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Sustainable investments and strategies for the proprietary trading of German savings banks

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Abbreviations

ARCH	Autoregressive conditional heteroscedasticity
ADF	Augmented Dickey-Fuller test
AIC	Akaike information criterion
CAGR	Compounded annual growth rate
GFSG	Green Finance Study Group
GLS	Generalized least square
KAGB	Kapitalanlagegesetzbuch
KPSS	Kwiatkowski-Philips-Schmidt-Shin test
LIQV	Liquiditaetsverordnung
LPM	Lower partial moments
MAR	Minimum acceptable return
SC	Schwarz information criterion
SER	Sequential elimination method
SDG	Sustainable development goals
SRI	Social responsible investment
SSE	Sum squared errors
SUR	Seemingly unrelated regression
UNEP	United Nations Environment Programme
VAR	Vector autoregressive model
VECM	Vector error correction model

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I. Introduction

As a consequence of the global financial crisis of 2007-2008 and within the framework of the Global Green New Deal, the United Nations Environment Programme (UNEP) developed the concept of Green Economy. It is defined “as one that results in improved human well-being and social equity, while significantly reducing environmental risks and ecological scarcities” (UNEP FI, 2011, p. 4). The concept of Green Economy seems suitable to implement the transformation process towards a low-emission and energy-efficient economy and society within the market-based environment. Furthermore, the significance of the financial sector to realise the concept of Green Economy is essential. The UNEP states the importance of the financial sector, "it is clear that across banking, investment and insurance – the core activities of the financial system – significant changes in philosophy, culture, strategy and approach, notably the overwhelming dominance of short-termism, will be required if capital and finance is to be reallocated to accelerate the emergence of a green economy" (UNEP, 2011, p. 44). In the course of China’s presidency of the G20 in 2016, the G20 Green Finance Study Group (GFSG) launched and was adopted by the G20 Finance and Central Bank Deputies. In the G20 Green Finance Synthesis Report, a Green Finance System is defined “to a series of policies, institutional arrangements and related infrastructure building that, through loans, private equity, issuance of bonds and stocks, insurance and other financial services, steer private funds towards a green industry” (Green Finance Task Force, 2015, p. 6). Thus, the essential contribution of banks to Green Finance is reflected in their economic roles as investor, lender, wealth manager, risk manager, insurance underwriter or general financial service provider.

At a national level, the reissue of the German sustainable strategy 2016 embodies the transformation of the sustainable development goals (SDGs) and the agenda 2030 of the United Nations. The implementation of the 2030 agenda represents a paradigm shift into a drastic transformation of the economy and the society (Bundesregierung, 2016). Key elements of the SDGs are the opportunities for shared values for the private sector in addressing social and environmental changes. These shared values serve as conjunction of market potential, social demands and policy actions to create a sustainable and inclusive path to economic growth, prosperity and well-being (KPMG International, 2016). Here, financial service opportunities for shared values lie in i) access, the financial inclusion for individuals (SDGs 1,2,3,4,10), small and medium sized enterprises (SDGs 5,8) and Governments (SDG 13) ii) investment, the investing, financing of renewable energy (SDGs 7,13) and other projects (SDGs 6,9), iii) risk, by leveraging risk expertise to create more resilience and to directly influence customers (SDGs 11,12), and iv) cross cutting (SDGs 13,14,15,16), positively influencing environmental, social and governance practices (United Nations Global Compact & KPMG International, 2015).

In all, the shared value opportunities in investment from the SDGs as well as the transformation to a green economy by enabling a green finance sector also comprises banks' proprietary investments.

This paper focuses on the suitability of sustainable investments and strategies for the proprietary trading of German public savings banks (Sparkassen). First, the paper analyses the financial statements of all German savings banks from the years of 2013 to 2015. It identifies and processes key data and ratios and develops a k-means clustering method of vector quantization. The data and ratios are based on the clustering done by Schäfer & Mayer (2013). In their paper, they identified four types of German savings banks. These types are: i) liquidity oriented Sparkassen, ii) treasury oriented Sparkassen iii) risk-adjusted return Sparkassen and iv) wealth generating oriented Sparkassen (Schäfer & Mayer, 2013).

Second, all German savings banks are clustered according to their identified types. In addition, the proportion of asset classes of their proprietary trading are identified. The asset classes are defined by the Verordnung über die Rechnungslegung der Kreditinstitute und Finanzdienstleistungsinstitute (Kreditinstituts-Rechnungslegungsverordnung - RechKredV)[1] into bonds and other interest-bearing securities and shares and other non-fixed interest securities. More, bonds and other interest-bearing securities have the sub-items i) money market securities issued by public bodies, ii) money market securities issued by other issuer, iii) bonds and debt securities issued by public bodies, iv) bonds and debt securities from other issuers, v) bonds issued by the bank.

Third, indices are matched and assigned to the imposed asset categories to reflect the return and risk characteristics of the asset classes. In regard of a lack in the provision

[1] For more details see § 16 Schuldverschreibungen und andere festverzinsliche Wertpapiere (Nr. 5) and § 17 Aktien und andere nicht festverzinsliche Wertpapiere (Nr. 6); http://www.gesetze-im-internet.de/rechkredv/index.html

of indices reflecting sustainable investment strategies, indices are constructed depicting two major sustainable investment strategies, negative screening and best in class.

Fourth, based on the results of the clustering, the analysis uses a vector error correction model (VECM), combined with a bootstrap simulation analysis, to compare different sustainable investment strategies and conventional investment strategies for the strategic asset allocation of German savings banks by their future return distribution paths. All strategic asset allocations are rebalanced with either a buy and hold or a constant mix strategy. This study focuses on static outright investment strategies for the simulation model. Further research in my upcoming dissertation also implements derivative overlay strategies including protective put, yield enhancement, collars and bond-call options.

Fifth, a detailed analysis of the simulation portfolios is provided, including performance, distribution and downside risk measure analysis.

Literature Review

Sustainable responsible investments (SRI) are largely analysed in the economic and academic literature. In this connection, often the same question is posed: Do sustainable responsible investments underperform comparable conventional type of investments based on risk-adjusted return? In a meta-analysis containing a total of 195 worldwide single studies, Kleine, Krautbauer, Weller (2013) investigate sustainable responsible investments. The advantage of a meta-analysis lies in the numerous basis of existing research results with different focuses on asset classes and methodological approaches. The results were explicit stating, that sustainable responsible investments had a better or neutral risk-adjusted return profile in 123 out of 195 studies, clearly indicating that SRI do not underperform comparable conventional type of investments (Kleine, et al., 2013). Further only 14 studies discovered a negative and 58 a mixed risk-return profile. Comparable meta-analysis found similar results (see Revelli & Viviani (2015), Rathner (2012) and DB Climate Change Advisors (2012)).

However, specific studies discussing the suitability of SRI to financial service provider and their asset allocation strategies are rare, especially for banks. The suitability of SRI in the investing process is investigated mainly for foundations and for pension insurance funds. In the area of foundations, the work of Schröder (2010) needs to be highlighted. His study addresses the question whether sustainable investments are suitable for the asset management of non-profit foundations in Germany. Here, the focus is on economic and econometric analysis of investment strategies and their assessment from the perspective of foundations via a Vector Error Correction Modell in conjunction with a bootstrap simulation to forecast future return paths. Key findings are, that SRI can be very interesting for foundations for two reasons, probable conflicts between foundation statute and portfolio management can be mitigated with sustainable investments and the achievement of specific goals of non-profit foundations can be improved with SRI. Further, the results of the simulation model to investigate the suitability of SRI in non-profit foundations exhibit an outperformance based on downside risk ratios (Schröder, 2010).

In the area of pension insurance funds Hertrich (2013) provides theoretical considerations and empirical evidence that Pension Insurance Funds in Germany should consider SRIs and alternative investments as part of their strategic asset allocation. Within his simulation model, SRI structured portfolios yield better average portfolio results than respective conventional portfolios and achieved superior downside risk measures (Hertrich, 2013). Both works use a multivariate vector error correction model (VECM) in order to capture the underlying time series' data generating process. The estimated VECM is then used to simulate out of sample future return paths distribution in connection with a bootstrap simulation process and 10,000 repetitions with replacement. The entire obtained return distribution paths of the single asset classes are analysed to describe the risk characteristics of the distribution (with expected mean, variance, skewness and kurtosis) and are employed as input for the underlying different asset allocation strategies of foundations and pension insurance funds, respectively. Moreover, the VECM has several advantages, which makes it highly appropriate for modelling. First, the technique includes long-term relationships with cointegration. Second, in addition to long-term relationships, the VECM also considers dynamic short-term features over the endogenous variables of a time series. Third, VECM is widely used in econometric modelling and has a high degree of forecasting precision, if modelled correctly. Other comparable literature for VECM applications in economic time series include Herring (2008), Gerke & Werner (2001) and Ács (2012).

Based on the econometric approaches of Schröder (2010) and Hertrich (2013), this paper analyses the suitability of SRI for German savings banks, which is unique to our knowledge based on the current state of literature.

II. Methodology

A) Preliminary analysis and clustering of savings banks

Our preliminary panel analysis comprises the financial statements of all German savings banks in the years 2013 to 2015. In total, the quantity of German savings banks was 417 in 2013, 416 in 2014 and 413 in 2015. Here, different key balance sheet data, key profit and loss data and other soft data are selected and processed.[2] Ratios and other bank specific key figures are calculated according to Botsis et al. (2015), if they are not provided in the respective financial statements. All data is collected via the Bundesanzeiger.[3]

After the collection of the financial statement data, German savings banks are clustered according to Schäfer & Mayer (2013). Both cluster German savings banks in i) liquidity oriented savings banks (L-Sparkassen), ii) treasury oriented savings banks (BR-Sparkassen), iii) risk-adjusted return savings banks (R-Sparkassen) and iv) wealth generating oriented savings banks (RT-Sparkassen). Key metrics and ratios of the theoretical clustering process include the percentage of proprietary trading to total balance sheet, liquidity requirement of the credit institute, the readiness to assume risk and the use of proprietary trading as an additional income source (Schäfer & Mayer, 2013).

2 A detailed list of all used data elements can be requested from the authors.

3 Bundesanzeiger is the official publication platform of Germany accessible via https://www.bundes-anzeiger.de/ebanzwww/wexsservlet

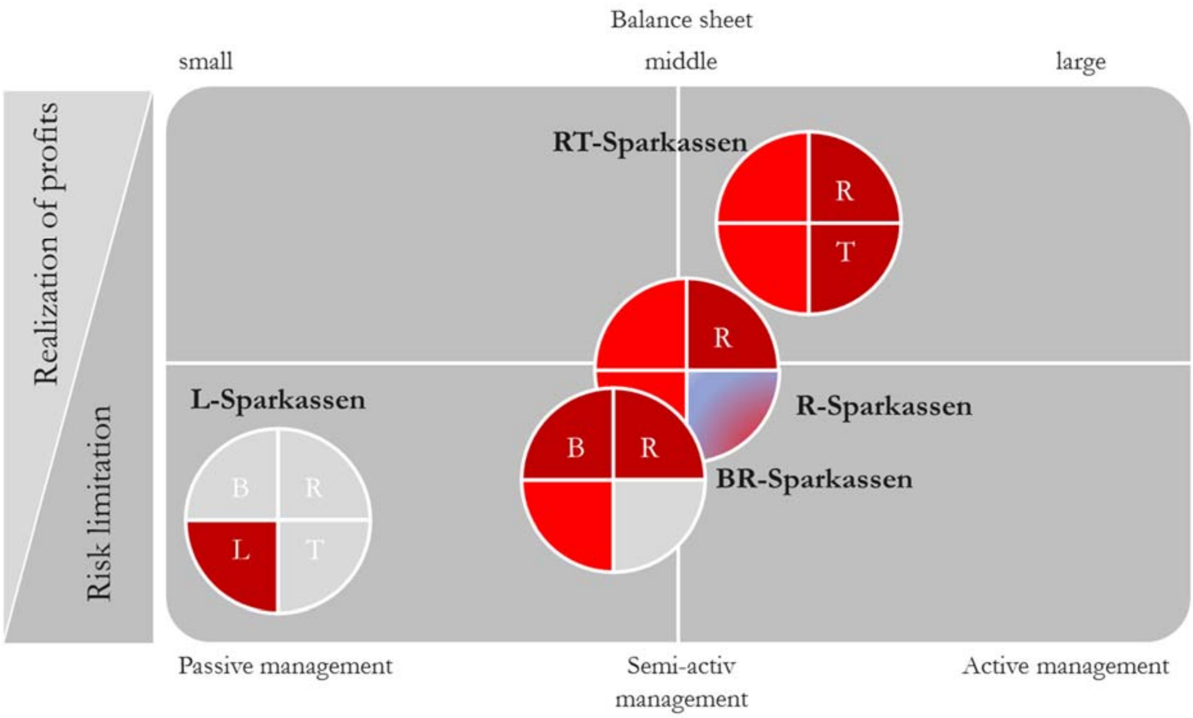

Figure 1: Proprietary trading cluster of German savings banks according to Schäfer & Mayer (2013)

The clustering process is done via k-means. K-means clusters a given set of observation (observation is a d-dimensional real vector) in pre-specified k groups to minimise the within cluster sum of squares (Singh, et al., 2011). The algorithm is defined as

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2$$

Where, $\left\| x_i^{(j)} - c_j \right\|^2$ $chosen$ distance measure between data point $x_i^{(j)}$ and cluster centre c_j.

The initial steps of a k-means clustering are, 1) select partition with k and repeat following steps 2) and 3) until cluster membership stabilizes, 2) generate new partition by assigning each pattern to its closest cluster centre and 3) compute new cluster centres (Jain, 2010). In our case, k-means is used with the Euclidean distance metric between data point and cluster centre. Besides having some limitations, k-means clustering is a widely used algorithm because of its simplicity and fast processing capability on large datasets (Singh, et al., 2011). The limitations include outliers, the handling of empty clusters and reduction of the error of sum squares (SSE) for a better clustering process. However, our dataset of German savings banks seems to be homogenous without major outliers, empty clusters and a reasonable SSE, so that an application of a k-means clustering algorithm is appropriate.

To match the characteristics of the clusters identified by Schäfer & Mayer (2013), the input observation ratios of the k-means clustering process are: i) liquidity ratio defined by the Verordnung über die Liquidität der Institute[4], ii) the ratio of proprietary trading to balance sheet, 3) the ratio of proprietary trading income to interest income, iii) the ratio of proprietary trading income from bonds and other interest-bearing securities to interest income and iv) the ratio of proprietary trading income from shares and other non-fixed interest securities to interest income. The following table gives a better overview of the matched characteristics and ratios.

Table 1: Based on Schäfer & Mayer 2013

Clustering ratios and characteristics based on Schäfer & Mayer 2013					
German savings banks cluster characteristics reflected by	*Percentage of proprietary trading to balance sheet total*	*Liquidity requirement*	*Readiness to assume risk*		*Use of proprietary trading as an additional income source*
Ratio	Ratio of proprietary trading to balance sheet total	Ratio based on LiqV	Ratio of proprietary trading income from bonds and other interest-bearing securities to interest income	Ratio of proprietary trading income from shares and other non-fixed interest securities to interest income	Ratio of proprietary trading income to interest income

The single ratios are then equally weighted and sorted within distribution and deviation intervals of outcomes to identify the four clusters of German savings banks. With the identification of the clusters, German savings banks are grouped and analysed to uncover the specific asset class weights of the proprietary trading, general income ratios and other main balance sheet ratios of the clusters.

Table 2: Clustering ratios and used descriptions

Clustering ratios and used desciptions				
German savings banks cluster	*Liquidity orientated savings banks (L-Sparkassen)*	*Treasury orientated savings banks (BR-Sparkassen)*	*Risk adjusted return savings banks (R-Sparkassen)*	*Wealth generating orientated savings banks (RT-Sparkassen)*
Used cluster description	Cluster 4	Cluster 3	Cluster 2	Cluster 1

[4] For more details, see https://www.gesetze-im-internet.de/liqv/__6.html

B) Data processing, Index creation and Portfolio construction

As input for the vector error correction model, three portfolios are constructed. These portfolios contain the asset classes of German savings banks specified by the RechKredV and are 1) conventional portfolio 2) SRI negative screening portfolio and 3) SRI best in class portfolio. All portfolios are composed with a certain number of indices, which will represent the asset classes. These indices represent a particular asset class with two exceptions. For bonds and debt securities issued by public, equally weighted indices of government and sub-sovereigns bonds will represent the asset class. For shares and other non-fixed interest securities, equally weighted indices of Stoxx Europe 600 and global real estate will represent the risk and return characteristics of this asset class. The depth analysis of the financial statements of German savings banks permit the assumption of a shared asset class representation, given that major portion of the asset classes are reflected by these two asset class types, respectively. However, the correct allocation of the respective asset classes could not be determined due to the summing up of balance sheet item and especially standard of Kapitalanlagegesetzbuch (KAGB), where only major investments (> 10% of the investments' capital) must be named in full detail.[5][6] The continued research will look into this subject.[7]

The chosen indices follow a simple matching principle[8], which ensures that comparable indices defined by risk, return, regional focus and return measurement characteristics are selected. Due to a lack of specialized sustainable investment strategies indices, that reflect the underlying approach, own SRI negative screening and SRI best in class indices are created for bonds and debt securities from other issuers (mainly corporate bonds) and for shares and other non-fixed interest securities (only for the Stoxx Europe Index). Basis of the SRI indices were iBoxx Euro Corporates total return index and Stoxx Europe 600 price index.

5 For more detail see KAGB § 1 Absatz 19, https://www.gesetze-im-internet.de/kagb/__1.html

6 The analysis of financial statements of German savings banks showed in addition, that major proportion of own securities are invested in special funds (Spezialfonds). These funds are categorised as shares and other non-fixed interest securities, but can contain a variety of asset classes that are not represented in return and risk characteristics by shares and real estate.

7 Schröder (2010) implemented an approach that deviates with asset class allocations with share class weighting schemes.

8 See Hertrich (2013) p. 215 for more details.

The negative screening index is based on the database Thomson Reuters Asset4. Negative screening excludes certain sectors or companies that are involved in controversial or unacceptable activities. All activities included for our negative screening index composition are represented in table 3. Companies that are engaged in these activities will be excluded from the index composition. The remainder of the basis indices are then strapped in newly calculated indices. The calculation of the respective SRI indices is based on Markit iBoxx Bond Index Calculus (2015) and on the Stoxx calculation guide (2016).

Table 3: Negative screening factors used in the composition of negative screening indices

Negative Screening Factors	
Negative Screening Factors - provided by Asset4	Animal Testing
	Alcohol
	Armaments
	Nuclear
	Tobacco
	Embryonic Stem Cell Research
	Gambling
	Pornography
	Contraceptives
	GMO Products
	Cluster Bombs
	Anti-personnel mines
	Agrochemical Products

The best in class index represents a relative best in class approach, which entails a combination with negative screening. Out of the respective sustainable negative screening asset universe, ESG scores, provided by Asset4, are processed and assigned to the negative screened assets. The Asset4 ESG score comprises an environmental, a social and a corporate governance score, which are equally weighted to calculate the total ESG score. All companies are then sorted based on their industry classification benchmark (data represented by ICB level 3). For each industry classification, the top 50% with the highest ESG score are selected to represent the best in class indices.[9] The same metrics as for negative screening indices are used to calculate the respective best in class indices.

To sum up, sustainability for SRI negative screening and SRI best in class portfolio can be achieved in the asset classes bonds and debt securities issued by public bodies, bonds and debt securities from other issuers and in the class of shares and

[9] For more detail of compositions of best in class indices see Schäfer & Bauer (2015).

other non-fixed interest securities. Money market instruments are covered by the 12-month Euribor rate, whereas bonds and debt securities issued by the bank are covered by a 3-month AA financial commercial paper interest rate, for both SRI and conventional portfolios. Thus, every portfolio consists of seven endogenous variables.

The following table gives detailed information of the used asset classes, the indices that represent the asset class, as well as the three constructed portfolio for the vector error correction model.

Table 4: Matching principle of the three used portfolios

Matching principle	Asset allocation of German savings banks					
Risk and return characteristics reflected by	**Bonds and other interest-bearing securities**					**Shares and other non-fixed interest securities**
	Money market		Bonds and debt securities			
	issued by public bodies	*from other issuers*	*issued by public bodies*	*from other issuers*	*Bonds issued by the Bank*	
Conventional portfolio	12-month Euribor rate	12-month Euribor rate	50 % IBOXX EURO EUROZONE - Tot. Rtn Idx Today; 50 % IBOXX EURO SUB-SOVEREIGNS - Tot. Rtn Idx Today	IBOXX EURO CORPORATES - Tot. Rtn Idx Today	3-month AA Financial Commercial Paper Interest Rate	50 % STOXX EUROPE 600 - PRICE INDEX; 50 % STOXX GLOBAL 1800 REAL ESTATE E - PRICE INDEX
SRI with negative screening portfolio	12-month Euribor rate	12-month Euribor rate	50 % ECPI ETHICAL EURO GVT INDEX - TOT RETURN IND; 50 % ECPI ETHICAL EURO AGCY & SUPRA IDX - TOT RETURN IND	Negative screening index based on IBOXX EURO CORPORATES - Tot. Rtn Idx Today	3-month AA Financial Commercial Paper Interest Rate	50 % Negative screening index based on STOXX EUROPE 600 - PRICE INDEX; 50 % ECPI GLOBAL ECO REAL ESTATE&BUILDING - PRICE INDEX
SRI with best in class portfolio	12-month Euribor rate	12-month Euribor rate	50 % ECPI ETHICAL EURO GVT INDEX - TOT RETURN IND; 50 % ECPI ETHICAL EURO AGCY & SUPRA IDX - TOT RETURN IND	Best in class Index based on IBOXX EURO CORPORATES - Tot. Rtn Idx Today	3-month AA Financial Commercial Paper Interest Rate	50 % Best in class index based on STOXX EUROPE 600 - PRICE INDEX; 50 % ECPI GLOBAL ECO REAL ESTATE&BUILDING - PRICE INDEX

The time series comprise monthly financial data from January 2005 to December 2015, altogether 11 years. When using autoregressive model techniques, which include long-term relationships, datasets should have a wide range, when applicable multiple business cycles. However, the period is limited by the provision of the Asset4 database, which has a resilient base of data starting from January 2005. Further, December 2015 as the period endpoint is limited by two factors, Asset4 database is based on relevant ESG information from financial and sustainable statements of the companies and the lagged publication of financial statements of German savings banks.

Thomson Reuters DataStream provides all used historical data in the empirical analysis. The obtained prices and returns of the indices are in nominal terms, so that no inflation adjustment is considered. In addition, transaction costs and tax aspects are not considered in the time series data, which is a probable assumption for our simulation model.

C) Vector error correction model and bootstrap simulation analysis

The time series are then basis of the stochastic simulation process. We implement a vector error correction model in conjunction with a bootstrap simulation as the stochastic simulation process. Where a VECM can represent both long-term relationships and short-term dynamics of financial and economic time series. The general form of VECM is[10]:

$$\Delta y_t = \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p} + u_t$$

$$where: y_t = vector\ of\ endogenous\ time\ series;\ p = number\ of\ lags; \Gamma_i = -\left(A_{i+1} + \cdots + A_p\right) for\ i = 1, \dots, p-1; A = n * n\ matrix\ parameter;\ u_t = error\ term;\ \alpha = speed\ of\ adjustment\ and\ \beta = long - run\ coefficient$$

Whether stationarity is, a compulsive or an optional characteristic in using time series data for VECM of vector autoregressive model is highly discussed in the academic literature.[11] All time series are used in the form log(y_t). The stationarity tests of our variables show clear results, that the endogenous variables are not stationary for level data but are stationary for first differenced variables, which make the variables applicable to the VECM. Stationary tests are performed by the Augmented Dickey-Fuller (ADF) Test, the Philips-Peron Test and the Kwiatkowski-Philipps-Schmidt-Shin (KPSS) Test.[12] In addition, our portfolios include binary dummy variables to remove the impact of special economic and financial events on our time series.

The key concept of the VECM are cointegrative relationships between time series, which means, that two or more data series appear to have same stochastic trends and thus can share same long-term movements. In case of no cointegrative relationships, the VECM is identical with a vector autoregressive model (VAR) that only considers short-term dynamics. Cointegration in financial and economic time series is widely present in the academic and economic literature. The long-term relationships of cointegration can be caused by contracts (e.g. relation between future and spot prices), by the economic theory (e.g. forward rate bias and purchasing power parity) or driven by dynamics of the financial markets (e.g. interest rates and share prices) (Hertrich,

[10] For more information on vector error correction models see: Lütkepohl & Krätzig (2004), Brooks (2008), Lütkepohl (2005), Schröder (2012).

[11] See Sims (1980), Sims et al. (1990) or Enders (2010).

[12] A separate data appendix including unit root tests, cointegration tests and diagnostic checks can be requested from the authors.

2013). The test for cointegration between the endogenous variables of each portfolio is carried out using the method developed by Johansen (Johansen, 1995). For the execution of the test, it is necessary to determine the number of lags as well as the type of deterministic trends. In general, an information criterion, such as the Akaike information criterion (AIC), the Schwarz information criterion (SC) or the Hannan–Quinn information criterion is generally used for the determination of the number of lags.[13] For the analysis, we used Hannan–Quinn information criterion with two lags for the SRI with best in class portfolio and three lags for the conventional portfolio as well as for the SRI negative screening portfolio.[14] The results of the cointegration test via Johansen are: Two cointegrating relationships for the SRI with best in class portfolio, two cointegrating relationships for the SRI with negative screening portfolio and two cointegrating relationships for the conventional portfolio (results are based on Trace test).[15]

Preliminary analysis and diagnostic checking of the computed VECM for the three portfolios show, that the model and each individual estimated equation include non-normality, autocorrelation and heteroscedasticity. However, the diagnosed errors can be i.i.d. as long as autocorrelated errors do not violate asymptotic results (Johansen, 2014) (Raissi, 2008). The analysis is processed by Jarque-Bera test for normality, Ljung-Box Q-Statistics and Breusch-Godfrey Serial Correlation LM test for auto-correlation and ARCH test for heteroscedasticity. To overcome a poor representation of the data generating process for our VECM, the model reduction technique sequential elimination method (SER) is used (Brüggemann & Lütkepohl, 2000). Within this method, variables that have t-values smaller than a predefined threshold are sequentially eliminated in order to increase an information criterion. The process of sequentially elimination is defined by

[13] Several academic papers discussing the power and use of information criterion for VECM/ VAR e.g. Khim & Liew (2004) or Gutierrez et al. (2009) or Brüggemann & Lütkepohl (2000). Clear results of which information criterion is best cannot be drawn.

[14] A detailed analysis of lag selection can be requested from the authors.

[15] A separate data appendix including unit root tests, cointegration tests and diagnostic checks can be requested from the authors.

$$\lambda = \left\{\left[\exp\left(\frac{c_t}{T}\right) - 1\right][T - N + j - 1]\right\}^\wedge\left({}^{1}/_{2}\right)$$

$$where: T = sample\ size; N = total\ number\ of\ regressors; j = step\ in\ elimination\ process\ and\ c_t(with\ AIC) = 2$$

For our purposes, we use a sequential elimination process based on Akaike information criterion.[16] After the implementation of the sequential elimination method, the hypothesis of autocorrelation based on Ljung-Box Q-Statistic and Breusch-Godfrey Serial Correlation LM test can be rejected at a 5% confidence level and thus the errors can be i.i.d. However, the model and the analysis of some individual estimated equation still suffer under slight non-normality and heteroscedasticity.[17] This may be the result of low number of lags for the VECM and the unique setting of persistent drastic low interest rates (non-normality mainly bond oriented variables, Euribor and commercial papers). The finalized VECM of the three individual portfolios is then estimated with a Seemingly Unrelated Regression (SUR) because of the sequential elimination process. This process lead to unequal lag length structures of the individual portfolio VECM equations. To overcome the inability, the SUR uses a generalized least square (GLS) estimation, which is a more efficient estimator when lag lengths are unequal.[18]

Each computed and estimated portfolio VECM is then used to generate simulations of all portfolio variables for a 96 month out of sample period. Thus, the out of sample period is from January 2016 to December 2019. Although as the methodical basis, a so-called bootstrap method is used which leaves the correlation structure between time series unchanged (Schröder, 2010). In this approach, the parameters of the model are estimated once for the out of sample period. Then, the residuals of the estimate are used for the simulation of the out of sample forecasts. The bootstrap process runs

[16] The use of the sequential elimination of regressor process as a VECM reduction technique is discussed ambivalently. Where some argue that SER process did not add value to VAR Kascha & Trenkler (2015) others argue that SER can add value to VAR Krolzig (2000), Hoxha (2010). In all, further comparison of forecast accuracy model reduction techniques and model without reduction technique were employed. The forecast accuracy models based on RMSE, MAE, MAPE, SMAPE, Theil U1 and Theil U2 showed that our SER VECM model added value or at least provided similar results than VEC models without reduction techniques, so that a use of our SER VECM is straight.

[17] A separate data appendix including unit root tests, cointegration tests and diagnostic checks can be requested from the authors.

[18] Detailed descriptions of the used SUR methodology can be find in Greene (2011)

10,000 repetitions per month and asset class according to the method of resampling with replacement out of the residuals of the individual portfolio VECM equations.

To rebalance the respective portfolios, we considered two outright strategies: buy and hold and constant mix. Rebalancing a portfolio has a simple trade-off: the cost of rebalancing versus cost of not rebalancing. With the assumption, that German savings banks choose the optimal strategic asset allocation, any divergence from the optimal strategic asset allocation is not desirable. By rebalancing, the investor can reduce the present value of expected losses from not tracking the optimal asset allocation. Further benefits of rebalancing include the maintenance of the investors desired systematic risk exposure, when higher risk assets earn higher returns on average higher risk assets then reflect larger proportions of the portfolio and thus the portfolio risk tend to drift. Rebalancing costs include transaction costs and tax costs for taxable investors (Maginn, et al., 2007).

A buy and hold strategy is a passive strategy, where the proprietary trading of German savings banks acquires the initial asset allocation and holds it over time without further adjustments. Often, it is classified as a “do-nothing” strategy. Buy and hold strategy generally have the features: i) the portfolio’s payoff function is linear, ii) the portfolio value increases as a function of a portfolio asset with a slope equal to the proportion of the asset in the initial asset allocation, iii) the upside potential of the strategy is unlimited and iv) the investor passively assumes that risk tolerance is positively and directly related to wealth (Perold & Sharpe, 1988). In our approach the asset allocation is unchanged during the investment period of one year. After one year, the initial weights of the strategic asset allocation are rebalanced to maintain the more conservative investor perspective of German savings banks.

In a constant mix strategy, investors continuously rebalance the portfolio to maintain the initial strategic asset allocation. This strategy requires to buy securities as they fall in value and selling securities as they increase in value. Therefore, constant mix investors often take a contrarian position and supply liquidity to markets. A constant mix strategy assumes a constant risk tolerance that varies proportionally with wealth. Consequently, constant mix strategies have concave payoff curves, which represent the sale of portfolio insurance (Maginn, et al., 2007). For our purposes, we implement a monthly constant mix rebalancing frequency because of our underlying monthly time series.

The success of buy and hold and constant mix strategies implemented in the strategic asset allocation process depends heavily on market environment. Several studies show, that buy and hold strategies outperform constant mix strategies when markets are trending in both, upwards and downwards markets. However, constant mix strategies outperform a comparable buy and hold strategy when markets are flat and oscillating. Hence, the selection of an appropriate strategy should be based by the degree of fit between the strategy's exposure and the investor's risk tolerance (Perold & Sharpe, 1988).

Given that our selected period from January 2005 to December 2015 can be considered upward trending, we expect that buy and hold strategies will outperform constant mix strategies for our simulation model. Further research in my upcoming dissertation also implements derivative overlay strategies including protective put, yield enhancement, collars and bond-call options.

Subsequent of the simulation process, a comparison of the conventional and the SRI portfolios will be executed. The comparison includes an analysis and evaluation of the entire future return distribution paths. Here, the analysis comprises the following statistical measures: i) mean, ii) median, iii) standard deviation, iv) maximum value, v) minimum value, vi) skewness and vii) excess kurtosis. Given that economic and financial return distribution tend to be asymmetric, downside risk measures are implemented for the evaluation part to quantify the risk and the risk-adjusted return. Downside risk measures are also known as lower partial movement (LPM) measures, since the moments of the distribution are measured over partitions of the distribution (Schröder, 2010). The used downside risk measures include:[19]

$$Downside\ Deviation = \sqrt{\frac{1}{N}\sum_{t=1}^{N} max\ [MAR - \mu, 0]^2}$$

$$where\ N = observation, \mu = average\ return\ distribution\ and\ MAR$$
$$= minimum\ acceptable\ return$$

[19] In this article the downside risk measures are not further discussed because this would go beyond the scope of the analysis. For further discussion of the properties of the used downside risk measures see: Kaplan & Knowles (2004); Sortino & van der Meer (1991); Sortino et al. (1999); Jarrow & Zhao (2006), Keating & Shadwick (2002) and Sortino & Price (1994)

$$Omega_{\mu}(MAR) = \frac{\mu - MAR}{LPM_1(MAR)} + 1$$

$Equivalent\ representation\ of\ Omega,$ where $LPM_1 =$ lower partial moment of order 1

$$Sortino\ ratio = \frac{\mu - MAR}{\sqrt{LPM_2(MAR)}}$$

$$where\ LPM_2 =\ lower\ partial\ moment\ of\ order\ 2$$

$$Upside\ potential\ ratio = \frac{HPM_1(MAR)}{\sqrt{LPM_2(MAR)}}$$

$$where\ HPM_1 = higher\ partial\ moment\ of\ order\ 1;\ LPM_2 = lower\ partial\ moment\ of\ order\ 2$$

$$Kappa\ 3\ ratio = \frac{\mu - MAR}{\sqrt{LPM_3(MAR)}}$$

$$where\ LPM_3 =\ lower\ partial\ moment\ of\ order\ 3$$

$$Where\ LPM_n(MAR) = \frac{1}{N}\sum_{t=1}^{N} max[MAR - \mu, 0]^n$$

$$and\ HPM_n(MAR) = \frac{1}{N}\sum_{t=1}^{N} max[\mu - MAR, 0]^n$$

The minimum acceptable return (MAR) is the interest cost margin of each respective cluster of the year 2015. With this approach, the analysis takes the view of an asset overlay management portfolio, where the goal of the portfolio is to generate an additional return beyond a lower value limit, in this case the interest costs, which in our opinion reflects the attitudes of all build clusters. The interest cost of each respective cluster are used to reflect cost management structures of the respective clusters. The last year of our observation period, 2015, is used because it replicates the current cost levels of German savings banks due to the low interest environment.

In addition to the introduced downside risk measure, Sharpe ratio is also used. Here, we are conscious, that the Sharpe ratio is defined as Sharpe (1966) and is not appropriate to use in our framework.

$$Sharpe\ ratio = \frac{\mu - r_f}{\sigma_{portfolio}}$$

$$where\ r_f = risk\ free\ rate, \mu = average\ return\ of\ portfolio\ and\ \sigma = portfolio\ standard\ deviation$$

The reasons for the inadequate use of Sharpe ratio include an assumption of normality of the distribution and general inaccuracies when applied to portfolios with significant nonlinear risks (Maginn, et al., 2007). However, Sharpe ratio is used for a better comparison between other portfolios because it is the most widely used method for calculating risk-adjusted return (Maginn, et al., 2007). The risk free rate in our analysis is the yield of a 10-year German treasury note of 31.12.2015.

The computation and analysis of the VECM, the bootstrap approach and other empirical work is processed via Eviews and jMulti.

III. Results

A) *Preliminary analysis and clustering of savings banks results*

Table 5 presents selected balance sheet data and ratios of German savings banks in the years 2013 to 2015. German savings banks are clustered according to the implemented k-means clustering which is based on the theoretic outcome of Schäfer & Mayer 2013. The selected balance sheet data and ratios comprise the number of savings banks, the average proprietary trading, the average balance sheet, the percentage of proprietary trading to balance sheet, the cost-income-ratio and the liquidity ratio after LiqV, respectively in their corresponding cluster.

Table 5: Selected Balance Sheet Data German savings banks (Sparkassen)

Selected Balance Sheet ratios	Year	Number of German savings banks	Average proprietary trading (Depot A); € thousand	Average Balance Sheet; € thousand	Percentage of proprietary trading to balance sheet total	Cost-income-ratio	Liquidity-ratio after LiqV
Cluster 1	2013	66	745,971.85	2,425,212.65	30.76%	64.64	3.01
	2014	56	862,034.34	2,290,802.36	37.63%	64.14	4.55
	2015	68	873,970.18	2,887,029.38	30.27%	65.75	2.97
Cluster 2	2013	116	676,250.15	2,743,321.63	24.65%	64.47	3.02
	2014	139	675,789.78	2,436,760.66	27.73%	66.21	3.17
	2015	69	604,974.80	2,213,763.52	27.33%	66.46	3.06
Cluster 3	2013	166	559,174.88	2,794,781.04	20.01%	64.53	2.86
	2014	146	477,904.32	2,560,199.49	18.67%	66.68	2.43
	2015	217	627,945.87	3,065,000.19	20.49%	66.79	2.71
Cluster 4	2013	68	354,154.94	2,483,773.09	14.26%	66.86	2.52
	2014	75	528,557.45	3,822,425.20	13.83%	65.95	1.99
	2015	58	380,919.32	2,252,008.09	16.91%	69.49	3.06

It can be seen that the number of German savings banks in their respective cluster is quite constant for cluster 1 and cluster 4. In the period of investigation, a shift from German savings banks from cluster 2 to cluster 3 can be identified, indicating a more passive orientation of proprietary trading management. Further findings can be drawn for the cost-income-ratio. First, the cost-income-ratio increases for all clusters but the rate of increase is different (Compounded annual growth rate (CAGR) of cost-income-ratio; cluster 1: 0.57%, cluster 2: 1.01% cluster 3: 1.15% and cluster 4 1.29% in the years between 2013 and 2015). An interpretation of the increase includes a more efficient income and cost management bank process for more active clusters in regards to their proprietary trading management. Second, the general level of the cost-income-ratio is smaller for more active proprietary trading savings banks (cluster 1) than for more passive proprietary trading savings banks (cluster 4). The other ratios behave as anticipated for the respective clusters, given that these ratios are mandatory in the creation of the clusters.

Additional, table 6 shows selected profit and loss data and ratios of German savings banks in the same time period. The data comprise interest margin, interest cost margin, net interest margin, the ratio of interest from bonds and other interest-bearing secure-ties and interest margin, the ratio of interest from shares and other non-fixed interest securities and interest margin and the ratio of interest from proprietary trading to interest margin.

Table 6: Selected P&L data of German savings banks (Sparkassen)

Selected P/L ratios	Year	Interest margin	Interest cost margin	Gross interest margin	Interest from bonds and other interest-bearing securities/ Interest margin	Interest from shares and other non-fixed interest securities / Interest margin	Interest from proprietary trading/ Interest Margin
Cluster 1	2013	3.38%	1.20%	2.18%	14.68%	13.62%	28.30%
	2014	3.04%	0.80%	2.24%	23.61%	13.66%	37.26%
	2015	2.86%	0.74%	2.12%	12.44%	14.61%	27.05%
Cluster 2	2013	3.34%	1.20%	2.14%	15.15%	6.78%	21.93%
	2014	3.06%	0.94%	2.12%	15.05%	7.12%	22.17%
	2015	2.83%	0.76%	2.07%	13.55%	8.78%	22.33%
Cluster 3	2013	3.45%	1.22%	2.23%	15.80%	2.92%	18.72%
	2014	3.21%	1.05%	2.16%	11.25%	3.45%	14.70%
	2015	2.91%	0.78%	2.13%	12.00%	3.47%	15.47%
Cluster 4	2013	3.47%	1.28%	2.19%	10.91%	1.04%	11.95%
	2014	3.24%	1.12%	2.11%	8.87%	1.01%	9.88%
	2015	2.87%	0.80%	2.07%	13.58%	1.51%	15.09%

Table 6 shows, that for every cluster in the years between 2013 and 2015 the interest margin of German savings banks is decreasing. However, the highest interest margin in 2015 is identified with cluster 3 with 2.91% followed by cluster 4 with 2.87%, cluster 1 with 2.86% and cluster 2 with 2.83%. In addition, the interest cost margin and thus the net interest margin is decreasing as well. Interest cost margin is lowest with cluster 1 followed by cluster 2, 3 and 4 (0.74%; 0.76%; 0.78%; 0.8%, respectively). Combined, the highest net interest margin in 2015 is with cluster 3 followed by cluster 1, 2 and 4 (2.13%; 2.12%; 2.07%; 2.07%, respectively). Especially, a shift in the application of interest from shares and other non-fixed interest securities to total interest margin can be observed for all clusters. Here, cluster 1 has the highest share of interest from shares and other non-fixed interest securities to total interest margin. Furthermore, the use of interest from bonds and other interest-bearing securities to total interest margin declines between the years 2013 to 2015 in all clusters, except for cluster 4. In total, more active proprietary trading management (cluster 1) uses more often interest from proprietary trading to total interest margin than cluster 2, 3 and 4.

Table 7: Asset allocation of proprietary trading of German savings banks

Average	Year	Money market securities issued by public bodies	Money market securities issued by other issuer	Bonds and debt securities issued by public bodies	Bonds and debt securities from other issuers	Bonds issued by the bank	Shares and other non-fixed interest securities
Cluster 1	2013	0.00%	0.01%	14.04%	46.37%	0.24%	39.35%
	2014	0.00%	2.73%	15.78%	45.70%	0.06%	35.72%
	2015	0.00%	3.26%	20.15%	33.32%	0.12%	43.15%
Cluster 2	2013	0.00%	0.54%	14.20%	51.98%	1.21%	32.07%
	2014	0.00%	0.78%	18.86%	46.43%	6.39%	27.54%
	2015	0.00%	1.21%	18.10%	46.18%	0.17%	34.34%
Cluster 3	2013	0.00%	0.18%	17.63%	63.35%	0.41%	18.43%
	2014	0.00%	1.63%	19.89%	53.79%	0.37%	24.31%
	2015	0.00%	4.74%	22.74%	51.37%	0.85%	20.29%
Cluster 4	2013	0.00%	0.12%	19.73%	71.11%	0.32%	8.72%
	2014	0.00%	8.76%	21.40%	54.76%	1.87%	13.21%
	2015	0.00%	5.34%	21.13%	58.84%	0.25%	14.43%

Table 7 identifies the asset allocation of the proprietary trading management of German savings banks for the identified clusters in the years of 2013 to 2015. Money market securities have an inferior standing in the asset allocation. A greater proportion can be found in cluster 3 and 4. The asset allocation towards to bonds and debt securities issued by public bodies increased for all clusters, whereas the allocation from bonds and debts securities from other issuers decreased. This may indicate a higher need for more liquid/ lower credit spread securities due to stricter capital and liquidity requirements. To absorb this dynamic, the allocation toward shares and other non-fixed interest securities increased for all clusters between 2013 and 2015. This can be interpreted as a consequence of the current environment of low interest rates to overcome interest deficits by investing in riskier assets. For the simulation process, we used the average asset allocation of each respective cluster of the years from 2013 to 2015 to overcome single period allocation effects. Table 8 summarizes the average asset allocation.

Table 8: Average asset allocation of proprietary trading of German savings banks from 2013 to 2015

Average 2013-2015	Money market securities issued by public bodies	Money market securities issued by other issuer	Bonds and debt securities issued by public bodies	Bonds and debt securities from other issuers	Bonds issued by the bank	Shares and other non-fixed interest securities
Cluster 1	0.00%	2.00%	16.66%	41.80%	0.14%	39.41%
Cluster 2	0.00%	0.84%	17.05%	48.20%	2.59%	31.32%
Cluster 3	0.00%	2.18%	20.09%	56.17%	0.54%	21.01%
Cluster 4	0.00%	4.74%	20.75%	61.57%	0.81%	12.12%

The conclusion of the financial statements of German savings banks draws enlightend findings. Proprietary trading management strategies are highly bank-specific and depend on various factors such as: - banks policy objective, - the size of the bank, - share of own investments in assets, - individual risk tolerance and - the profit potential with customer businesses. Nevertheless, it is possible to draw conclusions about the proprietary trading strategies of German savings banks. The majority of the institutes pursues a conservative investment policy and invests heavily in fixed-income securities. Liquidity management, balance sheet structure management and the achievement of a risk-adjusted additional yield are the focus. Large savings banks often invest in more profitable but also riskier assets, since those banks enforce a generation of wealth strategies. From 2013 to 2015, a shift in the allocation of assets can be identified from fixed income securities to shares and other non-fixed interest securities. The asset allocation for German savings banks seems to be split into two major parts, one driven by a conservative liquidity requirement part to cover for the higher liquidity requirements and one more active/ offensive part to cover the return need of German savings banks. A solution to this allocation shift can be liquidity coverage ratio competent special funds that fulfil the regulatory requirements, but have a higher interest margin than government securities (Schick, 2012).

B) Simulation process

The focus of the study is the quantitative analysis of the constructed conventional and SRI portfolios to determine the suitability of SRI for the proprietary trading of German savings banks. We will analyse each cluster separately by statistical measures and by risk-adjusted return measures. The investment horizon of all portfolios is four years from January 2016 to December 2019.[20][21]

Table 9: Distribution analysis of cluster 1

Cluster 1	Average	Median	CAGR	Standard deviation of distribution	Maximum value of distribution	Minimum value of distribution	Skewness	Excess Kurtosis
NEG - BH	**157.6**	149.4	12.1%	41.9	475.3	29.8	2.3	6.4
BIC - BH	151.3	145.7	10.9%	32.6	442.4	80.7	2.0	5.7
CONV - BH	<u>147.1</u>	142.6	10.1%	29.0	467.3	46.1	1.9	6.4
NEG - CM	**147.7**	143.4	10.2%	31.7	414.0	19.3	2.0	6.1
BIC - CM	145.5	142.6	9.8%	24.4	355.9	24.5	1.3	2.1
CONV - CM	<u>144.8</u>	142.2	9.7%	24.0	421.1	39.0	1.4	3.8

As expected, buy and hold strategies outperform constant mix strategies, due to their linear payoff schemes in up trending markets. This pattern can be observed for the entire distribution and downside risk measure analysis. The SRI portfolio with negative screening has the highest average portfolio values after four years in both buy and hold and constant mix strategies. Conventional portfolio results in the lowest average portfolio values after four years, also for both, buy and hold and constant mix strategies. The excess kurtoses are positive, indicating a leptokurtic distribution with a higher peak than the curvature of a normal distribution. In addition, skewness of all portfolios is positive, resulting in a right tail of the distribution that is longer/ fatter than the left tail of the distribution.[22]

Table 10: Downside risk analysis of cluster 1

Cluster 1	Sharpe	Downside Deviation	Omega	Sortino	Upside Potential	Kappa 3
NEG - BH	2.35	**0.00%**	**457.58**	**93.03**	**93.23**	**54.68**
BIC - BH	**2.60**	0.02%	30.69	9.53	9.85	6.14
CONV - BH	<u>1.50</u>	<u>0.09%</u>	<u>4.46</u>	<u>1.33</u>	<u>1.72</u>	<u>0.76</u>
NEG - CM	1.99	**0.03%**	**4.82**	**1.67**	**2.11**	**1.01**
BIC - CM	**2.33**	0.04%	<u>0.65</u>	<u>-0.32</u>	<u>0.58</u>	<u>-0.30</u>
CONV - CM	<u>1.43</u>	<u>0.08%</u>	1.22	0.16	0.86	0.11

20 Yearly period analysis is also computed and can be requested from the author.
21 Following abbreviations are used for tables 8 - 15:
NEG = SRI with negative screening portfolio, BIC = SRI with best in class portfolio, CONV = Conventional portfolio, BH = Buy and hold, CM = Constant mix; Excess Kurtosis = Kurtosis – 3. For distribution analysis, Highest average values are bold whereas lowest values are underlined highlighted. For the downside risk analysis highest downside risk measures are bold whereas lowest downside risk measures are underlined.

The downside risk analysis provides clear outperformance of SRI portfolios with a buy and hold strategy. Here, SRI with negative screening outperforms the other portfolios clearly in all downside risk measures. For constant mix strategies, SRI with negative screening portfolio outperforms the other portfolios as well, however, the conventional portfolio slightly outperforms the SRI best in class portfolio.

Table 11: Distribution analysis of cluster 2

Cluster 2	Average	Median	CAGR	Standard deviation of distribution	Maximum value of distribution	Minimum value of distribution	Skewness	Excess Kurtosis
NEG - BH	**151.6**	144.2	11.0%	37.9	444.9	34.4	2.3	6.4
BIC - BH	145.4	141.2	9.8%	28.1	381.5	82.8	1.8	4.2
CONV - BH	142.7	138.7	9.3%	25.9	401.5	49.3	1.9	5.8
NEG - CM	**144.5**	140.2	9.6%	29.9	387.3	21.5	1.9	5.3
BIC - CM	141.2	138.6	9.0%	23.3	329.4	39.4	1.3	1.8
CONV - CM	140.1	137.9	8.8%	21.9	358.3	43.9	1.3	3.5

For Cluster 2, the distribution analysis provides similar results than for cluster 1. SRI with negative screening portfolio outperforms the other portfolios for buy and hold and constant mix strategies based on average portfolio value after four years. Skewness and excess kurtosis measures provide comparable interpretations than for cluster 1 distribution analysis.

Table 12: Downside risk analysis of cluster 2

Cluster 2	Sharpe	Downside Deviation	Omega	Sortino	Upside Potential	Kappa 3
NEG - BH	2.38	**0.03%**	**19.59**	**6.76**	**7.13**	**4.63**
BIC - BH	**3.00**	0.04%	2.34	0.88	1.53	0.72
CONV - BH	1.60	0.08%	1.08	0.06	0.76	0.04
NEG - CM	2.09	0.04%	**0.90**	**-0.08**	**0.70**	**-0.06**
BIC - CM	**2.88**	**0.04%**	0.44	-0.51	0.41	-0.49
CONV - CM	1.53	0.08%	0.49	-0.43	0.42	-0.34

Based on downside risk analysis, SRI with negative screening portfolio outperforms SRI with best in class portfolio and conventional portfolio with a buy and hold strategy. In addition, the SRI with negative screening portfolio outperforms the other portfolios, whereas the conventional portfolio outperforms the SRI best in class portfolio for constant mix strategies.

Table 13: Distribution analysis of cluster 3

Cluster 3	Average	Median	CAGR	Standard deviation of distribution	Maximum value of distribution	Minimum value of distribution	Skewness	Excess Kurtosis
NEG - BH	134.3	131.2	7.7%	19.4	273.9	45.1	1.9	4.1
BIC - BH	**137.8**	134.1	8.3%	20.4	298.7	88.9	1.7	3.1
CONV - BH	129.8	128.1	6.7%	13.3	263.0	65.1	1.5	4.0
NEG - CM	125.8	124.8	5.9%	14.0	255.2	47.4	1.3	4.9
BIC - CM	**130.7**	129.5	6.9%	13.3	256.5	59.2	1.0	1.5
CONV - CM	126.7	126.2	6.1%	10.3	241.6	58.4	0.7	1.2

The distribution analysis of cluster 3 provides results that the SRI with best in class portfolio has the highest average portfolio value after four years followed by the SRI with negative screening portfolio and the conventional portfolio with buy and hold strategies. For constant mix strategies, the highest portfolio value after four years delivers also the SRI with best in class portfolio followed by the conventional portfolio and the negative screening portfolio. The measures of skewness and excess kurtosis are smaller than for cluster 2 and cluster 3, both converging to 0.

Table 14: Downside risk analysis of cluster 3

Cluster 3	Sharpe	Downside Deviation	Omega	Sortino	Upside Potential	Kappa 3
NEG - BH	2.08	0.11%	**0.25**	**-0.61**	**0.20**	**-0.53**
BIC - BH	**3.63**	**0.07%**	0.22	-0.65	0.18	-0.59
CONV - BH	1.46	0.10%	0.17	-0.77	0.16	-0.70
NEG - CM	1.55	0.07%	0.09	-0.88	0.09	-0.85
BIC - CM	**3.18**	**0.04%**	0.07	-0.90	0.06	-0.89
CONV - CM	1.31	0.09%	**0.12**	**-0.84**	**0.12**	**-0.79**

Cluster 3 downside risk analysis has mixed results. As for cluster 2 and cluster 1, with buy and hold strategies, the SRI with negative screening outperforms the SRI with best in class portfolio as well as the conventional portfolio. For constant mix strategies, the conventional portfolio outperforms the SRI with negative screening portfolio and the SRI with best in class portfolio. However, it can be seen, that the downside risk measures turning negative for all portfolios and with both strategies compared to cluster 2 and cluster 1 downside risk analysis. This is a clear indication, that the portfolios are not able to generate an excess return above the minimum acceptable return.

Table 15: Distribution analysis of cluster 4

Cluster 4	Average	Median	CAGR	Standard deviation of distribution	Maximum value of distribution	Minimum value of distribution	Skewness	Excess Kurtosis
NEG - BH	119.1	117.8	4.5%	11.6	206.5	49.2	1.6	3.9
BIC - BH	**126.8**	123.7	6.1%	14.1	207.8	80.7	1.9	2.4
CONV - BH	118.6	118.2	4.4%	6.8	187.5	80.6	0.9	2.3
NEG - CM	107.0	107.3	1.7%	13.3	230.0	42.7	0.0	-0.1
BIC - CM	**112.6**	112.9	3.0%	7.2	165.3	60.8	-0.5	-0.2
CONV - CM	104.3	103.9	1.1%	17.4	171.6	17.1	0.0	-2.6

The highest portfolio average values after four years has the SRI best in class portfolio followed by the SRI negative screening portfolio and the conventional portfolio for buy and hold strategies. For constant mix strategies, the SRI best in class portfolio outperforms the SRI negative screening portfolio and the conventional portfolio based on average portfolio values after four years. For the first time, skewness and excess kurtosis measures turning negative for constant mix strategies. Excess kurtoses are negative resulting in a platykurtic distribution with thinner tails. Skewness is zero or slightly below zero.

Table 16: Downside risk analysis of cluster 4

Cluster 4	Sharpe	Downside Deviation	Omega	Sortino	Upside Potential	Kappa 3
NEG - BH	1.38	0.17%	**0.07**	**-0.84**	0.06	**-0.78**
BIC - BH	**2.78**	0.12%	0.03	-0.90	0.02	-0.84
CONV - BH	1.14	**0.10%**	0.06	-0.91	**0.06**	-0.87
NEG - CM	0.35	0.10%	0.02	-0.96	0.02	-0.95
BIC - CM	**1.70**	**0.04%**	0.01	-0.98	0.01	-0.97
CONV - CM	0.84	0.10%	**0.05**	**-0.93**	**0.05**	**-0.90**

As for cluster 3, the downside risk analysis provides mixed results of outperformance for buy and hold strategies. For constant mix strategies, the conventional portfolio outperforms the SRI portfolios on four out of five downside risk measures. Negative downside risk measures persist for cluster 4, also indicating that portfolios are not able to generate an excess return above the minimum acceptable return.

IV. Discussion

A) General observations

The research study provided empirical evidence to evaluate the suitability of sustainable investments and investment strategies for the proprietary trading of German savings banks. We can conclude that sustainable investments and strategies are suitable for the proprietary trading of German savings banks and outperformed/ did not underperform conventional investments for our simulation period January 2016 to December 2019. The interpretation of the results is applicable for all computed clusters of German savings banks. In our simulation model, more active proprietary trading management savings banks (cluster 1) have higher beneficial downside risk measures than the other clusters. The downside risk advantage decreases continually from cluster 1 to cluster 4, which advocates a more active management/ an asset allocation towards shares and other non-fixed securities approach for the proprietary trading in the current low interest environment. Further, buy and hold management strategies outperformed constant mix management strategies for all computed clusters. This pattern was expected, due to the linear payoff schemes in up trending markets of buy and hold strategies and the concave payoff schemes in up trending markets of constant mix strategies. By comparing the individual strategies, the SRI with negative screening portfolio yielded mainly better downside risk measures than the SRI with best in class portfolio and the conventional portfolio for both, buy and hold and constant mix strategies. However, downside risk measure turning negative for cluster 3 and cluster 4 indicating, that the portfolios are not able to generate excess return above the minimum acceptable return. Thus, especially liquidity oriented and small German savings banks (as measured by balance sheet) need higher allocations towards shares and other non-fixed securities to cover the minimum acceptable return.

Additionally, the preliminary analysis of the financial statements of German savings banks brought illustrative findings in regard of balance sheet and profit and loss ratios. The key findings include i) a shift in the number of German savings banks shift from cluster 2 to cluster 3, which can be interpreted as a more passive orientation of proprietary trading management, ii) the cost-income-ratio increases for all cluster of the investigation period and the cost-income-ratio is smallest for cluster 1 and increases continually to cluster 4, iii) the interest margin, the interest cost margin as well as net interest costs are decreasing for all cluster from 2013 to 2015 as a reflection of the low interest environment, iv) the asset allocation of the proprietary trading of German savings banks reveals, that cluster 1 savings banks allocates more towards shares and other non-fixed securities than the other clusters. The allocation towards bonds and other fixed securities accumulates up to cluster 4.

B) Criticism

Our selected time frame from January 2005 to December 2015 can be criticized as too short as input data for our vector error correction model. Further, the period from 2009 to 2015 reflects a unique upward trending market. This pattern as base for the VECM, which acknowledges long-term relations and short-term dynamics to simulate future return paths, is questionable to persist in the future. However, a longer period as input data was pursued but could not be fulfilled because of lack in sustainable investment data of Thomson Reuters Asset4 database prior to 2005 to create individual negative screening and best in class indices. Thus, a longer period could be employed but only without the distinction of sustainable investment strategies, negative screening and best in class. Here, we would fall back for provided indices that often utilize mixed sustainable investment strategies, which in our opinion, cannot meet the requirements to compare sustainable investment strategies in total.

The computed vector error correction model can be i.i.d. given that the model has no serial correlation, however in regards to normality and heteroscedasticity the model has room through improvement. This can be implemented via a more robust model through the incorporation of structural breaks, additional dummy variables or additional technique for testing cointegration ranks of non-normal distributions.[23]

For my upcoming dissertation, further portfolio strategies including protective put, yield enhancement, collars and bond call options will be implemented additionally. Through this, a large variety of used German savings banks strategies can be simulated and applied. Controversially to the asset allocation computed via financial statement analysis, DekaBank evaluates the proprietary trading allocation of participating German savings banks through a survey. The issued results deviate from our asset allocation results based on financial statements. However, the survey does not distinguish between savings banks clusters, which is in our opinion a desirable partition. The

[23] See Chan (2013).

disparity of allocation shows moreover the shortcomings of rigour balance sheet accountings. Further, the time lag of balance sheet data and sustainable data through Thomson Reuters Asset4 database was large with a preliminary lead-time of about 1 year.

C) Outlook

The continued low interest environment affects the earnings situation of German savings banks heavily, especially, through the drop of the largest income source, the interest surplus. Besides, the fix operative costs could not down with comparable scale. More, the proprietary trading of German savings bank suffers due to low possibilities of income generation through maturity transformation and the reinvestment risk of expiring assets (Ihring, 2016). For these reasons, the proprietary trading of German savings banks must incorporate new strategies or new asset classes. These implements include for strategies e.g. risk parity approaches or overlay management approaches and for asset classes allocations towards shares and other non-fixed securities which can include emerging markets securities (or non-EU securities) and real estate securities.

Our study showed that sustainable investments and sustainable investment strategies could help German savings banks for generating additional or at least the same return objectives than conventional investments. Several dialogs and workshops with treasury manager of German savings banks revealed the willingness to incorporate sustainable investments. However, the lack of adequate sustainable instruments, the right course of implementation of sustainable investments in the proprietary trading and a universal sustainable corporate policy are the main obstacles to the incorporation of sustainable investments for German savings banks.

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