} - 1)$) is then calculated by equally weighting the individual differences of return betas to 1. The return betas are thereby estimated over a rolling window of 36 months.

[5] We conduct several robustness checks on the rolling window size for all risk commonality measures and find that it does not alter the conclusions drawn in this study. For the sake of brevity, we abstain from presenting those additional results.

For analyzing the development of the commonalities in liquidity risk, we calculate the average pairwise correlation of liquidity (LCORR), calculated analogous to VΔCORR and PCORR, and the variation in liquidity betas ($ABS(\beta_{Liq} - 1)$). Stock liquidity is measured as the change of the Amihud (2002) measure of stock illiquidity. The Amihud measure of stock illiquidity is defined as the average ratio of the daily return value to the dollar trading volume on the same day. The measure therefore captures the trading volume's price impact, which is expected to be larger for illiquid markets.

2.2. Within-region regression analysis

In order to draw conclusions about the relationship of the proposed variables and index linked investing, we will perform OLS regressions including a variance-covariance estimation based on Newey and West (1987). Thereby, the various measures are regressed on the proportion of index linked investing in the respective regions.

$$\gamma_t = \alpha_\gamma + \beta_{AMR} * AMR_t + \varepsilon_t \tag{1}$$

γ_t refers to the risk commonality measures described previously, which will be tested by separate regressions. The proportion of index linked investing is measured by the ratio of the assets of index linked funds in the respective market towards the market capitalization of the stocks within the respective index (AuM-market-capitalization-ratio, AMR). This regression setting intends to describe the relationship between index linked investing and risk commonalities for the various markets as well as for different size segments of the markets.

2.3. Cross-regional regression analysis

Additionally, we aggregate the findings of the various markets in a cross-regional perspective. We perform a multifactor regression, whereby the risk commonality measures of all regions are regressed on the proportion of index linked investing in the respective regions. We furthermore control for differences in market characteristics, which might lead to differences in the level of commonality but are not caused by the level of index linked investing.

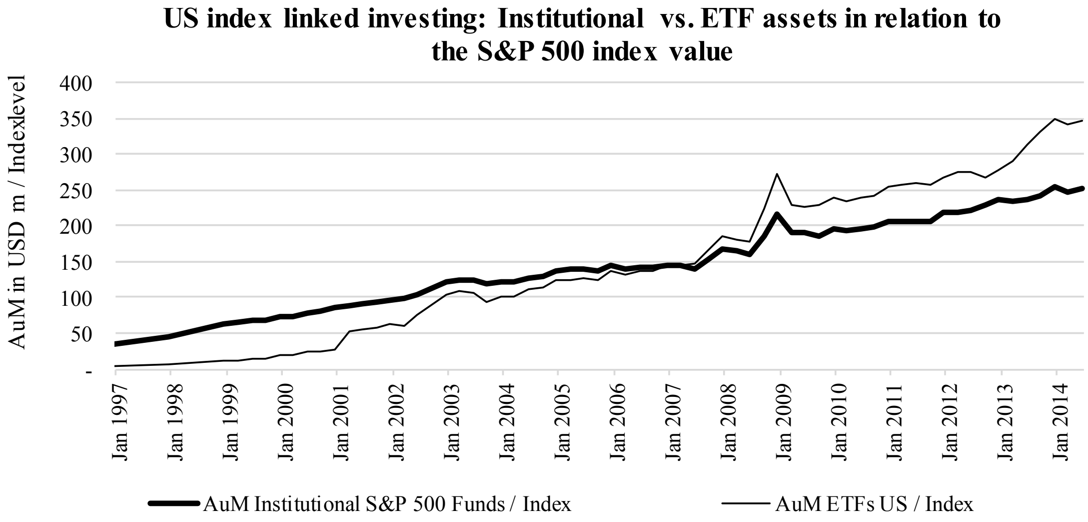
$$\gamma_{t,i} = \alpha_{\gamma} + \beta_{AMR} * AMR_{t,i} + \beta_{MS} * MS_{t,i} + \beta_{HHI} * HHI_{t,i} + \varepsilon_t \qquad (2)$$

As control variables, we include the region's market size (MS), represented by the free float market capitalization of the region's stock market as well as the Herfindahl Index (HHI), which accounts for the market concentration. The HHI is calculated with respect to the market capitalization of the index constituents.

3. Data

The study at hand investigates the stock markets in the Eurozone, the UK, Switzerland, the US and emerging markets and therefore covers the majority of the worldwide market capitalization. In the US, index linked investing of institutional as well as retail investors is most often conducted by investing in ETFs or passive mutual funds, for which data availability is high. However, in non-US markets, the proportion of index linked investing has to be approximated, given that institutional investors often also use personalized mandates and institutional funds, for which data availability is poor. We approximate the development of global index linked investing by analyzing ETF assets. Given that ETFs are most often used by private investors, the question arises whether they provide a good approximation for the overall index linked investment market, including institutional index linked investing. Figure 1 shows the development of institutional index linked assets as well as the development of ETF assets in the US. In order to eliminate any market impact, both variables are divided by the S&P 500 index value. The correlation of the changes between institutional and ETF assets, adjusted by the market impact, over the observed time period amounts to 78%. Therefore, it can be concluded that ETF assets are a good proxy for the overall market of index linked investing.

Figure 1: US index linked investing: Institutional vs. ETF assets



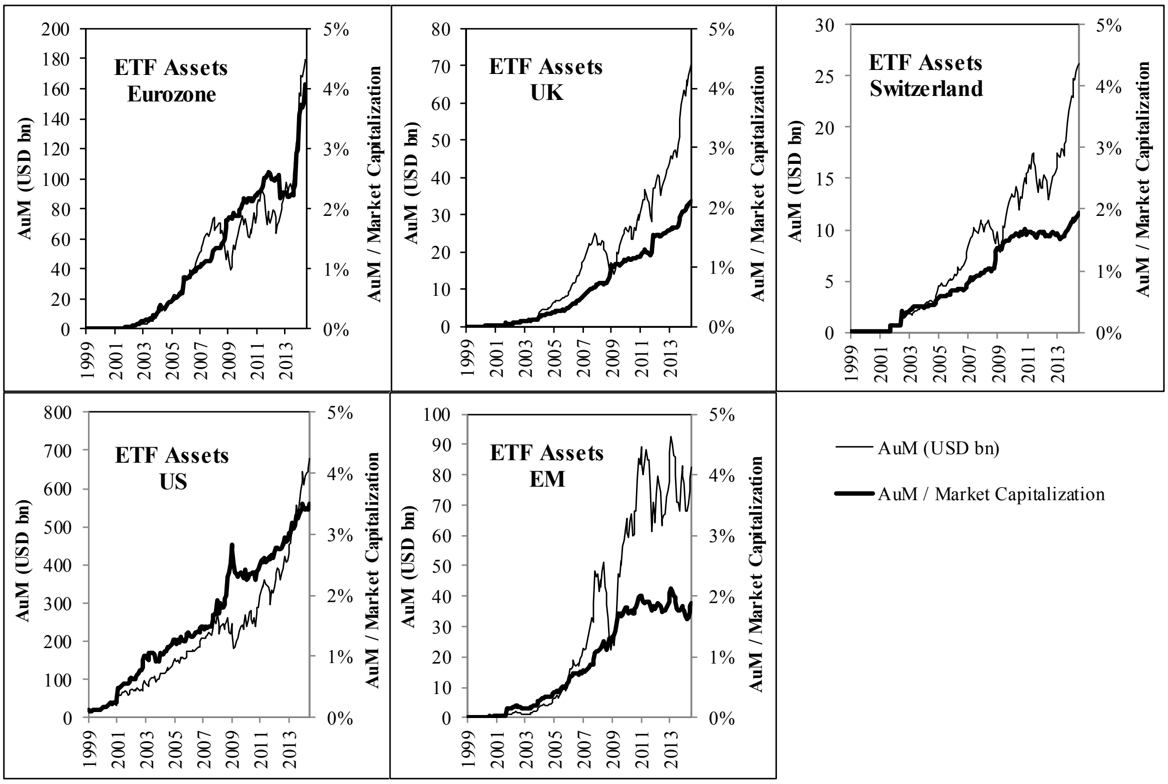
Notes*:* The graph shows the assets under management (in USD m) of institutional S&P 500 funds and US ETF assets on a quarterly basis, divided by the S&P 500 index value at every point in time (Source: WRDS, Bloomberg).

We create a dataset consisting of equity ETFs, which hold assets in the markets considered in the analysis. All ETFs linked to indices from MSCI, STOXX, S&P Dow Jones, NASDAQ, Russell, FTSE and all relevant European country indices (e.g., SMI, DAX, CAC) are considered in the analysis. ETFs following a leveraged or short investment strategy are excluded from the dataset. For those ETFs that hold assets in various regions, only the percentage of assets that is linked to the considered market is included in the analysis. For example, an ETF linked to the MSCI World Index might hold 53% US assets, 13% Eurozone assets, 13% UK assets, 4% Swiss assets and 0% emerging market assets. This allocation is then used to allocate the fund's assets under management to the respective regions. Our dataset accounts for over 900 ETFs and the AuM of the ETFs in our dataset sum up to USD 1.039 trn as of 30 June 2014.

We obtain information on the ETF AuM from Bloomberg on a monthly basis. Figure 2 shows the ETF's AuM, allocated to the regions analyzed, as well as the ratio of the ETF's AuM to the respective market capitalization of the total stock market index in the respective region (Euro Stoxx for the Eurozone, FTSE All Share for the UK, SPI for Switzerland, S&P 1500 for the US and Stoxx EM 1500 for emerging markets).

As expected, the figure shows a substantial increase in the assets under management of ETFs, both in absolute terms as well as in proportion to the market capitalization.

Figure 2: ETF assets under management and proportion of index linked investing by region



Notes: On the left axis, the graphs show the AuM of ETFs linked to the stock markets in the Eurozone (top left graph), in the UK (top middle graph), in Switzerland (top right graph), in the US (bottom left graph) and in emerging markets (bottom right graph). Total assets under management are measured in USD bn. On the right axis, the graphs show the proportion of index linked investing by ETFs, measured by the ratio total net assets of ETFs to the free float market capitalization of the stocks in the respective total market index (Euro Stoxx for the Eurozone, FTSE All Share for the UK, SPI for Switzerland, S&P 1500 for the US and Stoxx EM 1500 for emerging markets).

The risk commonality measures are calculated for different settings. First, we investigate the stock markets by analyzing the constituents of the main market indices of the regions: (i) the Euro Stoxx Large for the Eurozone, (ii) the FTSE 100 for the UK market, (iii) the SMI for Switzerland, (iv) the S&P 100 for the US and (v) the Stoxx Emerging Markets 50 for the emerging market region. Given that this analysis might be biased due to the focus on large cap companies, we also conduct an analysis based on the total market indices and investigate the differences in risk commonality between the different company size quartiles. The total market indices analyzed are

(i) the Euro Stoxx for the Eurozone, (ii) the FTSE All Share for the UK, (iii) the SPI for Switzerland, (iv) the S&P 1500 for the US and (v) the Stoxx EM 1500 for the emerging market region.

The risk commonality measures will be calculated for all index constituents of those indices. At any point in time, the calculations of the risk commonality measures only consider these stocks, which are listed as index constituents at that time. The only exceptions are the emerging market indices: due to the fact that they were launched only very recently, index constituent information is not available for the time period required. We therefore approximately use the constituents at inception of the index for the calculations of the entire observation period. As for all size quartile calculations, we only use stocks that have been part of the respective index for the entire observation period. This limitation is implemented in order to ensure stable size quartiles with a homogenous set of quartile constituents. The index constituent information is obtained on a quarterly basis from Bloomberg. Daily trading volume data, daily closing price information and daily market capitalization figures of the index constituents are obtained from Bloomberg.

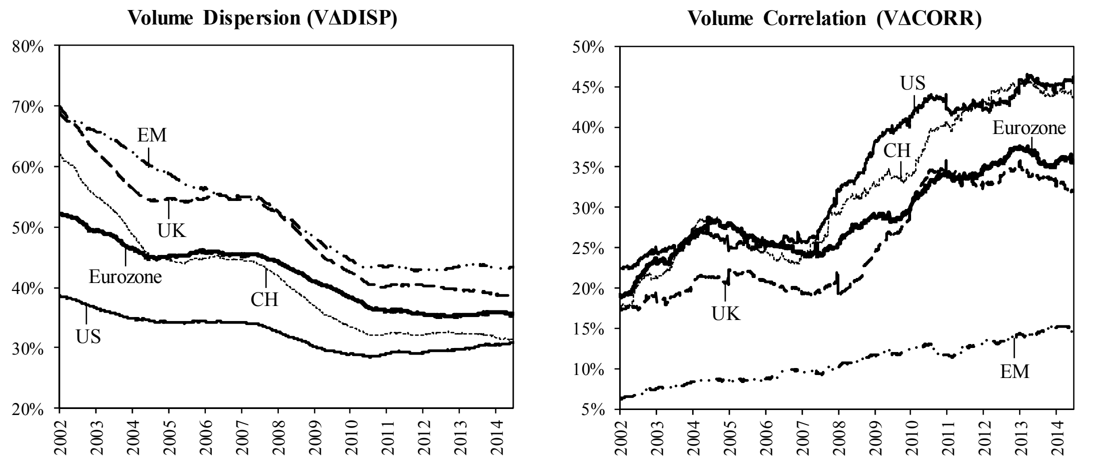
4. Results

First, we analyze the co-movement of financial assets within the different markets by calculating the risk commonalities with respect to trading patterns, price returns and liquidity risk. In a second step, we measure the relationship between the development of the risk commonalities and the development of the proportion in index linked investing.

4.1. Risk commonality measures

With respect to commonalities in trading patterns, we study the development of the cross-sectional dispersion in volume changes as well as the average pairwise correlation of volume changes of the index constituents. A decrease in the dispersion of trading volume changes indicates increased trading commonality. Similarly, an increase in the average pairwise correlation of volume changes indicates increased commonality in the markets. Figure 3 displays the results graphically and clearly shows an increase in trading pattern commonality in the recent decade for all markets analyzed. The dispersion in volume changes in the UK market and emerging market regions for example fell from around 70% to 40%. The US, already being on a lower level with respect to the dispersion in volume changes, experienced a less substantial reduction in the period analyzed. As for the average pairwise correlation of volume changes, a substantial increase in particular for the developed markets can be observed. Generally, the emerging market region shows the lowest level of trading pattern commonality whereas the US displays the highest co-movement in trading patterns.

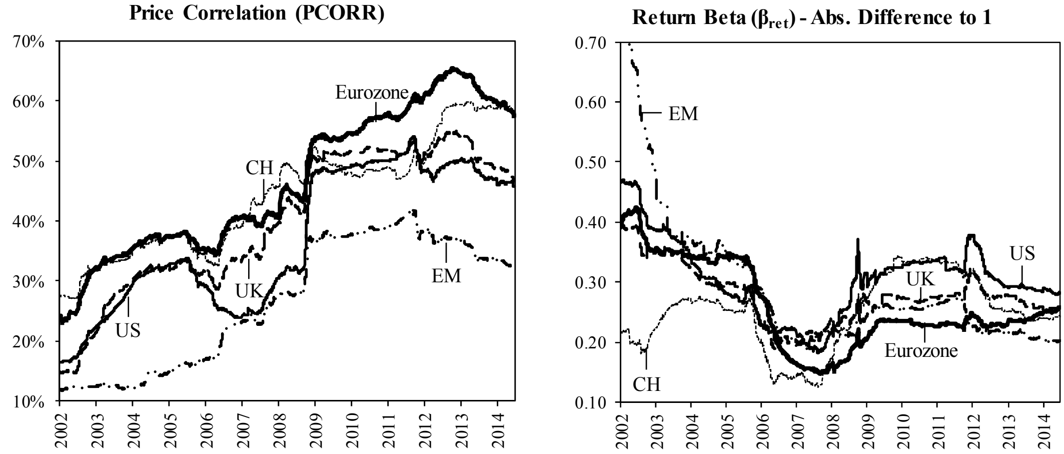
Figure 3: Commonalities in trading patterns (volume change dispersion and volume change correlation)



Notes: The figure illustrates the commonalities in trading patterns for the time period 31.12.2001 to 30.06.2014. The graph on the left shows the cross-sectional dispersion in daily trading volume changes, whereas the graph on the right displays the average pairwise correlation of the daily trading volume changes of the index constituents. Both variables are measured over a rolling window of 36 months. The commonality measures are calculated for the index constituents of the Euro Stoxx Large Index (Eurozone), FTSE 100 (UK), SMI (Switzerland), S&P 100 (US) and Stoxx EM 50 (emerging markets, EM).

Figure 4 illustrates that not only the commonalities in trading patterns clearly increased over the recent years, but also the average pairwise correlation of price returns. Although more volatile, a clear upward trend is visible and indicates an increased co-movement in price returns of the stocks. The developed markets show an increase in the return correlation of around 30 pps, whereas the emerging markets average price correlation increased by 20 pps. Similar to the trading pattern commonalities, the developed markets generally show a higher level of correlation in price returns than emerging markets. With respect to the return betas, commonality is tested by analyzing the average absolute difference of the return betas to 1. The right graph in Figure 4 clearly shows a reduction of the variation of return betas for most markets. Whereas in 2002, the average absolute difference of the US stock's return betas amounted to 0.47, in 2014 the difference was reduced to 0.28. The most pronounced reduction in the variation of return betas can be observed for the emerging markets.

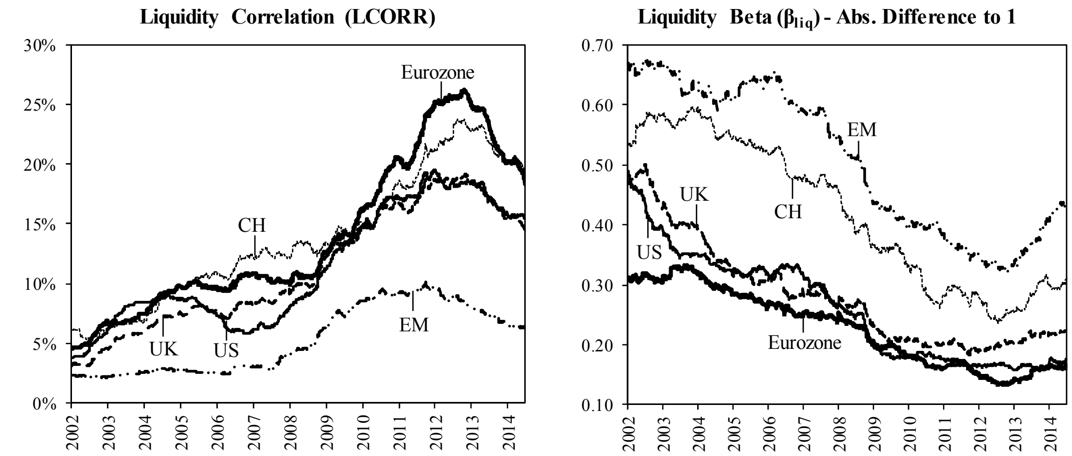
Figure 4: Commonalities in price returns (price correlation und return beta)



Notes: The figure illustrates the commonalities in price returns for the time period 31.12.2001 to 30.06.2014. The graph on the left shows the average pairwise correlation of the price returns of the index constituents, whereas the graph on the right displays the equally weighted average, absolute difference of the return betas to 1 (variation of return beta). Both variables are measured over a rolling window of 36 months. The commonality measures are calculated for the index constituents of the Euro Stoxx Large Index (Eurozone), FTSE 100 (UK), SMI (Switzerland), S&P 100 (US) and Stoxx EM 50 (emerging markets, EM).

Figure 5 shows the development of the commonalities in liquidity risk. For all markets analyzed, we can observe a clear trend of increased liquidity correlations for the years 2002 to 2012. In this time period, the average pairwise liquidity correlation of developed markets increased from a range of 3% (UK) to 6% (Switzerland) to a range from 18% (UK) to 25% (Eurozone). Similar to most of the other commonality measures, emerging markets show the lowest level of liquidity correlation. Following the approach seen for the return beta, we calculate the average absolute difference of the liquidity beta to 1. We can observe a substantial reduction in the variation of liquidity betas for all markets, indicating increased commonality in the securities' underlying liquidity. Whereas the Eurozone, the US and the UK show the lowest level of variation, emerging markets exhibit the highest level of variation but also a likewise declining trend. Those results indicate that the liquidity of equity is increasingly driven by factors affecting the entire market and to a lesser extent dependent on security specific characteristics.

Figure 5: Commonalities in liquidity risk (liquidity correlation and liquidity beta)



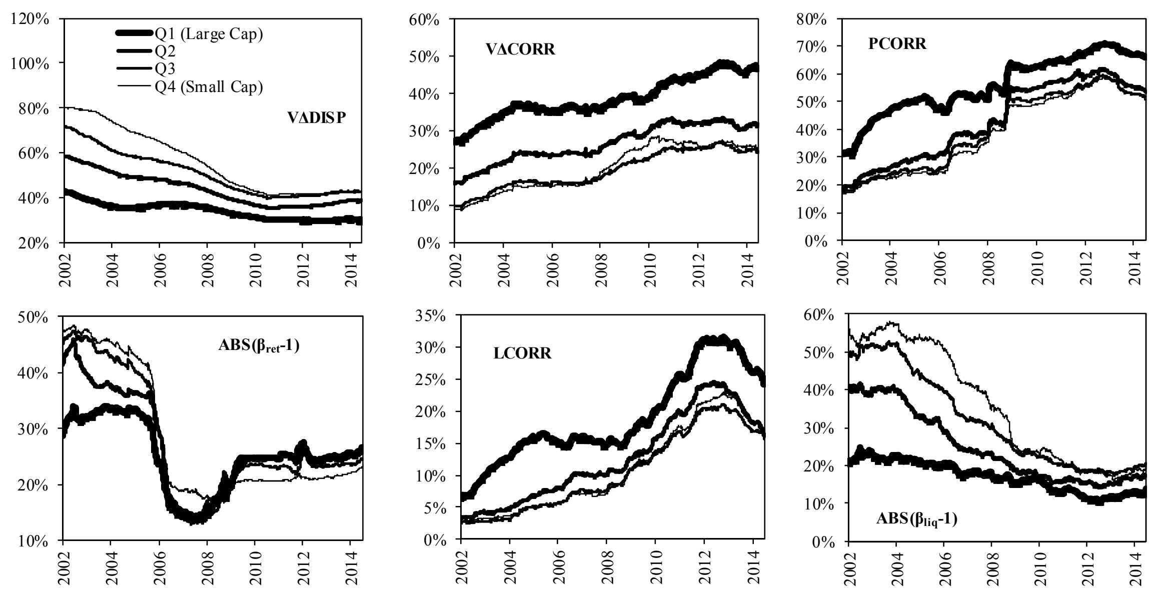
Notes: The figure illustrates the commonalities in liquidity risk for the time period 31.12.2001 to 30.06.2014. The graph on the left shows the average pairwise correlation of the change in the Amihud (2002) measure of illiquidity, whereas the graph on the right displays the equally weighted average, absolute difference of the liquidity betas to 1 (variation of liquidity beta). Both variables are measured over a rolling window of 36 months. The commonality measures are calculated for the index constituents of the Euro Stoxx Large Index (Eurozone), FTSE 100 (UK), SMI (Switzerland), S&P 100 (US) and Stoxx EM 50 (emerging markets, EM).

To summarize, we can see a clear increase of the commonalities in trading patterns, price returns and liquidity risk for all markets analyzed. One would expect the increase in commonality in particular for the time period of the financial crisis. For certain measures, such as the price correlation, the increase in co-movement was indeed in particular high during the year 2008. However, the increase in commonality can be observed for the entire period, including the pre-crisis years 2002 to 2006. Furthermore, we do not see a reversion back to pre-crisis commonality levels. The only exception is the recent trend in the average pairwise liquidity correlation, which seems to indicate a reversal in 2013.

4.2. Quartile analysis

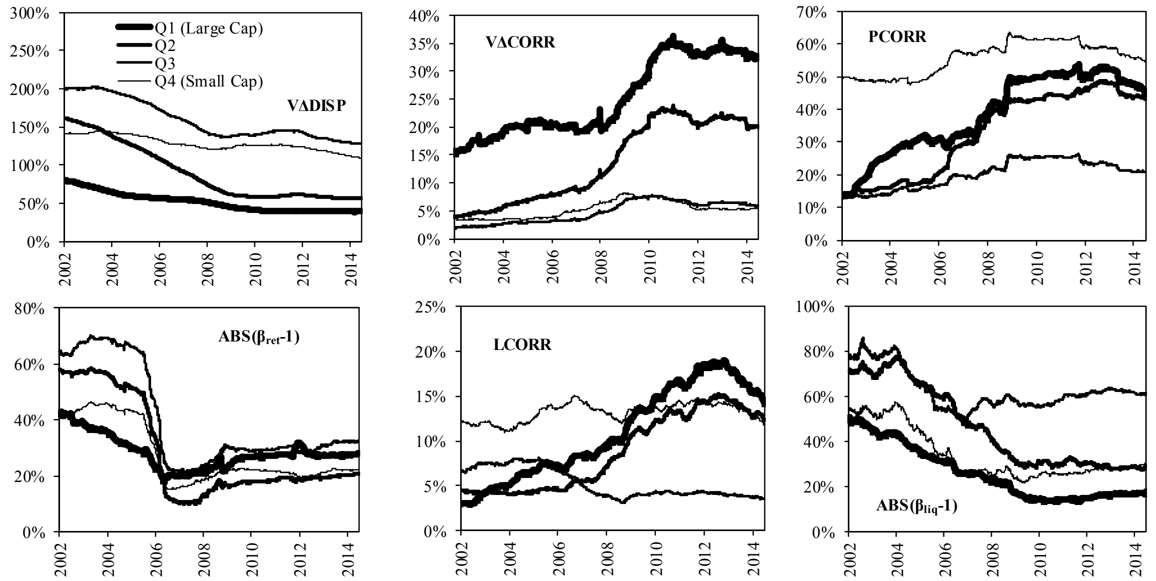
Given that the previous analysis of the main market indices exhibits a bias towards large cap companies, we investigate the different size quartiles of the total market indices. The companies that have been part of the respective total market index for the entire observation period are classified into quartiles based on their average market capitalization. Figures 6 to 10 show the risk commonality measures per size quartile for all five regions. The figures illustrate that the level of commonality is generally higher for large cap companies and is reduced stepwise with decreasing company size. An increase in commonality for all size quartiles can in particular be observed for the Eurozone and the US, where small and mid cap companies closely follow the trend of large cap companies, but on a lower commonality level. For the UK and Switzerland, mid cap companies also show a similar trend as large cap companies, whereas small cap companies exhibit a less pronounced increase in commonality.

Figure 6: Risk commonality measures for different quartiles – Eurozone



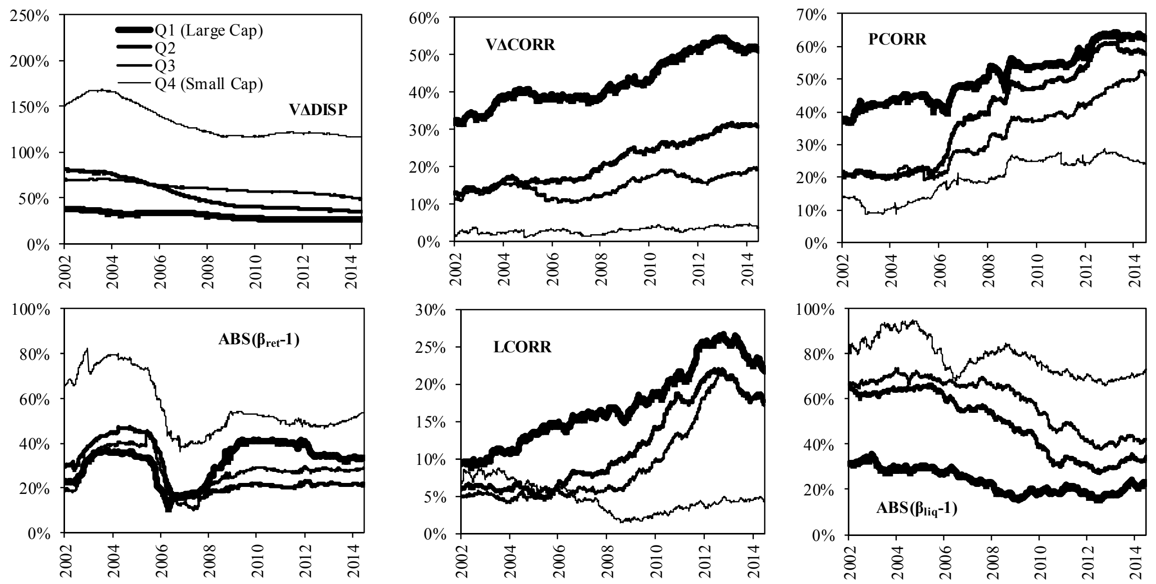
Notes: The figure illustrates the commonality measures for the index constituents of the Euro Stoxx Index.

Figure 7: Risk commonality measures for different quartiles – UK



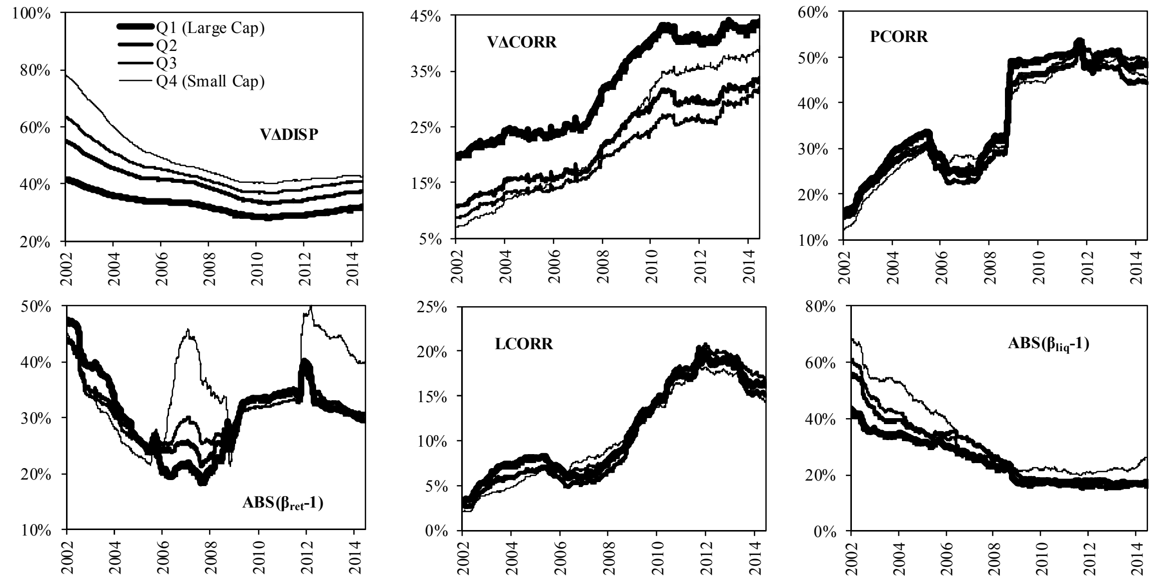
Notes: The figure illustrates the commonality measures for the index constituents of the FTSE All Share Index.

Figure 8: Risk commonality measures for different quartiles – Switzerland



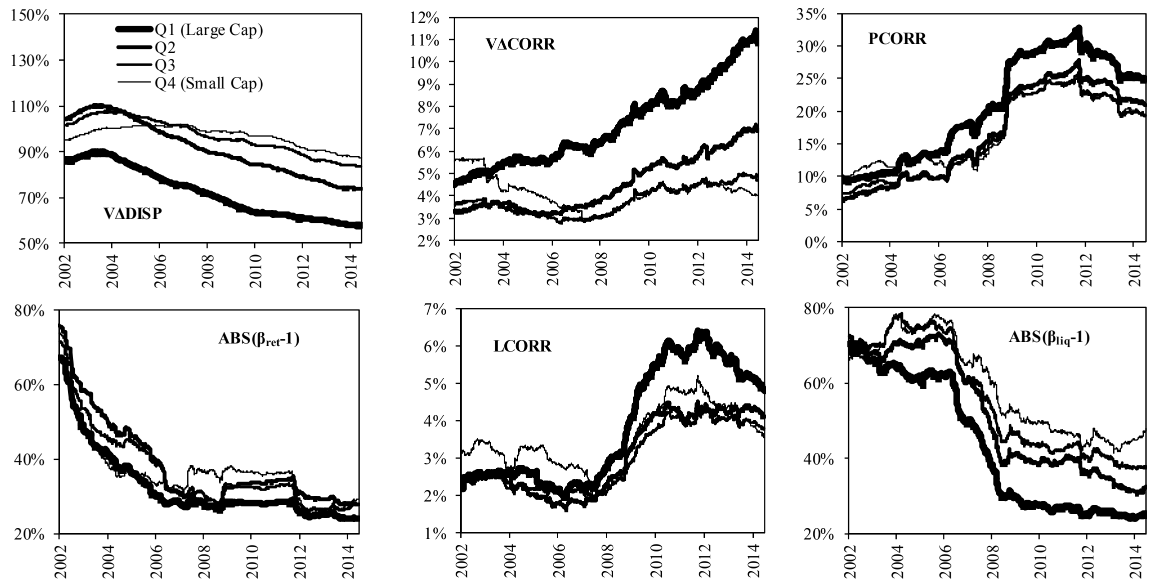
Notes: The figure illustrates the commonality measures for the index constituents of the SPI.

Figure 9: Risk commonality measures for different quartiles – US



Notes: The figure illustrates the commonality measures for the index constituents of the S&P 1500 Index.

Figure 10: Risk commonality measures for different quartiles – emerging markets



Notes: The figure illustrates the commonality measures for the index constituents of the Stoxx EM 1500 Index.

4.3. Within-region regression analysis

Whether the observed, substantial increase in risk commonality can be related to the increase in index linked investing, is tested in various regression settings. First, we conduct a within-region regression analysis to evaluate the relationship between the increased risk commonality and the development of index linked investing. Thereby, we run an individual regression for each of the regions with respect to each of the risk commonality measures. The results are displayed in Table 2.

The regression results illustrate a clear negative relationship between the increase in index linked investing and the development of the dispersion in trading volume changes for all regions analyzed. Furthermore, we see a positive relationship between the increase in index linked investing and the average pairwise correlation of volume changes. All betas of the trading pattern commonality measures are highly significant at the 1% level. For example, the results indicate that an increase of the proportion of index linked investing of 1 pp (e.g., from currently 2% to 3%) would lead to a decrease in the dispersion of volume changes of 6.1 pps in the Eurozone, 18.1 pps in the UK market, 13.5 pps in Switzerland, 3.2 pps in the US and 11.1 pps in the emerging market region. The results are thus not only statistically significant, but also economically relevant.

Columns 3 and 4 of Table 2 show the results for the regression analysis of the commonalities in price returns. We can observe clear positive relationships between the proportion of index linked investing and the average correlation of price return, indicating increased commonality in price movements due to the growth in passive investing for all markets analyzed. Furthermore, it is observable that the variation in return beta of the stocks in all markets except Switzerland is decreasing in dependence with the growing importance of index linked investing. However, we find the negative relationships to be significant only for the Eurozone and emerging markets. Switzerland even shows a high significance for the positive relationship. However, given that the Swiss main market index SMI only consists of 20 companies, we believe that the differences in price betas are per se low due to the very concentrated market structure in the Swiss large cap segment.

The remaining two columns of Table 2 show the regression results for the measures corresponding to liquidity commonalities. We find positive and at the 1% level significant relationships between the proportions of index linked investing and the correlations of the stock liquidity for all markets. The size of the sensitivities also indicates a substantial economic relevance of the relationship. Furthermore, the variation in liquidity beta is decreasing in relation to the growth of index linked investing for all markets.

Table 2: Within-region regression results – main markets

	Trading patterns		Price returns		Liquidity risk	
	VΔDISP	VΔCORR	PCORR	$ABS(\beta_{Ret} - 1)$	LCORR	$ABS(\beta_{Liq} - 1)$
Eurozone (Euro Stoxx Large)						
Beta	-6.1***	5.7***	14.1***	-3.7***	7.7***	-7.4***
	(0.0000)	(0.0000)	(0.0000)	(0.0047)	(0.0000)	(0.0000)
Adj. R square	85.3%	85.0%	86.8%	16.8%	87.9%	86.4%
UK (FTSE 100)						
Beta	-18.1***	13.9***	22.3***	-2.0	10.6***	-15.4***
	(0.0000)	(0.0000)	(0.0000)	(0.2454)	(0.0000)	(0.0000)
Adj. R square	78.1%	83.8%	65.2%	2.8%	83.6%	57.3%
Switzerland (SMI)						
Beta	-13.5***	14.6***	16.2***	3.3**	9.5***	-20.4***
	(0.0000)	(0.0000)	(0.0000)	(0.0174)	(0.0000)	(0.0000)
Adj. R square	75.3%	87.8%	88.3%	8.6%	94.2%	87.2%
US (S&P 100)						
Beta	-3.2***	10.1***	12.4***	-2.0	5.5***	-10.6***
	(0.0000)	(0.0000)	(0.0000)	(0.1875)	(0.0000)	(0.0000)
Adj. R square	73.0%	82.8%	69.6%	5.2%	77.3%	83.3%
Emerging Markets (Stoxx EM 50)						
Beta	-11.1***	3.6***	12.9***	-10.0***	3.4***	-16.6***
	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)
Adj. R square	73.1%	89.3%	62.9%	29.5%	64.4%	79.0%

Notes: ***/**/* denotes significance at the 1% / 5% / 10% level. The table shows the regression of the commonality measures with respect to trading patterns, price returns and liquidity risk on the proportion of index linked investing in the respective market. The OLS regressions include a variance-covariance estimation based on Newey and West (1987) and are based on monthly data points. The regressions analyze the time period from 31.01.2001 to 30.06.2014 and use 151 data points for each setting.

To summarize, we find that the growth in index linked investing is related to increased commonalities in trading patterns as well as liquidity risk commonalities and – to some extent – price return commonalities all around the globe. We believe that reverse causality is not an issue in our setting given that the trend towards index linked investing is not influenced by the increased risk commonalities – we argue that the opposite is true: an increase in risk commonalities might rather incentivize investors to pursue an active investment strategy in order to mitigate the risks induced by the growth in index linked investing. However, given the structure of this analysis, it cannot deliver conclusive evidence whether the growth in index linked investing is indeed the cause for the increased risk commonality in financial markets. To reach more robust insights, we further analyze the differences among size quartiles and compare the markets in a cross-regional analysis to leverage on the various stages in the evolution of index linked investing.

Table 3 provides the regression results for the different size quartiles. The results suggest that index linked investing leads to an increased co-movement within all size quartiles of the markets analyzed. The only exception can be observed for the variation in return beta, which in fact shows clear results for the Eurozone, the UK and emerging markets, but mixed outcomes for Switzerland and the US. Furthermore, the quartile regression analysis reveals that in the Eurozone and the US, the relationship of risk commonality and index linked investing is substantially more pronounced for smaller size companies than for larger cap companies. This observation is manifested in the mostly larger beta coefficients of the mid and small cap companies for a range of risk commonality measures. For the UK and the emerging markets, we see the opposite for most commonality measures: the risk commonalities of large cap companies tend to be more affected by the increase in index linked investing than small cap companies. A possible explanation for this observation lies in the fact that the US and the Eurozone represent the furthest developed regions with respect to index linked investing and exhibit a partially twice as large proportion of ETF investing as compared to the other markets. Given that within each region, passive investment vehicles are – in a first step – mainly launched for the large cap segment of the market, one may reasonably expect that the growth in index linked investing firstly affects the commonality within large cap stocks. With continuing growth of index linked investing, the effect spills over to smaller cap companies.

Table 3: Within-region regression results – quartile analysis

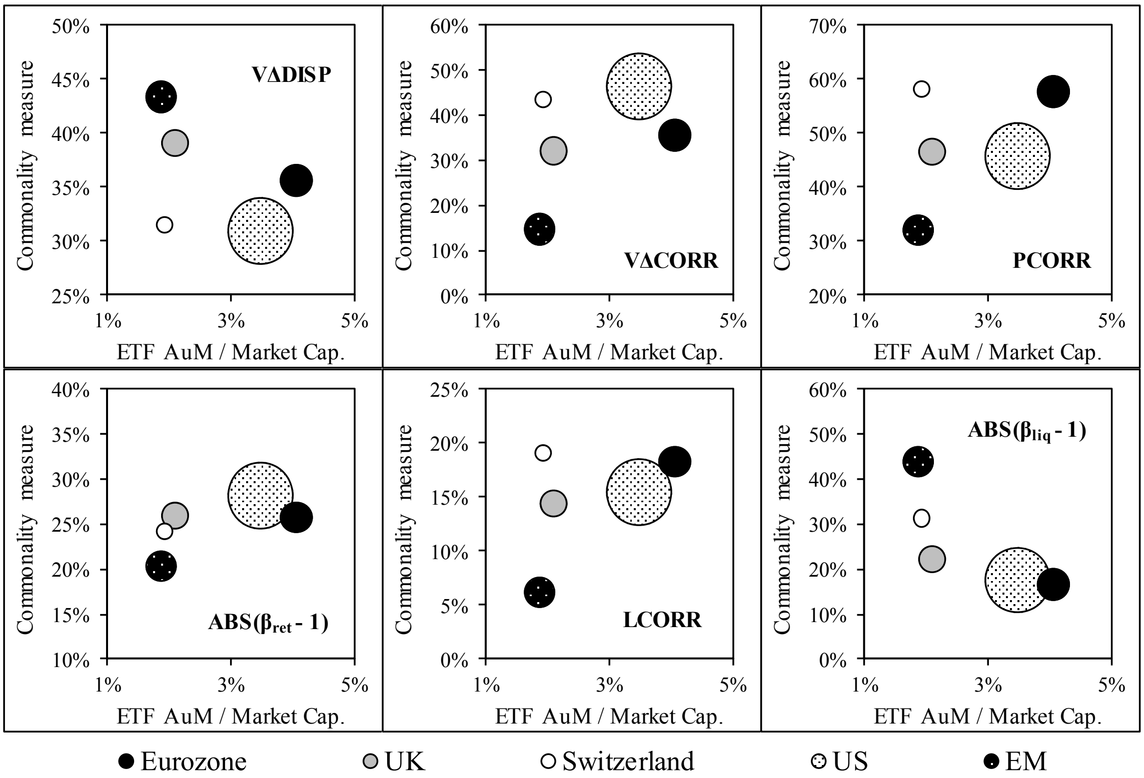
Eurozone (Euro Stoxx)	**Trading patterns**		**Price returns**		**Liquidity risk**	
Quartile Analysis	VΔDISP	VΔCORR	PCORR	$ABS(\beta_{Ret}-1)$	LCORR	$ABS(\beta_{Liq}-1)$
Quartile 1 (Large Caps)	-4.0***	6.5***	12.0***	-1.4	8.2***	-4.6***
Quartile 2	-7.4***	5.6***	15.9***	-4.2***	7.9***	-9.7***
Quartile 3	-10.2***	5.8***	16.0***	-6.5***	7.5***	-13.5***
Quartile 4 (Small Caps)	-15.4***	6.9***	16.5***	-9.0***	8.2***	-17.7***
UK (FTSE All Share)	**Trading patterns**		**Price returns**		**Liquidity risk**	
Quartile Analysis	VΔDISP	VΔCORR	PCORR	$ABS(\beta_{Ret}-1)$	LCORR	$ABS(\beta_{Liq}-1)$
Quartile 1 (Large Caps)	-23.4***	14.7***	23.0***	-3.0	11.0***	-21.0***
Quartile 2	-66.6***	14.6***	25.3***	-22.8***	9.1***	-34.5***
Quartile 3	-47.9***	3.5***	6.9***	-23.2***	-2.7***	-6.2*
Quartile 4 (Small Caps)	-18.5***	1.5***	6.8***	-14.3***	1.0**	-15.5***
Switzerland (SPI)	**Trading patterns**		**Price returns**		**Liquidity risk**	
Quartile Analysis	VΔDISP	VΔCORR	PCORR	$ABS(\beta_{Ret}-1)$	LCORR	$ABS(\beta_{Liq}-1)$
Quartile 1 (Large Caps)	-6.1***	11.3***	13.8***	4.8***	9.0***	-7.6***
Quartile 2	-25.9***	10.6***	25.6***	-11.6***	10.0***	-23.4***
Quartile 3	-10.8***	3.5***	18.1***	-2.2	9.7***	-19.7***
Quartile 4 (Small Caps)	-26.5***	1.2***	9.9***	-14.4***	-2.0***	-12.2***
US (S&P 1500)	**Trading patterns**		**Price returns**		**Liquidity risk**	
Quartile Analysis	VΔDISP	VΔCORR	PCORR	$ABS(\beta_{Ret}-1)$	LCORR	$ABS(\beta_{Liq}-1)$
Quartile 1 (Large Caps)	-3.6***	10.2***	13.0***	-0.9	6.0***	-9.1***
Quartile 2	-6.1***	8.9***	12.6***	0.5	6.5***	-13.1***
Quartile 3	-7.2***	8.4***	13.9***	0.3	7.0***	-14.1***
Quartile 4 (Small Caps)	-10.9***	13.3***	13.7***	4.9***	6.3***	-15.5***
EM (Stoxx EM 1500)	**Trading patterns**		**Price returns**		**Liquidity risk**	
Quartile Analysis	VΔDISP	VΔCORR	PCORR	$ABS(\beta_{Ret}-1)$	LCORR	$ABS(\beta_{Liq}-1)$
Quartile 1 (Large Caps)	-15.1***	2.8***	9.7***	-9.7***	2.0***	-22.6***
Quartile 2	-17.2***	1.8***	9.0***	-11.7***	1.4***	-21.2***
Quartile 3	-11.3***	0.8***	7.6***	-11.4***	1.2***	-19.7***
Quartile 4 (Small Caps)	-6.1***	0.0	6.2***	-9.3***	0.9***	-16.6***

Notes: ***/**/* denotes significance at the 1% / 5% / 10% level. The table shows the regression beta coefficients of the commonality measures with respect to trading patterns, price returns and liquidity risk on the proportion of index linked investing in the respective market and size quartile. The OLS regressions include a variance-covariance estimation based on Newey and West (1987) and are based on monthly data points. The regressions analyze the time period from 31.01.2001 to 30.06.2014 and use 151 data points for each setting.

4.4. Cross-regional regression analysis

To add more conclusive evidence on whether the growth in index linked investing is indeed a cause for the increased risk commonality in financial markets, we perform a cross-regional analysis of the data and leverage on the fact that the different regions exhibit different levels of index linked investing. As a starting point, Figure 11 graphically shows the relationship between the ETF AuM in proportion to the market capitalization of the respective market and the level of commonality as of June 30, 2014.

Figure 11: Cross-regional comparison of risk commonality and index linked investing (June 2014)



Notes: On the vertical axis, the graphs show for each commonality measure its level as of June 30, 2014 and, on the horizontal axis, the corresponding proportion of index linked investing. The size of the bubble illustrates the size of each market, measured as the free float market capitalization of the respective total market index.

If index linked investing was the only driver of risk commonality, we would expect the bubbles to be arranged on straight lines from the top left to the bottom right (for VΔDISP and the beta measures) or from the bottom left to the top right (for VΔCORR, PCORR and LCORR), respectively. We see a tendency towards this relationship, although not for all markets and commonality measures. We believe that the level of risk commonality might be influenced by other market characteristics, such as the market size and the market concentration (i.e., the proportion of large companies in a market).

We conduct a cross-regional, multifactor regression that accounts for the differences in market size and market concentration. Table 4 shows the results of the cross-regional regression analysis. The results confirm the highly significant relationship between the proportion of index linked investing and the risk commonalities. On average and across all markets, a 1 pp increase in ETF AuM results in a reduction of the dispersion in trading volume changes of 8.5 pps, an increase in the average pairwise correlation of volume changes of 8.3 pps, an increase in the average pairwise price correlation of 13.7 pps and an increase of the average pairwise liquidity correlation of 6.6 pps. The variation of return beta on average decreases by 3.4 pps, whereas the variation in liquidity beta is reduced by 10.8 pps.

Table 4: Cross-regional regression results

	Trading patterns		Price returns		Liquidity risk	
	VΔDISP	VΔCORR	PCORR	ABS($\beta_{Ret} - 1$)	LCORR	ABS($\beta_{Liq} - 1$)
Alpha	58.4%***	13.2%***	31.2%***	29.1%***	6.7%***	36.6%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ratio AuM / Market Cap	**-8.5*** **	**8.3*** **	**13.7*** **	**-3.4*** **	**6.6*** **	**-10.8*** **
	(0.0000)	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**
Market Size (MS)	-1.2%***	0.8%***	-0.8%***	0.5%***	-0.3%***	-0.1%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2935)
Concentration (HHI)	-0.6%***	0.6%***	0.1%	-0.1%**	0.1%***	1.1%***
	(0.0000)	(0.0000)	(0.2920)	(0.0367)	(0.0045)	(0.0000)
Adj. R square	70.3%	45.4%	47.5%	10.9%	54.3%	51.4%

Notes: ***/**/* denotes significance at the 1% / 5% / 10% level. The table shows the cross-regional regression of the commonality measures with respect to trading patterns, price returns and liquidity risk on the proportion of index linked investing. Market size (MS) is measured as the free float market capitalization of the respective market, whereas concentration refers to the Herfindahl Index value (HHI). The regressions analyze the time period from 31.01.2001 to 30.06.2014 and use 755 data points for each setting.

The cross-regional analysis adds more conclusive evidence that supports the hypothesis that the growth in index linked investing is a cause for the increased risk commonality in financial markets. The relationships remain significant also in the cross-regional perspective and when accounting for different market characteristics. The growth in index linked investing therefore leads to financial markets, which seem to be more prone to experience price and liquidity shocks. Portfolio managers consequently need to account for the increase in risk commonality within their risk management tools. Historical risk measures do not account for the increased level in risk commonality in markets with large proportions of index linked investing and might therefore underestimate the effective risks inherent in those markets today. Additionally, the higher level of risk commonality increases the probability of tail events. Portfolio managers are thus well advised to dedicate more resources within risk management towards managing and hedging tail risks. Furthermore, the increase in risk commonalities induced by the growth of index linked investing has major implications on portfolio diversification. Diversification possibilities within markets that are characterized by a large proportion of index linked investing are reduced. This development intensifies the importance for portfolio managers to diversify across asset classes and, in particular, into asset classes that exhibit a lower share of indexing. We even argue that it might be reasonable for portfolio managers to use the proportion of index linked investing within a market as a criteria in diversification considerations. Last, the increase in risk commonalities has an effect on active portfolio managers. Active investment strategies and the active managers' competitiveness are important elements to make markets more efficient. Some authors (e.g., Lorie, Dodd & Hamilton Kimpton, 1985; Woolley & Bird, 2003) argue that the rise of passive investing leads to new inefficiencies in the market, allowing active managers to outperform again.[6]

5. Conclusion

Index linked investing promotes a market environment where the purchasing and selling decisions with respect to individual securities are mostly driven by overall market trends and not by security specific characteristics. A market environment that is characterized by a large proportion of index linked investing might therefore show an increased co-movement of the securities in the index universe and, accordingly, an increased vulnerability of financial markets. First, we investigate whether financial markets around the world experienced an increase in risk commonalities over the

[6] Woolley & Bird (2003) believe that, due to the inability of the markets to recognize the inefficiencies, the past trend of passive investing will not reverse.

recent years. We find a substantial increase in the co-movement of stocks with respect to trading patterns, price returns and liquidity risks within all markets analyzed. Furthermore, we investigate whether the increase in risk commonalities can be attributed to the growth in index linked investing and find statistically significant and economically relevant evidence that the growth in index linked investing is related to the substantial increase in risk commonalities.

The relationship can be confirmed for all company size segments. However, the analysis illustrates that for regions in an earlier stage in the evolution of index linked investing, large cap companies are more affected by the increase in index linked investing. For regions with more mature passive investing markets, the effect of index linked investing on the risk commonalities starts to spill over to smaller cap companies. Overall, the results suggest a significant increase in market fragility for financial markets around the globe, leading to an increased danger of more severe reactions to unanticipated events in relation to an ongoing increase in the proportion of index linked investing. Portfolio managers are well advised to account for the increased proportion of index linked investing within their risk management tools, diversification approaches and active management strategies.

Given the continuous trend towards index linked investing, further research on its consequences with respect to the risk characteristics of financial markets is required. For example, we believe that it would be insightful to extend the research to include further asset classes. Additionally, we see a potential for future research on the consequences of the growth of index linked investing on the rise or revival of investment strategies, such as the rise of alternative indexing approaches or the revival of active investment strategies.

Appendix

Commonalities in trading patterns

Both the cross-sectional dispersion in trading volume (VΔDISP) and the average pairwise correlation of the change in trading volume (VΔCORR) are based on the day-to-day logarithmic difference in trading volume:

$$\Delta V_{i,t} = ln\left(\frac{V_{i,t}}{V_{i,t-1}}\right) \tag{3}$$

The daily trading volume is labelled $V_{i,t}$. The subscript i denotes the stocks in a market, whereas the subscript t refers to the time period. The variables measuring the commonalities in trading patterns are subsequently calculated as follows:

i. *Cross-sectional dispersion of the change in trading volume*: The cross-sectional dispersion of the change in trading volume is estimated by calculating the cross-sectional standard deviation of the volume changes for each time period t:

$$V\Delta DISP_t = \sqrt{\frac{1}{I-1}\sum_{i=1}^{I}\left(\Delta V_{i,t} - \overline{\Delta V_t}\right)^2} \tag{4}$$
$$where \ \ \overline{\Delta V_t} = \frac{1}{I}\sum_{i=1}^{I}\Delta V_{i,t} \tag{5}$$

I refers to the total number of stocks analyzed. The dispersion in trading volume change is averaged over a rolling window of 36 months to provide a long-term estimate of the variable.

ii. *Average pairwise correlation of change in trading volume*: This variable estimates the pairwise correlations of the change in trading volume between the stocks in a market. To provide an average correlation estimation, we equally weight the pairwise correlations:

$$V\Delta CORR = \left[\sum_{i=1}^{I}\sum_{j>i}^{J}\frac{(T-1)^{-1}\sum_{t=1}^{T}(\Delta V_{i,t}-\overline{\Delta V}_i)(\Delta V_{j,t}-\overline{\Delta V}_j)}{\sigma_{\Delta V_i}\sigma_{\Delta V_j}}\right]/N \tag{6}$$

$$where \quad N = \frac{I(I-1)}{2}, \; \overline{\Delta V_i} = \frac{1}{T}\sum_{t=1}^{T} \Delta V_{i,t} \tag{7}$$

T refers to the total number of time steps and $\sigma_{\Delta V_i}$ measures the standard deviation of the logarithmic change in trading volume of stock i. The pairwise correlations will be estimated over a rolling window of 36 months.

Commonalities in price returns

Both the average pairwise correlations of the price returns (PCORR) as well as the average return beta of the stocks ($\bar{\beta}_{Ret}$) are based on the daily price return:

$$\Delta P_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{8}$$

i. *Average pairwise correlation of price returns*: This variable estimates the pairwise correlations of the price returns between the stocks in a market. To provide an average correlation estimation, we equally weight the pairwise correlations:

$$PCORR = \left[\sum_{i=1}^{I} \sum_{j>i}^{J} \frac{(T-1)^{-1}\sum_{t=1}^{T}(\Delta P_{i,t} - \overline{\Delta P}_i)(\Delta P_{j,t} - \overline{\Delta P}_j)}{\sigma_{\Delta P_i}\sigma_{\Delta P_j}}\right] / N \tag{9}$$

$$where \quad \overline{\Delta P_i} = \frac{1}{T}\sum_{t=1}^{T} \Delta P_{i,t} \tag{10}$$

$\sigma_{\Delta P_i}$ refers to the return volatility of stock i. The pairwise correlations will be estimated over a rolling window of 36 months.

ii. *Average return beta*: We calculate an equally weighted average return beta, estimated over a rolling window of 36 months.

$$\bar{\beta}_{Ret} = \left[\sum_{i=1}^{I} \rho_{i,M}^{ret} \frac{\sigma_{\Delta P_i}}{\sigma_{\Delta P_M}}\right] / I \tag{11}$$

$\rho_{i,M}^{ret}$ refers to the correlation of the stock price returns with the market price returns and $\sigma_{\Delta P_M}$ denotes the market return volatility. For the purpose of our analysis, we are in particular interested in the average absolute difference of the return beta to 1, which is calculated as follows:

$$ABS(\beta_{Ret} - 1) = \left[\sum_{i=1}^{I} \left|\rho_{i,M}^{ret} \frac{\sigma_{\Delta P_i}}{\sigma_{\Delta P_M}} - 1\right|\right] / I \tag{12}$$

Commonalities in liquidity risk

Both the average pairwise correlation of liquidity (LCORR) and the average liquidity beta of the stocks ($\bar{\beta}_{Liq}$) are based on the Amihud (2002) measure of stock illiquidity. The Amihud measure of stock illiquidity is defined as the average ratio of the daily return value to the dollar trading volume on the same day:

$$ILLIQ_{i,t} = \frac{|P_{i,t} - P_{i,t-1}|}{V_{i,t}} \tag{13}$$

For our purposes, we are interested in the change in illiquidity, which we define following Kamara, Lou and Sadka (2008):

$$\Delta ILLIQ_{i,t} = ln\left[\frac{ILLIQ_{i,t}}{ILLIQ_{i,t-1}}\right] \tag{14}$$

i. *Average pairwise correlation of liquidity*: This variable is used to estimate the pairwise correlations of the liquidity measure between the stocks in a market. To provide an average correlation estimation, we equally weight the pairwise correlations:

$$LCORR = \left[\sum_{i=1}^{I} \sum_{j>i}^{J} \frac{(T-1)^{-1} \sum_{t=1}^{T} (\Delta ILLIQ_{i,t} - \overline{\Delta ILLIQ}_i)(\Delta ILLIQ_{j,t} - \overline{\Delta ILLIQ}_j)}{\sigma_{\Delta ILLIQ_i} \sigma_{\Delta ILLIQ_j}}\right] / N \tag{15}$$

$$where \quad \overline{\Delta ILLIQ}_i = \frac{1}{T} \sum_{t=1}^{T} \Delta ILLIQ_{i,t} \tag{16}$$

$\sigma_{\Delta ILLIQ_i}$ refers to the standard deviation of the change in the Amihud measure of illiquidity of stock i. The pairwise correlations will be estimated over a rolling window of 36 months.

ii. *Average liquidity beta*: We define the change in market illiquidity as the market value weighted average of the stocks' illiquidity measure $\Delta ILLIQ_{i,t}$.

$$\Delta ILLIQ_{M,t} = \sum_{i}^{I} \mathrm{w}_i (\Delta ILLIQ_{i,t}) \tag{17}$$

w_i refers to the market value weight of stock i. As a next step, we will measure the sensitivity of the stocks' changes in liquidity to changes in the market liquidity (liquidity beta) and equally weight those estimates to provide an average estimation of the liquidity beta.

$$\bar{\beta}_{Liq} = \left[\sum_{i=1}^{I} \rho_{i,M}^{liq} \frac{\sigma_{\Delta ILLIQ_i}}{\sigma_{\Delta ILLIQ_M}}\right] / I \tag{18}$$

$\rho_{i,M}^{liq}$ refers to the correlation of the stocks' change in the Amihud illiquidity measure with the market's change in the Amihud illiquidity measure. The liquidity betas will be estimated over a rolling window of 36 months. For the intention of our analysis, we are in particular interested in the average absolute difference of the liquidity beta to 1, which is calculated as follows:

$$ABS(\beta_{Liq} - 1) = \left[\sum_{i=1}^{I} \left|\rho_{i,M}^{liq} \frac{\sigma_{\Delta ILLIQ_i}}{\sigma_{\Delta ILLIQ_M}} - 1\right|\right] / I \tag{19}$$

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets, 5*(1), 31-56.

Barberis, N., Shleifer, A. & Wurgler, J. (2005). Comovement. *Journal of Financial Economics, 75*(2), 283-317.

Beneish, M.D. & Whaley, R.E. (1996). An Anatomy of the "S&P Game": The Effects of Changing the Rules. *The Journal of Finance, 51*(5), 1909-1930.

Biktimirov, E.N. & Li, B. (2014). Asymmetric stock price and liquidity responses to changes in the FTSE SmallCap index. *Review of Quantitative Finance and Accounting, 42*(1), 95-122.

Chan, K., Kot, H.W. & Tang, G. (2013). A comprehensive long-term analysis of the S&P 500 index additions and deletions. *Journal of Banking & Finance, 37*(12), 4920-4930.

Claessens, S. & Yafeh, Y. (2013). Comovement of Newly Added Stocks with National Market Indices: Evidence from Around the World. *Review of Finance, 17*(1), 203-227.

Deutsche Bank Securities Inc. (2014). ETF Annual Review & Outlook. Available online at < http://www.fullertreacymoney.com/system/data/files/PDFs/2014/January/20th/ETFreport.pdf> [accessed on 15 August 2014].

Jensen, M.C. (1968). The Performance of Mutual Funds in the Period 1945-1964. *The Journal of Finance, 23*(2), 389-416.

Kamara, A., Lou, X. & Sadka, R. (2008). The divergence of liquidity commonality in the cross-section of stocks. *Journal of Financial Economics, 89*(3), 444-466.

Kamara, A., Lou, X. & Sadka, R. (2010). Has the U.S. Stock Market Become More Vulnerable over Time? *Financial Analyst Journal, 66*(1), 41-52.

Lorie, J., Dodd, P. & Hamilton Kimpton, M. (1985). *The stock market: theories and evidence*. Homewood, Ill.: Irwin.

Malkiel, B.G. (2003). Passive Investment Strategies and Efficient Markets. *European Financial Management, 9*(1), 1-10.

Newey, W.K. & West, K.D. (1987). A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica, 55*(3), 703-708.

Petajisto, A. (2011). The index premium and its hidden cost for index funds. *Journal of Empirical Finance, 18*(2), 271-288.

Sharpe, W.F. (1966). Mutual Fund Performance. *The Journal of Business, 39*(1), 119-138.

Shleifer, A. (1986). Do Demand Curves for Stocks Slope Down? *The Journal of Finance, 41*(3), 579-590.

Sullivan, R.N. & Xiong, J.X. (2012). How Index Trading Increases Market Vulnerability. *Financial Analyst Journal, 68*(2), 70-84.

Woolley, P. & Bird, R. (2003). Economic implications of passive investing. *Journal of Asset Management, 3*(4), 303-312.

Curriculum Vitae

Personal Information

Name:	Lidia Pia Bolla
Date of birth:	May 28, 1985
Place of birth:	Berne
Nationality:	Swiss

Professional Experience

2013 – today	**Algofin AG, St. Gallen, Switzerland**
	Investment Consulting and Corporate Consulting
2011 – 2013	**Swiss Re, Zurich, Switzerland**
	Asset Management
2010	**J.P. Morgan, London, England**
	Mergers and Acquisitions
2008	**Man Investments, Pfäffikon SZ, Switzerland**
	Product Structuring

Education

2013 – 2015	**University of St. Gallen, Switzerland**
	Doctor of Philosophy in Finance (Ph.D. HSG)
2009 – 2011	**CFA Institute**
	Chartered Financial Analyst (CFA)
2009 – 2011	**University of St. Gallen, Switzerland**
	Master of Arts in Banking and Finance (M.A. HSG)
2007	**University of Wollongong, Australia**
2005 – 2008	**University of St. Gallen, Switzerland**
	Bachelor of Arts in Law and Economics (B.A. HSG)
2001 – 2004	**Gymnasium Kirchenfeld, Switzerland**
	Matura