Testing Rebalancing Strategies for Stock-Bond Portfolios: Where Is the Value Added of Rebalancing?

HUBERT DICHTL, WOLFGANG DROBETZ and MARTIN WAMBACH*

ABSTRACT

We apply a novel double block bootstrap approach that enables us to test the value added of rebalancing for stock-bond portfolios using historical data from the United States, the United Kingdom, and Germany. Analyzing the Sharpe ratio of different rebalancing strategies, historical simulation results indicate that all rebalancing strategies outperform a buy-and-hold strategy. We attribute this outperformance to both a higher return and a reduced volatility. Moreover, depending on the specific stock and bond market characteristics of the three countries under investigation, the optimal rebalancing frequency ranges between quarterly and yearly intervals.

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Having identified an investor's risk preference and regulatory environment, it is the primary objective of any institutional asset manager to implement and supervise the most suitable asset allocation for his client. Once this initial asset allocation has been implemented, the literature differentiates between three reasons for portfolio rebalancing: (i) rebalancing due to a shift in an investor's risk profile and/or modified regulatory requirements; (ii) rebalancing based on changes in the expectations about future returns and risks; and (iii) rebalancing due to market movements. As discussed in Fabozzi, Focardi, and Kolm (2006) as well as in Leibowitz and Bova (2011), the first two reasons require the asset manager to construct a new optimal portfolio. In this study, we focus on the third reason: As different assets generate different rates of returns, a portfolio's relative asset composition will deviate from the target weights over time. In order to remain consistent with the institutional investor's initially evaluated return and risk preferences, the portfolio manager has to rebalance the assets back to their predefined target weights. However, as rebalancing strategies imply selling a fraction of the better performing assets and investing the proceeds in the worse performing, it is a highly challenging question whether rebalancing strategies generate a value added for institutional investors and – if so – what the sources of this value added are.

Due to its high importance for institutional portfolio management, several aspects of rebalancing and its practical implications have been analyzed in previous studies. In order to obtain a brief overview, we present those rebalancing studies that are closely related to our investigation in Table I. The following discussion focuses on the primary research objectives and main results of these related rebalancing studies.[1]

[1] All other details as, for example, the applied asset allocation and the implemented rebalancing algorithms etc., are shown in Table I.

[Insert Table I here]

Our empirical analysis is based on the theoretical findings of Perold and Sharpe (1988), who discuss various portfolio strategies under different market scenarios. Focusing on a two-asset portfolio consisting of stocks and bills, they document that a buy-and-hold strategy offers a downside protection that is proportional to the amount allocated into bills, while the upside potential is proportional to the amount allocated into stocks. In contrast to buy-and-hold, rebalancing strategies exhibit less downside protection. As rebalancing requires buying stocks and selling bonds when stocks have decreased, this portfolio strategy represents the sale of portfolio insurance. Moreover, facing a persistent market upswing, a frequent reallocation to the less performing asset also leads to a lower upside potential. However, rebalancing strategies perform best in relatively trendless, but volatile markets, gaining advantage of the much more pronounced mean-reversion in this environment. These reversals could improve portfolio returns while simultaneously reducing the risk of rebalancing strategies. Investigating the average return, the volatility, and the Treynor ratio of several rebalancing strategies over the period from 1968 to 1991, Arnott and Lovell (1993) provide empirical evidence that rebalancing strategies are indeed able to generate a value added to institutional investors. They document that a monthly rebalancing strategy features the highest return while the corresponding volatility is only slightly higher compared to the strategy with the lowest volatility. However, using the Treynor ratio as a performance measure that incorporates both a strategy's return and systematic risk, the empirical results are weaker. Nine out of ten rebalancing strategies exhibit a higher Treynor ratio than the corresponding buy-and-hold strategy. While this finding seems to indicate that rebalancing outperforms a simple buy-and-hold strategy during the underlying 24-year sample period, all Treynor ratios lie very close together within the interval [0.784; 0.794], and hence it is not obvious which strategies actually perform best. Nevertheless, inferring from their analysis that rebalancing offers enhanced returns without increasing risk, Arnott and Lovell (1993) recommend a monthly rebalancing strategy to investors with a long investment horizon. Evaluating the performance on the basis of the Sharpe ratio over the period from 1986 to 2000, Tsai (2001) also shows that rebalancing outperforms a simple buy-and-hold strategy for all analyzed risk profiles.[2] Thus, a frequent reallocation back to the target weights seems to provide some value added to institutional investors. However, as no strategy is consistently better across portfolios of different risk profiles, Tsai (2001) argues that it does not matter much which rebalancing strategy is applied.[3] Examining the period from 1995 to 2004, Harjoto and Jones (2006) report that a rebalancing strategy with an incorporated no-trade interval of 15% leads to both the highest average return and the lowest standard deviation which also results in the highest Sharpe ratio. This empirical finding also remains valid when the sample period is divided into an economic boom, a bust, and a recovery subsample. Taken as a whole, Harjoto and Jones (2006) conclude that investors should readjust their portfolio structure, but not too frequently.[4] Tokat and Wicas (2007) conduct Monte Carlo simulations in order to provide evidence that re-

[2] Tsai (2001) constructs five stock-bond portfolios with a 20%, 40%, 60%, 80%, and 98% equity allocation. These varying portfolio compositions are assumed to represent different risk profiles of institutional investors.

[3] Transaction costs are omitted from the analysis which weakens the explanatory power of the results, as one would expect that the Sharpe ratios of rebalancing strategies are overestimated compared to a buy-and-hold strategy.

[4] Three potential drawbacks are worth noting: (i) The analysis is based on one single 10-year period, intensifying the potential problem of data snooping. (ii) Transaction costs must be incorporated as they could have a major influence on any reallocation decisions. (iii) It is possible that the standard deviations of the bust and the recovery period do not represent suitable estimators as these calculations are based on only 27 and 30 observations, respectively.

balancing could be a powerful instrument for controlling risk.[5] Investigating the impact of both different market scenarios and of several rebalancing strategies, they conclude that rebalancing achieves minimizing risk relative to a predefined asset allocation in all market environments. Jaconetti, Kinniry, and Zilbering (2010) also assume that the value added of rebalancing can primarily be attributed to the reduction of risk relative to the predefined target allocation. In contrast to Tokat and Wicas (2007), they conduct a historical analysis over the period from 1926 to 2009 to support their hypothesis. Examining several rebalancing strategies, Jaconetti, Kinniry, and Zilbering (2010) show that buy-and-hold exhibits the highest average annualized return with a value of 9.1% after an investment period of 84 years, but also the highest volatility with a value of 14.4% due to an average stock allocation of 84.1%. All remaining rebalancing strategies feature average returns that differ only slightly, ranging between 8.5% and 8.8%, whereas the standard deviations lie within the narrow 11.8% and 12.3% band. While it is evident that most institutional investors cannot apply a buy-and-hold strategy on a long-term basis, it is again not obvious which rebalancing strategy leads to superior results. Accordingly, Jaconetti, Kinniry, and Zilbering (2010) conclude that there is no universally optimal rebalancing strategy.

Despite many similarities, our investigation of the value added of portfolio rebalancing differs from the studies presented above. In particular, we make two major contributions to the literature. The first contribution refers to the applied methodology. In contrast to all previous studies, we are able to statistically test the value added of a set of different rebalancing

[5] The calibration of the mean, the volatility, and the cross-correlation parameters is based on a historical sample of the US bond and stock markets from 1960 to 2003. In order to model the return generating process of both the bond and the stock market, Tocat and Wicas (2007) assume a normal return distribution. However, Mandelbrot (1963), Fama (1965), and Clark (1973) all provide strong evidence that at least stock market returns are non-normally distributed. Moreover, recent crises have impressively shown that today's stock market returns are still highly non-normally distributed.

strategies. To the best of our knowledge, there are no studies which examine rebalancing strategies in terms of statistical inference. Previous research based on historical analyses remains incomplete as it merely investigates a single realization or a fairly small number of realizations of the stock and bond markets. Moreover, these studies document similar results for different variants of rebalancing strategies, making it impossible to recommend one specific strategy to institutional investors. The only systematic finding is that a buy-and-hold strategy seems to underperform rebalancing strategies when both the return and the risk of these strategies are taken into account. But even in this case, a major concern is whether these findings are statistically significant. It is possible that the return observations are more influenced by specific characteristics of the underlying sample period rather than by the properties of the rebalancing strategy under investigation. As this danger of data snooping can be severe, the empirical results of these studies do not allow reliable interpretations (Brock, Lakonishok, and LeBaron (1992)). Dividing the sample period into disjunctive subperiods, e.g., up- and downswings of the stock market (Harjoto and Jones (2006)), does not solve this fundamental inference problem either, as this procedure cannot generate enough observations to conduct a statistical test. Monte Carlo simulations avoid this problem by deriving distributions under different economic scenarios. Nevertheless, this simulation technique generally suffers from the shortcoming that it is not based on historical financial markets' data. Instead, specific assumptions have to be made in advance which strongly predetermine the empirical outcome in many cases. Moreover, if time series characteristics of assets as well as of entire financial markets are not correctly or not completely incorporated, simulations' results will be biased, making it very difficult to draw meaningful economic conclusions.

Given these shortcomings of both historical analyses and Monte Carlo simulations, we implement a double block bootstrap approach that is based on the theoretical foundations of Davison and Hinkley (1997), Politis, Romano, and Wolf (1997) as well as Politis (2003). As this test procedure enables us to report statistical significance levels for the different rebalancing strategies' performance measures, we are able to conduct a systematic analysis of the value added of rebalancing strategies. In particular, we are in the position to investigate whether the value added of rebalancing arises due to a return effect, a volatility effect, or both. In contrast to a common *t*-test, our test statistic is also robust against time series dependencies which are inherent in historical data. In addition to our major objective to provide statistical significance, two other aspects are of paramount importance for our analysis. First of all, in order to model the requirements of institutional investors in a realistic setup, we focus on investment horizons of 5, 7, and 10 years, respectively.[6] Secondly, in order to substantiate resulting economic implications drawn on the basis of our empirical results, we apply two distinct methods of the data generating process and show that our empirical findings are robust.

Our second contribution relates to the observation that prior rebalancing studies mostly focus on the US market. While Buetow et al. (2002), Masters (2003) as well as McLellan, Kinlaw, and Abouzaid (2009) consider international equities in a multi-asset class portfolio, Plaxco and Arnott (2002) analyze an internationally balanced portfolio consisting of bonds and stocks of 11 countries. Nevertheless, to the best of our knowledge, there are no studies that investigate rebalancing strategies with a focus on institutional investors outside the US.

[6] Although Harjoto and Jones (2006), Donohue and Yip (2003), and Tsai (2001) investigate typical investment horizons between 10 and 15 years, Jaconetti, Kinniry, and Zilbering (2010), Tokat and Wicas (2007), and Arnott and Lovell (1993) all analyze exceptionally long investment horizons of 84, 44, and 24 years, respectively.

This is an important issue because country-specific characteristics could lead to different empirical findings. Apart from various regulatory peculiarities, each country features unique stock and bond markets properties that potentially have an impact on rebalancing strategies with regard to the asset allocation, investment horizon, and optimal rebalancing frequency. Thus, any conclusions drawn from the empirical findings of one specific country or financial market cannot immediately be transferred to other financial markets. For these reasons, we analyze the value added of rebalancing strategies by considering the different stock and bond market characteristics of the United States, the United Kingdom, and Germany. Overall, these two contributions – deriving statistical inference and using an international dataset – constitute the novel path that our analysis takes and which separates us from previous rebalancing studies.

Our historical simulations provide results which have immediate practical implications. First of all, despite the strong performance of stocks relative to bonds during the sample period, our empirical simulation results provide only weak evidence that the average return of a buy-and-hold strategy is higher than that of different rebalancing strategies. In addition to average annualized returns, we investigate net asset values in order to incorporate the compound interest effect, and cannot uncover significant economic differences. According to Perold and Sharpe (1988), these findings indicate that neither the mean reversion nor the momentum effect in the return data is strong enough to produce superior returns of either strategy. Secondly, we report that rebalancing strategies at all trading frequencies exhibit a significant lower volatility compared to the corresponding buy-and-hold strategy due to better diversification properties. Thirdly, analyzing the Sharpe ratio as a performance measure that incorporates both the return and the volatility of an investment strategy, our simulation results reveal that all rebalancing strategies significantly outperform buy-and-hold strategies. This finding is robust against all analyzed trading frequencies of 5, 7, and 10 years, respectively, contributing to the explanation as to why rebalancing strategies are popular in the investment practice. Fourthly, comparing different rebalancing intervals, we document that quarterly rebalancing produces significantly higher Sharpe ratios compared to monthly rebalancing. These findings suggest that there is an optimal rebalancing frequency, with both excessive rebalancing and no rebalancing leading to lower Sharpe ratios. However, these patterns can change with respect to different rebalancing intervals when we incorporate no-trade regions around the target weights. Our simulations incorporate realistic transaction costs, and the results are qualitatively the same in all countries.

The remainder of this paper is structured as follows: Section I presents the implemented rebalancing strategies and Section II discusses the data set as well as the applied data generating processes. The test design of our introduced double block bootstrap approach is outlined in Section III, while Section IV presents and discusses the main results of our simulation analysis. Section V reports on various robustness checks regarding the implemented rebalancing strategies as well as the applied double block bootstrap approach. The paper concludes in Section VI and points out implications for portfolio management and institutional investors.

I. Implemented Rebalancing Strategies

Academic literature as well as institutional portfolio managers differentiate between periodic and interval rebalancing strategies. Advising a periodic rebalancing mandate, a portfolio manager has to rebalance the assets to their initial target weights at the end of each predetermined period (e.g., yearly, quarterly, or monthly). In contrast, an interval rebalancing mandate requires the portfolio manager to adjust the asset allocation whenever an asset moves beyond a prespecified threshold (e.g., ±3%, ±5%, or ±10%). Our study focuses on a mixture of both methodologies, hence periodic rebalancing with the additional option to incorporate a symmetric no-trade interval around the target weights.

Moreover, one has to distinguish between two different approaches with regard to the implementation of the symmetric no-trade interval. In particular, when an asset exceeds the predetermined interval boundaries, either a strict adjustment to the target weights (Buetow et al. (2002), Harjoto and Jones (2006)) or a rebalancing to the corresponding interval boundaries (Leland (1999)) must be implemented. Following the argumentation of Perold and Sharpe (1988) who emphasize that different strategies can produce strongly different risk and return characteristics, we implement the most common rebalancing strategies: (i) buy-and-hold, (ii) periodic rebalancing, (iii) periodic interval rebalancing with a strict adjustment to the initial target weights (‘threshold approach’), and (iv) periodic interval rebalancing with a reallocation to the nearest edge of the corresponding thresholds (‘range approach’). With respect to these strategies, we look at yearly, quarterly, and monthly trading frequencies. Table II presents the resulting classification of all implemented rebalancing strategies.

[Insert Table II here]

A simple example demonstrates how our periodic interval rebalancing methodology works. Assume a 60% stocks and 40% bonds asset allocation with a quarterly rebalancing frequency and a threshold of ±5% around the target weights. The portfolio strategy ‘5% quarterly rebalancing to target weights’ implies a strict adjustment to the original stock allocation of 60% whenever the stock allocation exceeds the threshold of ±5% at the end of each quarter. In contrast, the portfolio strategy ‘5% quarterly rebalancing to range’ requires the asset manager to check whether the weight of stocks exceeds 65% or falls below 55% of the portfolio's current market capitalization at the end of each quarter. In the first case, the manager must rebalance stocks to the upper threshold of 65%, whereas in the second case an adjustment of stocks to the lower threshold of 55% is required. In all other cases, no transactions are necessary because the stocks' target weight falls within the predetermined no-trade interval [55%; 65%]. According to Leland (1999), this approach reduces transaction costs and may potentially lead to superior portfolio performance. When no thresholds are specified, our rebalancing method reduces to the general periodic approach.

Moreover, we concentrate on a two-asset-class portfolio with an initial asset allocation of 60% stocks and 40% bonds.[7] On the one hand, this approach adequately reflects common investment behavior in practice. On the other hand, it allows the comparison of our empirical findings with related rebalancing studies. Despite our focus on only two asset classes for the purpose of simplification, one should consider that each index constitutes a well-diversified representative of an entire asset class of the analyzed country. In addition, we also model realistic transaction costs of 15 bps per roundtrip in all our simulations. Particularly, we quote 10 bps for buying/selling stocks and 5 bps for selling/buying bonds.[8]

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7 In order to conduct a comprehensive analysis of whether rebalancing is able to generate a value added to institutional investors, we vary the parameters country (USA, United Kingdom, and Germany), the implemented rebalancing strategies (buy-and-hold as well as periodic, threshold, and range rebalancing) the underlying trading frequencies (yearly, quarterly, and monthly), the applied data generating processes (rolling window approach and bootstrap approach), the performance measures (return, volatility, and Sharpe ratio), and the investment horizons (5, 7, and 10 years). As all these determinants are linked by multiplication, we have to keep the asset allocation of 60% stocks and 40% bonds constant in order to stay focused on the main contribution of our study. However, being one of the world's largest institutional investors as of 2011, the Norwegian Government Pension Fund Global is a prominent example of pursuing a 60% stocks and 40% bonds asset allocation (Norwegian Ministry of Finance (2011); Chambers, Dimson, and Ilmanen (2011)).

8 The applied transaction costs of 15 bps per roundtrip solely relate to the assets' reallocation subject to the underlying rebalancing algorithm, though further costs do incur investing in a stock-bond portfolio with respect to the administration and the management of the portfolio. Exchange traded funds (ETFs) represent a cost-effective method to implement rule-based portfolio strategies such as rebalancing. The total expense ra-

II. Data

A. Sample

In contrast to almost all previous rebalancing studies, we not only concentrate on domestic institutional investors of the United States, but also on domestic institutional investors of the United Kingdom and Germany. We use monthly return data of well-diversified stock and government bond market indices as well as money market rates for each country from Thomson Datastream. The sample period ranges from January 1982 to December 2011. This 30-year period is necessary in order to implement a statistical test. However, government bond time series of this length are only available for the financial markets of the United States, the United Kingdom, and Germany. Moreover, the government bonds exhibit maturities of 5, 7, and 10 years in order to match the analyzed investment horizons. We use Treasury bills (United States), LIBOR (United Kingdom), and FIBOR (Germany) as proxies for the risk free rates with 3-month maturities.

B. Data Generating Processes

Almost all previous rebalancing studies employ an empirical analysis based on either historical data or on a Monte Carlo simulation. However, previous historical analyses suffer from the shortcoming of being unable to provide information about statistical significance. Performing a standard *t*-test for differences in means, a sufficient number of independent observations is necessary in order to achieve a given level of statistical confidence. Neither the

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tio (TER) of the most liquid ETFs ranges between 15 and 20 bps for government bonds and between 15 and 52 bps for equities (*iShares (2012), Lyxor Asset Management (2012), db X-trackers (2012)*). However, these costs are independent from the rebalancing frequency and are charged regardless of the applied portfolio strategy. Thus, we exclude the TER from our analysis as it does not affect the issue whether rebalancing provides a value added to institutional investors.

investigation of full sample periods (Jaconetti, Kinniry, and Zilbering (2010), Tsai (2001)) nor the examination of disjunctive subperiods (Harjoto and Jones (2006)) is able to fulfill this statistical requirement.

Accordingly, many studies apply Monte Carlo simulations for evaluating rebalancing strategies (Jones and Stine (2010), Albota et al. (2006), Donohue and Yip (2003), and Buetow et al. (2002)). As Monte Carlo simulations allow for deriving the entire return distribution under different economic scenarios, changing stock, bond, and money market characteristics and their impact on rebalancing strategies can be examined in more detail. Nevertheless, as it is difficult to appropriately incorporate all relevant information into the return-generating process, Monte Carlo simulations represent only simplified models for the time series properties of financial assets and even entire markets. Most important, Monte Carlo simulations often assume normally distributed stock returns even though stock market returns generally violate a normality assumption by exhibiting fat tails and heteroskedasticity as well as by tending to be left-skewed (Annaert, Van Osselaer, and Verstraete (2009)).[9] Moreover, De Bondt and Thaler (1985), Poterba and Summers (1988), as well as Brennan, Li, and Torous (2005) provide evidence that stock returns exhibit positive autocorrelation in the short-run and mean reversion in the long-run. Finally, asset class correlations tend to increase during recession periods (Longing and Solnik (2001)). While Monte Carlo simulations are unable to capture all return characteristics appropriately, a statistical test that is based on historical data is more suitable to incorporate all different time series properties.

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9 Eraker (2004) uses a stochastic volatility process with jumps in asset values. This process follows the geometric Brownian motion as a special case but allows for heavier tails in the return distribution.

Due to these shortcomings of both historical analyses and Monte Carlo simulations, we implement a double block bootstrap approach that is based on real world data in order to draw meaningful, economic conclusions for institutional portfolio management. This simulation-based, historical analysis clearly separates our investigation of the value added of rebalancing from both historical analyses and Monte Carlo simulations. In particular, the implementation of the double block bootstrap approach is motivated by two reasons.

First of all, given country-specific characteristics of financial markets, one cannot assume that particular relationships that hold in one country are also observable in any other country. Presenting the descriptive statistics for the stock, bond, and money markets of the United States, the United Kingdom, and Germany over the period from January 1982 to December 2011, Table III illustrates these cross-sectional differences. For example, featuring a value of 21.69%, the German stock market has the highest annualized volatility of all three countries, whereas the German government bond market simultaneously exhibits the lowest annualized volatility with a value of 5.56%. Therefore, an analysis of the US, the UK, and the German financial market can help us check whether our empirical findings are robust in the cross-section.

[Insert Table III here]

Secondly, previous research has already shown that the time series properties themselves can change over time, making it very difficult to appropriately calibrate the parameters for a Monte Carlo simulation.[10] However, by using historical data, all times series information is fully incorporated into our simulation analysis. In order to get a detailed insight into the time

[10] Cf. Harvey and Ferson (1991), Ferson, Kandel, and Stambaugh (1987), and Gibbons and Ferson (1985) for studies related to time-varying risk premia, Engle, Lilien, and Robins (1987) and Engle (1982) for research on time-varying risk, as well as Buraschi, Porchia, and Trojani (2010), Longing and Solnik (2001), Ball and Torous (2000), and Erb, Harvey, and Viskanta (1994) for studies with a focus on asset class correlations.

variation of the underlying time series characteristics, we divide the entire 30-year sample period into three disjunctive 10-year subperiods. Although the time series characteristics of the United Kingdom and Germany are slightly different compared to those of the United States, all three countries exhibit qualitatively similar patterns. Table IV exemplarily shows the descriptive statistics of the US stock, government bond, and money markets over the full sample period as well as the three corresponding 10-year subperiods. Clearly, substantial variation is exhibited by the distributional characteristics over time. For example, the US stock market features an average annualized return of 17.49% over the period from January 1982 to December 1991 which drops to only 3.00% over the period from January 2002 to December 2011.

[Insert Table IV here]

Due to the fact that our 30-year sample period does not provide sufficient observations to divide the full sample period into disjunctive subperiods, we apply two distinct data generating processes in order to increase the number of 'observations' that are necessary to conduct a statistical test. Both methodologies – the rolling window approach and the bootstrap approach – enable us to efficiently evaluate the available information of the underlying sample period. Based on historical data, all time series' properties and financial markets' dependencies (such as positive autocorrelation in the short-run and negative autocorrelation in the long-run, heteroskedasticity, fat tails, left-skewed return distributions and asset class correlations) are preserved within the given investment horizon. Instead of analyzing the entire sample period or a set of disjunctive subperiods, we investigate investment horizons of 5, 7, and 10 years, respectively. Moreover, the implementation of both the rolling window approach and the bootstrap approach also contributes to a better understanding of the underlying assumptions and their impact on the empirical outcome. This double-check of our empirical results enables us to draw meaningful economic conclusions for institutional portfolio management.

B.1. Rolling Window Approach

The rolling window approach constitutes our first method to raise the number of observations. We explain this procedure with the help of an example. Analyzing the statistical properties of a 5-year investment horizon of any rebalancing strategy requires that 60 monthly return observations are included into the rolling time window. For each of these rolling time windows, we compute the strategy's annual return, its annual volatility and its corresponding Sharpe ratio. We start by calculating these statistical measures for the period from January 1982 to December 1986. Afterwards, we move the rolling time window one month ahead and repeat the same procedure for the period from February 1982 to January 1987, and so on. Overall, applying a 30-year sample period with 360 monthly return observations and a 5-year investment horizon, we receive 301 values for each statistical measure of interest.[11]

In addition to the vital preservation of time series characteristics, a further advantage of the applied rolling window approach is its potential to enable an analysis of all investment horizons which have actually been realized during the underlying sample period. However, an important caveat is that moving the rolling time window on a monthly basis step-by-step alongside the entire sample period produces high autocorrelation in each statistical measure due to construction. Hence, the rolling window approach involves a trade-off between the

[11] In general, the number of the generated observations is subject to both the full sample period and the analyzed investment horizon: $g = t - r + 1$, where g represents the number of generated observations, t is fixed at 360 monthly observations and r denotes the number of months of the analyzed investment horizon.

length of the investment horizon, the number of generated ‘observations’, and the serial dependencies induced by the rolling time windows. The longer the investment horizon is, the fewer ‘observations’ can be generated and the more pronounced the resulting serial dependencies will be. Within a given set of information, we are only able to vary the parameter ‘length of the investment horizon’ at the expense of the parameters’ ‘number of observations’ and ‘serial dependencies’, and vice versa. Therefore, we restrict our analysis to investment horizons of a maximum of 10 years, although investment horizons of institutional investors may range between 5 and up to 30 years.

B.2. Bootstrap Approach

Our second method that contributes to increasing the number of observations is a bootstrap approach. In contrast to the rolling window approach, we have to make an additional assumption with regard to the selection method of the data we draw. More precisely, we assume a uniform distribution when we resample the data. Again, we explain this procedure with the help of an example. In order to investigate the statistical properties of a 5-year investment horizon of any rebalancing strategy, we construct 1,000 time series each with a length of 60 return observations by randomly drawing blocks with replacement from the original 30-year sample period. We further assume a fix block length of 6 in order to preserve both the underlying time series properties and most of the dynamics of entire business cycles. For each of these 1,000 bootstrapped time series, we calculate the annualized return, the annualized volatility, and the corresponding Sharpe ratio, ending up with 1,000 observations for each measure of interest.

In contrast to the rolling window approach, the bootstrap approach does not induce any serial dependence due to construction.[12] The only assumption we have to make affects the resampling of the original time series. Applying a uniform distribution seems to be most suitable in order to ensure that all bootstrapped time series have very similar characteristics compared to the original time series. However, although the bootstrap approach is based on historical data, we are not able to analyze investment horizons that have actually been realized in the past by institutional investors.

As both procedures are based on historical data (in order to preserve the time series properties), a common t-test cannot be applied because it would require independent random variables. Therefore, we address this autocorrelation problem by implementing a double block bootstrap approach. This framework is appropriate even under strong serial dependencies.

III. Double Block Bootstrap Approach

We implement a double block bootstrap approach that is based on the theoretical foundations of Politis, Romano, and Wolf (1997), Davison and Hinkley (1997) and Politis (2003). In contrast to more standard Monte Carlo simulations, our historical simulation framework does not require specific assumptions with respect to the return distribution. Following Hall, Horowitz, and Jing (1995), we apply a 'block' bootstrap approach in order to account for the time series properties of stocks and bonds. More precisely, drawing blocks of fixed length allows us to account for the serial autocorrelation (which is inherent in historical data and also pro-

[12] In general, bootstrap methodologies require stationary processes. Representing highly non-stationary processes, none of the applied money market rates fulfills this necessary requirement. Indeed, analyzing the volatility of the cash market by applying a bootstrap approach would induce a volatility that could be traced back to the non-stationary characteristics of the cash market. Nevertheless, as the money market rates are only included in the calculations of the Sharpe ratio, such difficulties do not emerge in our analysis.

nounced to a much higher degree in the rolling window approach due to construction) when we resample the data. Hall, Horowitz, and Jing (1995) suggest that the length of the optimal block size to be sampled should be $n^{1/5}$ when calculating block bootstrap estimators of two-sided distribution functions where n denotes the length of the time series which is subject to the applied data generating process. Following this rule, the block length for an underlying 5-year investment horizon would be 3 for both the rolling window approach $\left(3 = \lfloor 301^{1/5} \rfloor\right)$ and the bootstrap approach $\left(3 = \lfloor 1{,}000^{1/5} \rfloor\right)$. Due to the high autocorrelation induced by the rolling window approach, we instead use $n^{1/3}$ throughout our entire analysis. This alternative choice leads to a longer block length of 6 $\left(6 = \lfloor 301^{1/3} \rfloor\right)$. Longer block lengths lead to confidence intervals with a higher tendency of including 0, making it more difficult to find evidence for statistical significance and constituting our statistical inference more conservatively. To allow a better comparison of the empirical results to be made between the two distinct data generating processes, we also apply a block length of 6 concerning the bootstrap approach.

Another aspect of our methodology is that we implement a 'double' bootstrap approach. According to Politis, Romano, and Wolf (1997), a double block bootstrap approach mitigates the problem of selecting the appropriate block length. Furthermore, McCullough and Vinod (1998) document that this method also features better convergence properties compared to a single bootstrap approach, making the empirical results more stable.

The implementation of our double block bootstrap approach follows an algorithm introduced by Politis, Romano, and Wolf (1997). In order to compare different rebalancing strategies by reporting statistical significance levels, we compute asymptotic confidence intervals for the null hypothesis that the mean of a difference series is equal to zero. Any difference series is computed by subtracting the two respective raw series (i.e., return, volatility or the Sharpe ratio) from the applied data generating process (rolling window approach or bootstrap approach) of the respective strategies (e.g., buy-and-hold vs. quarterly rebalancing) from each other. Having determined the block length, the confidence level, and the number of simulations, we hand this difference series over to our double block bootstrap simulator.[13] The computation of the asymptotic confidence intervals takes place in two steps.

We exemplarily describe this procedure for an investment horizon of 5 years, a block length of 6, and 10,000,000 simulations. Given these assumptions, the rolling window approach [bootstrap approach] generates an 'original' difference time series consisting of 301 [1,000] observations for any statistical measure under investigation.[14] Based on this time series, we create 10,000 new vectors V1 with a length of 300 [996] each.[15] Each of these 10,000 new vectors V1(x), with $x \in \{1; \ldots; 10{,}000\}$, consists of 50 [166] blocks with length 6 that are randomly drawn with replacement from the 'original' difference time series. In a second step, we create for each vector V1(x) 1,000 new vectors V2(y), with $y \in \{1; \ldots; 1{,}000\}$, that are based on the data of V1(x). Therefore, each of these 1,000 new vectors V2(y) also consists of 50 [166] blocks with length 6 that are now randomly drawn with replacement

[13] Prior to the fixing of the double block bootstrap parameters, we have to determine the asset allocation (which is hold constant at 60% stocks and 40% bonds throughout our entire analysis), the transaction costs (15 bps per roundtrip), the applied data generating process (rolling window or bootstrap approach), the rebalancing strategy (see Table II), the performance measure (return, volatility, or Sharpe ratio), and the investment horizon (5,7, or 10 years).

[14] In contrast to the bootstrap approach, the number of observations generated by the rolling window approach is subject to both the length of the full sample period and the analyzed investment horizon. However, applying the bootstrap approach, we generate 1,000 'original' time series each with a length of 60 return observations.

[15] In general, the length of vector V1(x) with $x \in \{1,; \ldots; 10{,}000\}$ is b×k with $k = \lfloor n/b \rfloor$, where n denotes the length of the generated time series (based on either the rolling window or the bootstrap approach) and b the block length.

from the respective vector V1(x). According to Davison and Hinkley (1997), this double bootstrap approach accounts for potential biases in the bootstrap distribution and leads to better convergence properties when calculating asymptotic confidence intervals. Our example involves 10,000,000 historical simulations of the statistical measure under investigation, and from each of these 10,000,000 simulated series, we construct the corresponding difference time series, calculate the average of each difference time series, and sort these values according to their size. Based on these sorted observations, we derive a distribution (of the difference time series) of the measure of interest that enables us to calculate asymptotic confidence intervals of the underlying difference time series at predefined confidence levels. The high number of 10,000,000 simulations is necessary due to the asymptotic convergence of the calculated confidence intervals. Repeated simulations reveal that our results are stable in capturing the underlying patterns in our sample.

IV. Empirical Simulation Results

This section presents the main results of our simulation analyses. In order to stay focused on the primary contribution of our analysis - the issue whether rebalancing generates a value added to institutional investors and if so, where this value added arises from - we start our discussion by comparing the returns of a buy-and-hold strategy and periodic rebalancing with yearly, quarterly, and monthly trading intervals. Afterwards, we shed light on the risk of these strategies. Finally, we focus on the Sharpe ratio as a widely used performance measure that incorporates both the return and the volatility of an investment strategy.

A. Returns

Any rebalancing strategy requires the selling of a fraction of the better performing assets and investing the proceeds in the less performing assets. Focusing on the portfolio return as the measure of interest, one would therefore expect that buy-and-hold strategies outperform rebalancing strategies with increasing investment horizons. Provided that one asset outperforms the other in every single period, this notion is always correct given the mechanics of rebalancing. However, as this assumption is very restrictive, it is not reflected in real world data. In particular, stock markets are characterized by recurring up- and downswings. There are time periods in which stock market returns substantially outperform bond market returns, and vice versa. By using a 30-year historical data sample and implementing periodic rebalancing (strategies 2-4 in Table II), our analysis takes this aspect into consideration.

Table V illustrates the average annualized returns of each strategy, classified by investment horizon, country, and data generating process. At first, it is apparent that the empirical results seem to be mixed, depending on the underlying data generating process. Under the rolling window approach, a buy-and-hold strategy features the lowest average annual return in 7 out of 9 cases. However, this pattern changes to the opposite when we perform the bootstrap approach. In 7 out of 9 cases, we now observe that buy-and-hold produces an equal or higher average annualized return compared to the remaining rebalancing strategies. Secondly, it is also worth noting that we receive higher average annual returns across all investment strategies, all investment horizons, and all countries under the bootstrap approach. This difference in return levels grows even further across all countries with increasing investment horizons. It ranges between 0.44% and 0.88% for an investment horizon of 5 years, between 0.52% and 1.26% for 7 years, and between 0.56% and 1.40% for 10 years. However, both observations – the mixed results and the difference in return levels – can be explained by shedding light on the underlying assumptions of the applied data generating processes and the resulting implications.

[Insert Table V here]

Applying a rolling window, we implicitly assume a trapezoidal weighting function by putting less weight on the observations near the outer edge and accordingly more weight on the observations in the middle of our 30-year sample period. For example, analyzing a 5-year investment horizon, the first return observation in January 1982 and the last in December 2011 are each weighted one time, whereas the second return observation in February 1982 and the second to last in November 2011 are included two times in our calculations, and so on. Accordingly, all observations between December 1986 and January 2007 are weighted 60 times. Taken as a whole, observations in the middle of the sample period have a much higher impact on our calculations compared to observations that lie near the outer boundaries. Hence, the empirical outcome will be considerably influenced, if there are substantial changes in the time series characteristics between these less weighted observations near the outer boundaries and the comparatively more weighted observations in the middle of the sample period. This finding applies exactly to our sample period. The annualized return of a 5-year investment horizon at the beginning of the sample period is considerably higher compared to the annualized returns of a 5-year investment horizon in the middle of the sample period. Although the annual returns also have decreased at the end of the sample period, the very high annualized returns of the underlying 5-year investment horizons at the beginning of the sample period explain the difference in return levels between the rolling window approach and the bootstrap approach. In contrast to the rolling window approach, almost all observations have the same weight under the bootstrap approach, which consequently leads to higher average annualized returns as shown in Table V.[16] Moreover, this weighting issue even intensifies for larger investment horizons, contributing to explain the increasing differences in return levels with longer investment horizons. Last but not least, we are also able to explain the different performances of buy-and-hold and rebalancing which seem to be subject to the underlying data methodology. According to Perold and Sharpe's notion (1988), rebalancing strategies perform best in volatile sideway markets whereas buy-and-hold strategies lead to superior results in strongly pronounced market upswings and downswings, respectively. The business cycle dates from the *National Bureau of Economic Research (2012)* give us detailed information about the length of upswing and downswing markets. Our sample period includes four business cycles. The two contraction periods in the middle of our data sample (July 1990 to March 1991 and March 2001 to November 2001) each lasts eight months, but the two contraction periods which lie near the outer boundaries and are underweighted by the rolling window approach lasts 16 months (July 1981 to November 1982) and 18 months (December 2007 to June 2009), respectively. These much more pronounced and underweighted market downswings lead to a superior performance of buy-and-hold under the bootstrap approach. Although we find mixed results, Table V also shows that the return differences between the strategies seem to be not well-pronounced and tend to be of rather marginal economic importance.[17]

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[16] By drawing blocks with a fix length of 6 in order to capture the underlying time series properties, the bootstrap approach also implicitly assumes a trapezoidal weighting function. However, compared to investment horizons of 5 to 10 years, possible repercussions are negligible. The issue of a trapezoidal weighting function would only completely disappear if we performed a bootstrap approach with a 'block length' of 1.

[17] However, performing the rolling window approach, the average annualized returns of Germany are supposed to be an exception. Buy-and-hold seems to be outperformed by any rebalancing strategy by at least 0.15%, 0.28%, and 0.45% for investment horizons of 5, 7, and 10 years, respectively.

Table VI reports whether these small return differences are statistically significant or whether they can simply be attributed to specific characteristics of the underlying sample period. In a first step, we compute the difference of the time series with annualized returns (derived from either the rolling window approach or the bootstrap approach) of any two strategies that we compare (e.g., monthly rebalancing vs. buy-and-hold). In a second step, we hand this difference time series over to our block bootstrap approach in order to compute confidence intervals. These confidence intervals provide detailed information on whether a specific strategy generates a significantly higher or lower mean return. If both boundaries are positive (negative), rebalancing boasts a significantly higher (lower) return compared to a buy-and-hold strategy. Otherwise, the confidence interval includes zero, implying that the difference is lost in estimation error and that no statistical inferences can be drawn. As we have already pointed out, our empirical results are subject to the underlying return generating process. Applying the rolling window approach, our findings in Table VI suggest that the return differences between rebalancing (at any frequency) and buy-and-hold are statistically significant at the 1% level in the UK and Germany for investment horizons of at least 7 years. In contrast, this finding cannot be confirmed for the US, where zero is included in the simulated confidence interval, implying that the differences in mean returns are lost in estimation error. However, applying the bootstrap approach, we find that buy-and-hold produces a significantly higher return in most instances. These results are weaker for the financial markets of the UK and Germany.

[Insert Table VI here]

Due to the fact that our empirical findings in Table V and Table VI provide mixed results, we additionally investigate the corresponding net asset values (NAV) in order to find out whether differences in returns of the underlying strategies are economically significant. Looking at investment horizons with different lengths, this alternative approach provides the advantage that the compound interest effect is accurately taken into account. If one strategy produces consistently higher returns than other strategies, this strategy also boasts a higher NAV. As a result, the difference in the performance of the NAVs increases with longer investment horizons. Table VII reports the growth rates of the NAVs, which are classified by strategy, investment horizon, country, and data generating process. Although all rebalancing strategies require the selling of past winners and the buying of past losers, differences between the growth rates of the NAVs of the underlying strategies tend to be not well-pronounced and hence, economically irrelevant. Again, the German market seems to be an exception, but it exhibits mixed results which are subject to the applied data methodology. Although Perold und Sharpe’s (1988) theoretical analysis suggests that time series properties – such as short-run momentum or long-run mean reversion – have an impact on the return of rebalancing strategies, they do not seem to be strongly pronounced in our sample. Otherwise, one would expect that a specific rebalancing frequency leads to higher NAVs compared to other rebalancing frequencies as well as to a buy-and-hold strategy.

[Insert Table VII here]

Despite the strong performance of stocks relative to bonds over the entire sample period as it is shown in Table VIII, one cannot necessarily conclude that a buy-and-hold strategy performs better than periodic rebalancing. As an example, Table VIII illustrates the development of a $100 investment at the beginning of 1982. Although stocks substantially outperform bonds during the entire sample period, a buy-and-hold strategy produces the lowest NAV of all strategies after a 30-year time horizon. In contrast, looking at the $100 investment after 20 years, the buy-and-hold strategy dominates all other strategies in terms of NAVs. Accordingly, given that rebalancing is a dynamic portfolio strategy, its performance is path-dependent. The time series characteristics of the underlying assets, such as the volatility of the spread between the underlying assets (and hence the correlation between these assets), can have a substantial influence on the performance of any rebalancing strategy.

[Insert Table VIII here]

Analyzing the notion of path-dependency in more detail, Panel A in Figure 1 presents the development of a $100 investment, starting at the beginning of December 2007 and assuming a quarterly rebalancing (with a 0% threshold) as well as a buy-and-hold strategy. Panel B depicts the corresponding relative market capitalization of stocks in both strategies at the beginning of each month after the rebalancing event has taken place. As shown in Panel A, quarterly rebalancing performs worse compared to buy-and-hold during the strong stock market meltdown in 2008, which caused a decline of the US stock market capitalization by almost 50%. This observation is explained by the regular reallocation at the end of each quarter to the initial 60/40 asset allocation. Accordingly, in a trending market environment with falling stock prices, frequent rebalancing leads to inferior NAVs. Panel A further reveals that during the subsequent market upswing, quarterly rebalancing outperforms the buy-and-hold strategy. This finding can be traced back to the fact that the performance of an investment strategy not only depends on the return of the underlying assets, but also on their corresponding portfolio weights. In particular, during the following market recovery quarterly rebalancing produces higher NAVs compared to the buy-and-hold strategy because of its initial 60/40 stock-bond allocation at the start of the market recovery and the immediate readjustment at the end of each quarter. In contrast, the buy-and-hold strategy suffers from the decrease to a much lower stock allocation when the market recovery starts. The initial stock-bond allocation at the lower turning point is roughly 40/60 (rather than 60/40) because of the poor stock performance during the prior market crash. As shown in Panel B, the stock allocation cannot recover from this market crash within the remaining investment period. Due to its lower average stock allocation in the subsequent upside market, the buy-and-hold strategy is outperformed by a quarterly rebalancing strategy. This empirical result supports the theoretical findings of Perold and Sharpe (1988). They argue that rebalancing strategies perform best in volatile sideway markets whereas buy-and-hold strategies lead to superior results in strongly pronounced market upswings and downswings, respectively.

[Insert Figure 1 here]

Overall, Perold and Sharpe (1988) show that dynamic portfolio strategies, such as buy-and-hold, CPPI, and rebalancing strategies, will produce different risk and return characteristics. They emphasize that the choice of an appropriate strategy is subject to the investor’s risk preference. Therefore, not only the return of a strategy, but also its risk must be taken into account carefully.

B. Volatilities

Providing mixed results in terms of average returns and NAVs, our empirical findings show no clear pattern whether rebalancing produces higher returns compared to buy-and-hold or not. Hence, a frequent rebalancing must offer other key benefits that explain their importance for institutional investors. In order to further analyze the value added of rebalancing, Table IX presents the average annualized portfolio standard deviations classified by strategy, investment horizon, country, and data generating process. As buy-and-hold boasts the highest average annualized volatility for all investment horizons, all countries, and both data generating methodologies, the empirical results of Table IX provide a first hint that rebalancing lead to a lower volatility. Moreover, a monthly rebalancing strategy also has a higher average annualized volatility compared to quarterly and yearly rebalancing strategies. Again, this finding is robust for all countries, for all investment horizons and for both data generating methodologies.

[Insert Table IX here]

Applying our double block bootstrap approach, we are again able to statistically evaluate these volatility differences. Our simulation results of Table X confirm that buy-and-hold exhibits the highest volatility for all investment horizons and for all countries at the 1% level (bootstrap approach). Performing the rolling window approach, our results are weaker but also provide strong evidence that buy-and-hold features the highest volatility. Repeated simulations reveal that the statistical significance is robust for all investment horizons and for all countries. An immediate explanation is that a buy-and-hold strategy involves an increasing relative proportion of stocks which constitute the riskier asset class compared to bonds. With an increasing time horizon, the higher volatility of stocks affects the volatility of the buy-and-hold strategy more and more. In contrast, a periodic reallocation back to the original target weights prevents an extreme shift to riskier stocks. Against all expectations, our results also indicate that quarterly (and, to some extent, yearly) rebalancing produces a lower volatility than monthly rebalancing. In results not shown in Table X, this pattern shows up even if we omit transaction costs.

[Insert Table X here]

C. Sharpe Ratio

In order to appropriately evaluate portfolio performance, it is necessary to apply a performance measure that includes both the return and the volatility of the underlying strategies in a next step. Being well-established and widely used in practice, we choose the Sharpe ratio (Sharpe (1966)) as a risk-adjusted performance measure.

Observing that rebalancing leads to only slightly (if any) superior mean returns, but to a significant reduction in risk, one would expect that this volatility pattern would also have an impact on the observed Sharpe ratio. Given our findings so far, we hypothesize that quarterly and/or yearly rebalancing will most likely generate the highest excess return per unit risk. Table XI reports the average annualized Sharpe ratios classified by strategy, investment horizon, country, and data generating process. As expected, both quarterly and yearly rebalancing tend to exhibit higher Sharpe ratios than a buy-and-hold strategy as well as monthly rebalancing. For example, the average Sharpe ratio of a buy-and-hold strategy using US data and assuming a 10-year investment horizon is 0.540 (rolling window approach) and 0.611 [bootstrap approach]. A monthly rebalancing strategy produces an average Sharpe ratio of 0.580 [0.630], and the Sharpe ratio increases to 0.586 and 0.587 [0.639 and 0.643] on average for quarterly and yearly rebalancing, respectively.

[Insert Table XI here]

As expected, these patterns are also reflected in the statistical significance levels for differences in Sharpe ratios. Table XII shows the results of our double block bootstrap approach for all time horizons, all countries, and both data methodologies. Again, a buy-and-hold strategy produces the lowest Sharpe ratio, and differences in Sharpe ratios are significant at the 1% level over all time horizons, all countries, and both return generating processes when comparing buy-and-hold and rebalancing strategies. Moreover, quarterly (and, to some extent, yearly) rebalancing strategies produce significantly higher Sharpe ratios than monthly rebalancing. Although the literature advises block lengths of $n^{1/5}$ or $n^{1/4}$, we choose to apply longer block lengths of $n^{1/3}$ throughout our entire analysis in order to account for very high serial dependencies. Our results are robust and statistically significant at the 1% level. Even when we extend the block length to 20, our main results for differences in Sharpe ratios are at least significant at the 10% level.

[Insert Table XII here]

Overall, our simulation setup allows us to determine whether a rebalancing strategy is able to generate a value added compared to a buy-and-hold strategy and to identify the source of this value added. Specifically, we document that the average returns of rebalancing strategies are only marginally (if any) higher than those of a buy-and-hold strategy. In contrast, rebalancing strategies exhibit a significantly lower volatility compared to a buy-and-hold strategy. Considering both the return and the risk of a given strategy, we further document that the Sharpe ratio – as a simple measure of value added – of all different rebalancing strategies is significantly higher compared to a buy-and-hold strategy. In conclusion, while the return effect is only marginally responsible for the superiority of the Sharpe ratio – if at all –, it is the volatility effect which drives the value added of rebalancing strategies compared to a buy-and-hold strategy.

Observing that rebalancing strategies generally produce higher Sharpe ratios than a buy-and-hold strategy, an additional question is whether there is an optimal rebalancing frequency. For example, Jaconetti, Kinniry, and Zilbering (2010) conclude from their analysis that there is no universally optimal rebalancing strategy. In contrast, our results do not support this notion. Comparing different rebalancing frequencies (monthly, quarterly, and yearly) based on the simple periodic rebalancing methodology, our double bootstrap approach indicates that quarterly rebalancing produces the highest Sharpe ratio. This result suggests that both excessively frequent rebalancing as well as no rebalancing leads to inferior Sharpe ratios, and hence, the optimal rebalancing frequency ranges between quarterly and yearly intervals.

Another noteworthy observation is that buy-and-hold leads to significantly higher returns than rebalancing under the bootstrap approach (Table VI). Nevertheless, it generates significantly lower Sharpe ratios (Table XII). Recognizing that in this case, the return effect and the volatility effect work in different directions, our results strongly suggest that the volatility effect outweighs the return effect and represents the major source of the value added of rebalancing strategies. Accordingly, we conclude that it is primarily a risk management argument that justifies the widespread use of rebalancing strategies in the asset management practice.

V. Robustness Checks

A. Threshold and Range Approach

Our simulation results in Section IV are based on a simple periodic rebalancing back to the target weights without a threshold. In the context of Table II, this approach refers to rebalancing strategies (2)-(4) with different rebalancing frequencies (monthly, quarterly, and yearly). Once a rebalancing threshold (hence a symmetric no-trade interval) is introduced, there are two cases that have to be distinguished regarding to the practical implementation. In the first alternative strategy, a strict adjustment to the target weights (Buetow et al. (2002), Harjoto and Jones (2006)) is required when an asset exceeds the predetermined interval boundaries within a given interval. This ‘threshold approach’ is captured by strategies (5)-(7) in Table II. In contrast, the second alternative rebalancing strategy requires a rebalancing back to the nearest edge of the given threshold rather than the initial portfolio weights (Leland (1999)). This ‘range approach’ refers to strategies (8)-(10) in Table II.

As a robustness test, Table XIII shows the confidence intervals for these two alternative rebalancing strategies. Specifically, we assume a threshold (or symmetric no-trade interval) of ±5% and a block length of 6. Confirming our previous results for the simpler periodic rebalancing strategy, a buy-and-hold strategy is significantly dominated by both the ‘threshold approach’ and the ‘range approach’ in terms of Sharpe ratios at all rebalancing frequencies; the difference is always significant al the 1% level. This result is robust when the threshold is changed to ±2% or ±10% (not tabulated). Accordingly, the dominance of rebalancing over a buy-and-hold strategy is independent of the choice of a specific rebalancing strategy. In contrast, in results not shown in Table XIII, our simulations are unable to uncover clear patterns with regard to a comparison of different rebalancing frequencies. While the optimal rebalancing frequency ranges between quarterly and yearly intervals under a periodic rebalancing strategy, no clear patterns emerge under the ‘threshold approach’. Saving transaction costs by reallocating the assets back to the nearest edge of the predefined no-trade region, the ‘range approach’ suggests monthly rebalancing as the optimal rebalancing frequency.

[Insert Table XIII here]

VI. Conclusion

This study addresses the question why institutional investors prefer rebalancing even though these strategies require the selling of a fraction of the better performing assets and investing the proceeds in the less performing assets. Analyzing the value added of several rebalancing strategies for institutional investors, we document that the return effect is only of marginal importance while it is primarily a risk management argument which justifies the widespread use of these strategies. Minimizing risk (defined as return volatility) with respect to a given asset allocation seems to be the primary objective of any rebalancing strategy.

In contrast to prior rebalancing studies, we investigate the potential risk-return-benefits of different rebalancing strategies by implementing a double block bootstrap approach. This methodology enables us to derive statistical inference. In fact, our study is the first to test the value added of rebalancing strategies based on statistical significance levels. Most important, our simulation framework is appropriate under strong serial time series dependencies.

Our simulations are based on data from the US, the UK, and Germany and deliver results that have immediate practical implications. Firstly, given the strong performance of stocks relative to bonds during the 30-year sample period, rebalancing strategies hardly outperform a buy-and-hold strategy in terms of their average return and net asset value (NAV). According to Perold and Sharpe’s (1988) notion, these empirical findings indicate that neither the mean reversion nor the momentum effects are strong enough in the return data to produce superior returns for either strategy. Secondly, we document that all rebalancing strategies exhibit a significantly lower volatility compared to the corresponding buy-and-hold strategy. This risk reduction can be explained by a diversification effect. More precisely, rebalancing the portfolio back to the original allocation prevents a drift away from the worse performing (but less risky) asset class towards the better performing (but more risky) one, thereby reducing diversification and increasing risk. The reallocation to the less risky asset ultimately leads to a reduced volatility. Thirdly, analyzing the Sharpe ratio as a performance measure that incorporates both the return and the risk of any given portfolio strategy, our findings indicate that all different variants of rebalancing strategies (periodic rebalancing, threshold rebalancing and range rebalancing) significantly outperform a buy-and-hold strategy. Accordingly, risk reduction seems to be the main factor which presumably explains why rebalancing strategies are very popular in the investment practice.

Finally, for a periodic rebalancing strategy, monthly rebalancing generates significantly lower Sharpe ratios compared to quarterly rebalancing. This finding is robust for all countries and for all analyzed investment horizons. It provides a hint that there may be an optimal rebalancing frequency where excessively frequent rebalancing as well as no rebalancing leads to inferior results in terms of Sharpe ratios. While the optimal rebalancing frequency seems to lie between quarterly and yearly intervals for a periodic rebalancing strategy, these data patterns do not show up for threshold rebalancing and range rebalancing strategies.

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Table I

Literature Overview

This table provides a brief summary of rebalancing studies focusing on the question whether rebalancing generates a value added for institutional investors. For the sake of brevity, we solely consider rebalancing studies most closely related to our analysis. They are sorted by the year of publication.

Year of Publication / Authors	Data / Investment Horizon	Asset Allocation / Transaction Costs	Approach / Report of Significance Levels	Rebalancing Method / Key Results
2010	Jan 1926 - Dec 2009 US data Monthly and daily data	60% stocks 40% bonds	Historical analysis	Periodic rebalancing Intervall rebalancing Periodic intervall rebalancing to target weights
Jaconetti Kinniry Zilbering	Entire sample period Monthly: Jan 1926 -Dec 2009 Daily: 01/01/1989 - 12/31/2009	Included	Not reported	There is no universally optimal rebalancing strategy. However, a semiannual or annual rebalancing with a threshold of about 5% seems to provide an appropriate risk control.
2007	Jan 1960 - Dec 2003 US data Monthly data	60% stocks 40% bonds	Monte Carlo simulation	Periodic intervall rebalancing to target weights
Tokat Wicas	Classification in trending and mean-reverting markets and in Random-Walk environment	Included	Not reported	Rebalancing achieves the goal of minimizing risk relative to a target asse allocation in all market enviroments.
2006	Jan 1995 - Dec 2004 US data Monthly frequency	60% stocks 40% bonds	Historical analysis	Intervall rebalancing to target weights
Harjoto Jones	Classification in different market phases	Not included	Not reported	Investors need to rebalance, but not frequently. 15% threshold rebalancing is superior compared to other rebalancing strategies during all market phases.

Table I – *Continued*

2003	Jan 1987 - Dec 1996 US and international data Monthly and daily data	US stocks US bonds Non-US stocks	Historical analysis Monte Carlo simulation	Periodic rebalancing Interval rebalancing Self-developed rebalancing routine
Donohue Yip	10-year investment horizon Monthly: Jan 1987-Dec 1996 Daily: Simulation (10 years)	Included	Not reported	Optimal rebalancing can provide both higher returns and lower risk than other common rebalancing heuristics.
2001	Jan 1986 - Dec 2000 US and international data Monthly data	US stocks US bonds Non-US stocks	Historical analysis	Periodic rebalancing Periodic interval rebalancing to target weigths
Tsai	Entire sample period	Not included	Not reported	Portfolios should be periodically rebalanced. However, no strategy is consistently better across portfolios of differing risk profiles. Thus, it does not matter much which strategy is adopted.
1993	Jan 1968 - Dec 1991 US data Monthly frequency	50% stocks 50% bonds	Historical analysis	Periodic rebalancing Intervall rebalancing Intervall rebalancing to target weights
Arnott Lovell	Entire sample period	Included	Not reported	Efficient rebalancing has enhanced returns without increasing risk. These modest excess returns compound over time to multimillion dollar gains to any but the smallest funds.
1988	Theoretical stock market data	60% stocks 40% bonds	Theoretical analysis	Periodic Rebalancing
Perold Sharpe	Theoretical analysis of dynamic portfolio strategies in different market scenarios	Not included	Not reported	Different strategies produce different return and risk characteristics. An appropriate strategy is subject to the investor's risk preference.

Table II

Classification of Implemented Rebalancing Strategies

This table presents all rebalancing strategies under investigation. The periodic rebalancing strategies 2, 3, and 4 are characterized by a regular reallocation to the predetermined target weights at the end of each period. Strategies 5, 6, and 7 represent periodic interval rebalancing with a strict adjustment to the target weights (threshold approach). In strategies 8, 9, and 10, the assets are rebalanced to the nearest edge of the predefined interval boundaries (range approach). A threshold of ±5% is applied to both periodic interval rebalancing to target weights and periodic interval rebalancing to range.

Rebalancing Strategies	Frequency	Threshold	Reallocation	Classification	No.
Buy-and-hold	No adjustments	No threshold	No reallocation	Buy-and-hold	1
Yearly rebalancing	Yearly	No threshold	Target weights	Periodic	2
Quarterly rebalancing	Quarterly	No threshold	Target weights	Periodic	3
Monthly rebalancing	Monthly	No threshold	Target weights	Periodic	4
Yearly rebalancing to target weights	Yearly	Threshold	Target weights	Threshold	5
Quarterly rebalancing to target weights	Quarterly	Threshold	Target weights	Threshold	6
Monthly rebalancing to target weights	Monthly	Threshold	Target weights	Threshold	7
Yearly rebalancing to range	Yearly	Threshold	Interval boundaries	Range	8
Quarterly rebalancing to range	Quarterly	Threshold	Interval boundaries	Range	9
Monthly rebalancing to range	Monthly	Threshold	Interval boundaries	Range	10

Table III

Descriptive Statistics

This table presents the descriptive statistics of the stock, bond, and money markets over the sample period from January 1982 to December 2011. Bonds denote government bonds with a maturity of 10 years. Cash represents the corresponding 3-month money market rates. All statistics are calculated on a monthly basis using discrete returns. The rows Mean and Volatility are the annualized mean returns and volatilities, respectively. Skewness and Kurtosis are calculated as the third and fourth normalized centered moments.

Asset	Statistics	USA	UK	Germany
Stocks	Mean (%)	11.01	11.45	9.15
	Volatility (%)	15.63	15.92	21.69
	Skewness	-0.63	-0.80	-0.57
	Kurtosis	5.07	6.01	4.82
	Autocorrelations			
	Lag 1	0.06	0.03	0.07
	Lag 2	-0.01	-0.08	0.00
	Lag 3	0.04	-0.03	0.05
Bonds	Mean (%)	8.94	10.73	7.62
	Volatility (%)	7.97	8.08	5.56
	Skewness	0.14	0.06	-0.23
	Kurtosis	3.72	4.39	3.22
	Autocorrelations			
	Lag 1	0.09	0.05	0.12
	Lag 2	-0.05	0.00	-0.06
	Lag 3	0.06	-0.03	0.10
Cash (level)	Mean (%)	4.59	7.20	4.56
	Volatility (%)	0.78	1.02	0.66
	Skewness	0.18	0.24	0.56
	Kurtosis	2.72	2.40	2.64
	Autocorrelations			
	Lag 1	0.99	0.99	0.99
	Lag 2	0.98	0.98	0.99
	Lag 3	0.97	0.97	0.97
Correlations	Stocks/Bonds	0.05	0.21	-0.06
	Stocks /Cash	0.07	0.09	-0.03
	Bonds/Cash	0.12	0.17	0.10

Table IV

Descriptive Statistics: USA

This table presents the descriptive statistics of the stock, bond, and money markets of the USA over the sample period from January 1982 to December 2011. Bonds denote government bonds with a maturity of 10 years. Cash represents the corresponding 3-month money market rates. The columns Mean, Volatility, Skewness, and Kurtosis are the annualized mean return, volatility, skewness, and kurtosis, which are calculated on a monthly basis using discrete returns. Skewness and Kurtosis are calculated as the third and fourth normalized centered moments. Min and Max are the monthly minimum and maximum returns, respectively.

Stocks

Period	Start of Period	End of Period	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	Min. (%)	Max. (%)
Subperiod 1	Jan-82	Dec-91	17.49	16.54	-0.696	6.487	-21.22	13.28
Subperiod 2	Jan-92	Dec-01	13.05	14.09	-0.574	3.715	-13.90	9.98
Subperiod 3	Jan-02	Dec-11	3.00	16.04	-0.622	4.179	-17.10	10.99
Full Sample	Jan-82	Dec-11	11.01	15.63	-0.634	5.071	-21.22	13.28

Bonds

Period	Start of Period	End of Period	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	Min. (%)	Max. (%)
Subperiod 1	Jan-82	Dec-91	13.8	8.73	0.151	2.667	-4.40	7.57
Subperiod 2	Jan-92	Dec-01	6.41	6.58	-0.140	2.992	-4.25	5.66
Subperiod 3	Jan-02	Dec-11	6.79	8.35	0.131	4.716	-7.09	9.86
Full Sample	Jan-82	Dec-11	8.94	7.97	0.144	3.716	-7.09	9.86

Cash (levels)

Period	Start of Period	End of Period	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	Min. (%)	Max. (%)
Subperiod 1	Jan-82	Dec-91	7.57	0.49	0.807	3.670	0.36	1.04
Subperiod 2	Jan-92	Dec-01	4.50	0.28	-0.597	2.465	0.14	0.50
Subperiod 3	Jan-02	Dec-11	1.79	0.47	0.688	2.115	0.00	0.41
Full Sample	Jan-82	Dec-11	4.59	0.78	0.179	2.716	0.00	0.01

Table V

Average Annualized Returns

Classified by the underlying investment horizon, this table shows the average annualized returns of yearly, quarterly, and monthly rebalancing strategies as well as a buy-and-hold strategy over the sample period from January 1982 to December 2011 for both the rolling window approach and the bootstrap approach. All strategies are based on a 60% stocks and 40% bonds asset allocation with a threshold of 0%. Transaction costs are quoted at 15 bps per roundtrip.

		Rolling Window Approach			Bootstrap Approach		
Period	Investment Strategy	USA	UK	Germany	USA	UK	Germany
5	Buy-and-Hold	10.10	10.08	8.48	10.57	10.82	9.36
5	Yearly Rebalancing	10.08	10.13	8.88	10.54	10.79	9.36
5	Quarterly Rebalancing	10.04	10.14	8.76	10.49	10.77	9.26
5	Monthly Rebalancing	9.99	10.11	8.63	10.42	10.74	9.14
7	Buy-and-Hold	10.27	10.11	8.52	10.91	11.37	9.66
7	Yearly Rebalancing	10.34	10.27	9.15	10.89	11.37	9.68
7	Quarterly Rebalancing	10.30	10.30	9.03	10.84	11.35	9.58
7	Monthly Rebalancing	10.25	10.28	8.90	10.77	11.33	9.44
10	Buy-and-Hold	10.22	9.95	8.15	10.86	11.35	9.50
10	Yearly Rebalancing	10.23	10.13	8.81	10.83	11.35	9.53
10	Quarterly Rebalancing	10.20	10.17	8.73	10.79	11.34	9.45
10	Monthly Rebalancing	10.16	10.16	8.60	10.72	11.31	9.30

Table VI

Calculated Confidence Intervals: Return

This table shows the confidence intervals for the annualized returns for a 5, 7, and 10-year investment horizon, respectively. All strategies are based on a 60% stocks and 40% bonds asset allocation with a threshold of 0%. Transaction costs are quoted at 15 bps per roundtrip. BAH denotes buy-and-hold, Y yearly rebalancing, Q quarterly rebalancing, and M monthly rebalancing. For each two strategies that are compared, the lower and upper boundary of the corresponding confidence interval is calculated. 10 million simulations with a fixed block length of 6 are performed. Repeated simulations reveal that the results are stable. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

		Rolling Window Approach						Bootstrap Approach					
	Strategies	USA		United Kingdom		Germany		USA		United Kingdom		Germany	
5 years	M-BAH	-0.0031	0.0003	-0.0012	0.0011	-0.0004	0.0029	-0.0017	-0.0007 ***	-0.0010	-0.0001 ***	-0.0025	-0.0005 ***
	Q-BAH	-0.0026	0.0009	-0.0009	0.0014	0.0002	0.0047 **	-0.0009	-0.0001 **	-0.0005	0.0001	-0.0007	0.0005
	Y-BAH	-0.0020	0.0013	-0.0009	0.0014	0.0003	0.0073 ***	-0.0003	0.0002	-0.0002	0.0003	-0.0001	0.0014
	M-Q	-0.0009	-0.0002 ***	-0.0004	-0.0001 ***	-0.0016	-0.0008 ***	-0.0008	-0.0006 ***	-0.0004	-0.0002 ***	-0.0015	-0.0012 ***
	M-Y	-0.0017	-0.0002 **	-0.0007	0.0003	-0.0040	-0.0014 ***	-0.0014	-0.0009 ***	-0.0007	-0.0004 ***	-0.0027	-0.0019 ***
	Q-Y	-0.0009	0.0002	-0.0004	0.0005	-0.0025	-0.0002 ***	-0.0007	-0.0002 ***	-0.0004	-0.0001 ***	-0.0012	-0.0005 ***
7 years	M-BAH	-0.0018	0.0013	0.0010	0.0029 ***	0.0017	0.0056 ***	-0.0017	-0.0007 ***	-0.0010	-0.0001 ***	-0.0033	-0.0013 ***
	Q-BAH	-0.0013	0.0019	0.0009	0.0031 ***	0.0029	0.0072 ***	-0.0008	-0.0001 **	-0.0003	0.0002	-0.0015	-0.0001 **
	Y-BAH	-0.0010	0.0023	0.0005	0.0029 ***	0.0031	0.0099 ***	-0.0004	0.0002	-0.0002	0.0003	-0.0005	0.0006
	M-Q	-0.0008	-0.0003 ***	-0.0003	-0.0001 ***	-0.0017	-0.0011 ***	-0.0008	-0.0006 ***	-0.0003	-0.0002 ***	-0.0016	-0.0013 ***
	M-Y	-0.0016	-0.0001 **	-0.0004	0.0006	-0.0040	-0.0015 ***	-0.0013	-0.0009 ***	-0.0005	-0.0002 ***	-0.0026	-0.0020 ***
	Q-Y	-0.0008	0.0002	-0.0001	0.0007	-0.0025	-0.0002 ***	-0.0005	-0.0002 ***	-0.0003	0.0000 ***	-0.0011	-0.0006 ***
10 years	M-BAH	-0.0021	0.0008	0.0014	0.0026 ***	0.0026	0.0061 ***	-0.0027	-0.0015 ***	-0.0012	-0.0002 ***	-0.0033	-0.0013 ***
	Q-BAH	-0.0016	0.0013	0.0015	0.0028 ***	0.0039	0.0075 ***	-0.0019	-0.0007 ***	-0.0008	-0.0001 **	-0.0016	-0.0001 **
	Y-BAH	-0.0015	0.0016	0.0011	0.0026 ***	0.0040	0.0090 ***	-0.0015	-0.0003 ***	-0.0006	0.0000	-0.0007	0.0005
	M-Q	-0.0007	-0.0002 ***	-0.0003	0.0000 ***	-0.0015	-0.0012 ***	-0.0009	-0.0007 ***	-0.0003	-0.0002 ***	-0.0016	-0.0013 ***
	M-Y	-0.0013	-0.0001 **	-0.0002	0.0006	-0.0033	-0.0011 ***	-0.0014	-0.0010 ***	-0.0006	-0.0003 ***	-0.0025	-0.0019 ***
	Q-Y	-0.0006	0.0002	0.0000	0.0007	-0.0016	0.0000 **	-0.0006	-0.0003 ***	-0.0003	0.0000 ***	-0.0010	-0.0004 ***

Table VII

Average Growth of Net Asset Values

Classified by the underlying investment horizon, this table shows the average growth of the NAVs of yearly, quarterly, and monthly rebalancing strategies as well as a buy-and-hold strategy over the sample period from January 1982 to December 2011 for both the rolling window approach and the bootstrap approach. All strategies are based on a 60% stocks and 40% bonds asset allocation with a threshold of 0%. Transaction costs are quoted at 15 bps per roundtrip.

		Rolling Window Approach			Bootstrap Approach		
Period	Investment Strategy	USA	UK	Germany	USA	UK	Germany
5	Buy-and-Hold	66.78	66.04	55.42	69.11	70.82	63.39
5	Yearly Rebalancing	65.90	66.05	57.56	68.45	70.33	62.49
5	Quarterly Rebalancing	65.69	66.19	56.75	68.05	70.10	61.71
5	Monthly Rebalancing	65.36	66.04	55.92	67.60	69.89	60.88
7	Buy-and-Hold	106.46	104.03	83.83	113.84	119.81	104.01
7	Yearly Rebalancing	106.02	105.64	90.02	112.69	119.32	102.21
7	Quarterly Rebalancing	105.77	106.30	88.81	112.07	119.05	100.83
7	Monthly Rebalancing	105.23	106.17	87.30	111.22	118.74	99.23
10	Buy-and-Hold	183.88	176.17	128.67	196.86	209.19	176.63
10	Yearly Rebalancing	181.31	179.80	141.10	193.65	207.85	171.26
10	Quarterly Rebalancing	181.22	181.43	139.91	192.45	207.32	168.92
10	Monthly Rebalancing	180.39	181.25	137.17	190.76	206.74	165.74

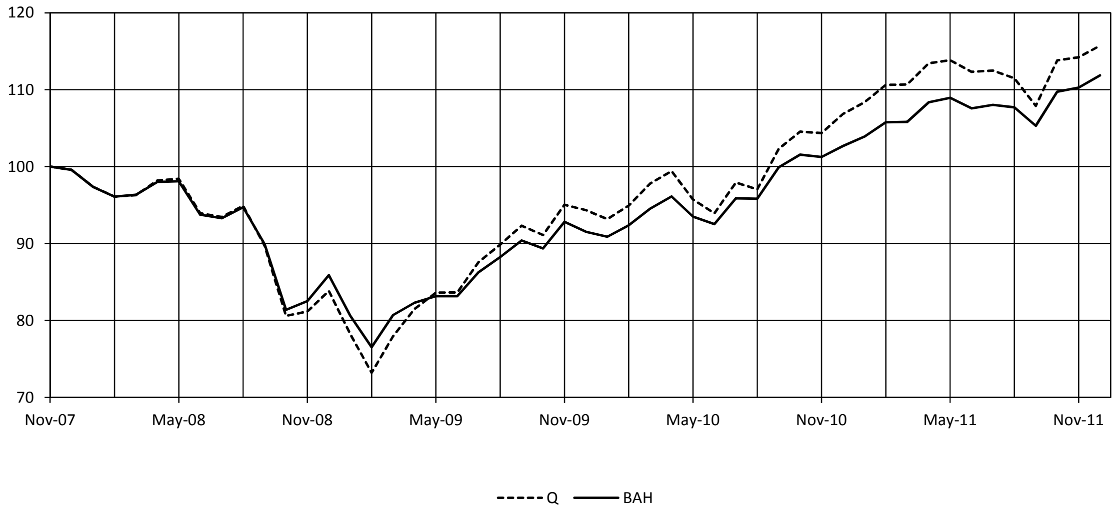
Table VIII

Development of Net Asset Values: USA

This table illustrates the development of NAVs of the USA over the sample period from January 1982 to December 2011. All strategies are based on a 60% stocks and 40% bonds asset allocation with a threshold of 0%. Transaction costs are quoted at 15 bps per roundtrip.

Investment Horizon	Period	Stocks	Bonds	BAH	Yearly Rebalancing	Quarterly Rebalancing	Monthly Rebalancing
5	01/82-12/86	246.4	242.6	244.9	246.1	246.6	247.2
10	01/82-12/91	501.4	364.0	446.4	445.8	455.6	454.4
15	01/82-12/96	1036.0	494.7	819.5	785.4	799.0	796.9
20	01/82-12/01	1710.0	677.4	1296.9	1237.4	1264.8	1247.2
25	01/82-12/06	2303.3	853.8	1723.5	1669.1	1699.6	1664.3
30	01/82-12/11	2298.3	1306.8	1901.7	2117.2	2121.7	2034.6

Panel A. Performance of a 100$-investment



Panel B. Portfolio weights of stocks

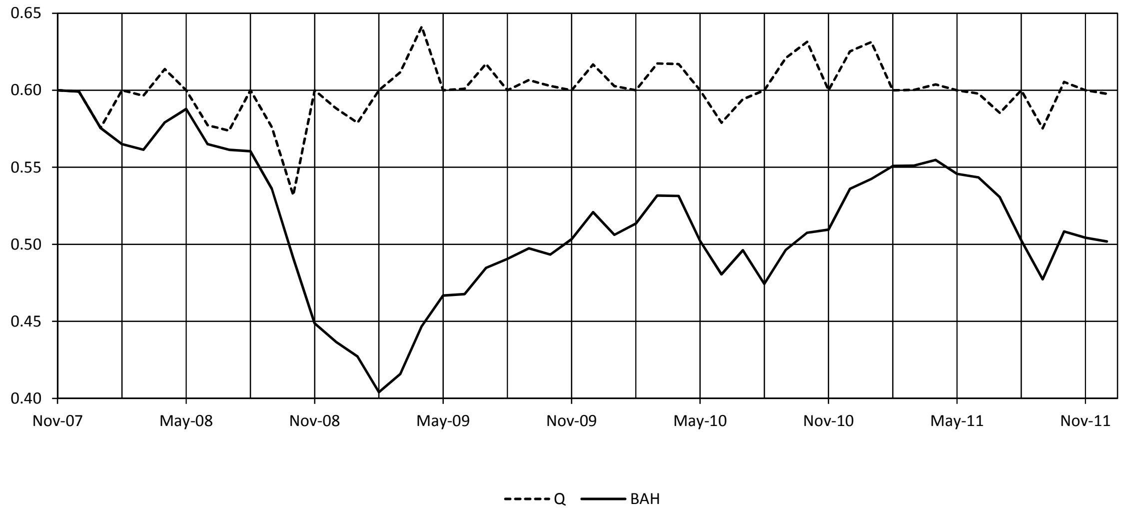


Figure 1. Performance of a 100$-investment and corresponding portfolio weights of stocks. Both strategies – buy-and-hold (BAH) as well as quarterly rebalancing (Q) – are based on a 60% stocks and 40% bonds asset allocation with a threshold of 0%. Transaction costs are quoted at 15 bps per roundtrip. In order to better illustrate the mechanics of rebalancing, our subsample period starts by the beginning of the last contraction period in December 2007 (*National Bureau of Economic Research (2012)*).

Table IX

Average Annualized Volatilities

Classified by the underlying investment horizon, this table shows the average annualized volatilities of yearly, quarterly, and monthly rebalancing strategies as well as a buy-and-hold strategy over the sample period from January 1982 to December 2011 for both the rolling window approach and the bootstrap approach. All strategies are based on a 60% stocks and 40% bonds asset allocation with a threshold of 0%. Transaction costs are quoted at 15 bps per roundtrip.

		Rolling Window Approach			Bootstrap Approach		
Period	Investment Strategy	USA	UK	Germany	USA	UK	Germany
5	Buy-and-Hold	9.40	10.19	13.17	9.68	10.28	12.90
5	Yearly Rebalancing	9.13	9.93	12.74	9.47	10.11	12.64
5	Quarterly Rebalancing	9.16	9.94	12.83	9.48	10.10	12.67
5	Monthly Rebalancing	9.20	9.98	12.92	9.53	10.13	12.75
7	Buy-and-Hold	9.76	10.31	13.46	9.94	10.39	13.01
7	Yearly Rebalancing	9.33	10.03	12.93	9.71	10.27	12.75
7	Quarterly Rebalancing	9.37	10.05	13.04	9.73	10.26	12.80
7	Monthly Rebalancing	9.41	10.09	13.14	9.78	10.30	12.89
10	Buy-and-Hold	10.18	10.46	13.74	10.26	10.76	13.29
10	Yearly Rebalancing	9.58	10.27	13.15	9.94	10.60	12.88
10	Quarterly Rebalancing	9.60	10.30	13.24	9.95	10.59	12.92
10	Monthly Rebalancing	9.63	10.33	13.34	9.99	10.63	13.02

Table X

Calculated Confidence Intervals: Volatility

This table shows the confidence intervals for the annualized volatility for a 5, 7, and 10-year investment horizon, respectively. All strategies are based on a 60% stocks and 40% bonds asset allocation with a threshold of 0%. Transaction costs are quoted at 15 bps per roundtrip. BAH denotes buy-and-hold, Y yearly rebalancing, Q quarterly re-balancing, and M monthly rebalancing. For each two strategies that are compared, the lower and upper boundary of the corresponding confidence interval is calculated. 10 million simulations with a fixed block length of 6 are performed. Repeated simulations reveal that the results are stable. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% level, respectively.

		Rolling Window Approach						Bootstrap Approach					
	Strategies	USA		United Kingdom		Germany		USA		United Kingdom		Germany	
5 years	M-BAH	-0.0042	0.0012	-0.0044	0.0003	-0.0073	0.0035	-0.0021	-0.0008 ***	-0.0021	-0.0010 ***	-0.0031	-0.0003 ***
	Q-BAH	-0.0046	0.0007	-0.0047	-0.0001 *	-0.0079	0.0022	-0.0025	-0.0013 ***	-0.0024	-0.0014 ***	-0.0039	-0.0012 ***
	Y-BAH	-0.0045	-0.0003 *	-0.0048	-0.0003 **	-0.0080	0.0001	-0.0026	-0.0015 ***	-0.0022	-0.0013 ***	-0.0040	-0.0016 ***
	M-Q	0.0002	0.0006 ***	0.0002	0.0005 ***	0.0002	0.0016 ***	0.0004	0.0005 ***	0.0003	0.0003 ***	0.0007	0.0009 ***
	M-Y	0.0000	0.0017 *	-0.0002	0.0011	0.0002	0.0036 *	0.0005	0.0008 ***	0.0000	0.0003 ***	0.0008	0.0015 ***
	Q-Y	-0.0003	0.0012	-0.0005	0.0007	-0.0003	0.0024	0.0000	0.0003 ***	-0.0002	0.0000	0.0001	0.0005 **
7 years	M-BAH	-0.0065	-0.0001 **	-0.0047	-0.0001 *	-0.0083	0.0022	-0.0021	-0.0008 ***	-0.0014	-0.0001 ***	-0.0032	-0.0002 ***
	Q-BAH	-0.0068	-0.0005 **	-0.0054	-0.0002 **	-0.0091	0.0010	-0.0026	-0.0012 ***	-0.0017	-0.0004 ***	-0.0041	-0.0011 ***
	Y-BAH	-0.0078	-0.0003 ***	-0.0061	-0.0003 ***	-0.0103	-0.0002 **	-0.0027	-0.0014 ***	-0.0017	-0.0005 ***	-0.0042	-0.0015 ***
	M-Q	0.0002	0.0006 ***	0.0002	0.0005 ***	0.0004	0.0015 ***	0.0004	0.0005 ***	0.0003	0.0004 ***	0.0008	0.0010 ***
	M-Y	0.0000	0.0015 *	0.0004	0.0040 **	0.0004	0.0040 **	0.0005	0.0007 ***	0.0002	0.0005 ***	0.0008	0.0015 ***
	Q-Y	-0.0003	0.0010	-0.0004	0.0006	0.0000	0.0024 *	0.0000	0.0003 ***	-0.0001	0.0001	0.0000	0.0004 **
10 years	M-BAH	-0.0082	-0.0016 *	-0.0038	0.0007	-0.0088	0.0025	-0.0034	-0.0020 ***	-0.0019	-0.0007 ***	-0.0043	-0.0010 ***
	Q-BAH	-0.0102	-0.0004 ***	-0.0041	0.0003	-0.0096	0.0013	-0.0038	-0.0025 ***	-0.0022	-0.0011 ***	-0.0052	-0.0021 ***
	Y-BAH	-0.0101	-0.0009 ***	-0.0040	-0.0002 *	-0.0101	-0.0007 *	-0.0040	-0.0027 ***	-0.0022	-0.0011 ***	-0.0055	-0.0025 ***
	M-Q	0.0002	0.0005 ***	0.0003	0.0005 ***	0.0005	0.0015 ***	0.0004	0.0005 ***	0.0003	0.0003 ***	0.0009	0.0011 ***
	M-Y	0.0000	0.0013 *	0.0001	0.0010 *	0.0005	0.0037 **	0.0005	0.0007 ***	0.0002	0.0004 ***	0.0011	0.0017 ***
	Q-Y	-0.0003	0.0008	-0.0002	0.0006	0.0000	0.0021	0.0001	0.0003 ***	-0.0001	0.0000	0.0002	0.0007 ***

Table XI

Average Annualized Sharpe Ratios

Classified by the underlying investment horizon, this table shows the average Sharpe ratios of yearly, quarterly, and monthly rebalancing strategies as well as a buy-and-hold strategy over the sample period from January 1982 to December 2011 for both the rolling window approach and the bootstrap approach. All strategies are based on a 60% stocks and 40% bonds asset allocation with a threshold of 0%. Transaction costs are quoted at 15 bps per roundtrip.

		Rolling Window Approach			Bootstrap Approach		
Period	Investment Strategy	USA	UK	Germany	USA	UK	Germany
5	Buy-and-Hold	0.593	0.261	0.294	0.627	0.369	0.366
5	Yearly Rebalancing	0.628	0.289	0.364	0.658	0.388	0.412
5	Quarterly Rebalancing	0.628	0.292	0.362	0.656	0.388	0.414
5	Monthly Rebalancing	0.623	0.289	0.354	0.649	0.386	0.406
7	Buy-and-Hold	0.574	0.246	0.284	0.639	0.410	0.376
7	Yearly Rebalancing	0.620	0.281	0.360	0.670	0.429	0.424
7	Quarterly Rebalancing	0.618	0.283	0.353	0.667	0.430	0.423
7	Monthly Rebalancing	0.611	0.281	0.343	0.658	0.427	0.412
10	Buy-and-Hold	0.540	0.231	0.238	0.611	0.390	0.352
10	Yearly Rebalancing	0.587	0.260	0.309	0.643	0.408	0.402
10	Quarterly Rebalancing	0.586	0.263	0.304	0.639	0.408	0.399
10	Monthly Rebalancing	0.580	0.261	0.293	0.630	0.404	0.387

Table XII

Calculated Confidence Intervals: Sharpe Ratio

This table shows the confidence intervals for the Sharpe ratio for a 5, 7, and 10-year investment horizon, respectively. All strategies are based on a 60% stocks and 40% bonds asset allocation with a threshold of 0%. Transaction costs are quoted at 15 bps per roundtrip. BAH denotes buy-and-hold, Y yearly rebalancing, Q quarterly rebalancing, and M monthly rebalancing. For each two strategies that are compared, the lower and upper boundary of the corresponding confidence interval is calculated. 10 million simulations with a fixed block length of 6 are performed. Repeated simulations reveal that the results are stable. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% level, respectively.

		Rolling Window Approach						Bootstrap Approach					
	Strategies	USA		United Kingdom		Germany		USA		United Kingdom		Germany	
5 years	M-BAH	0.0140	0.0490 ***	0.0151	0.0371 ***	0.0405	0.0818 ***	0.0166	0.0246 ***	0.0152	0.0205 ***	0.0389	0.0455 ***
	Q-BAH	0.0202	0.0542 ***	0.0173	0.0400 ***	0.0494	0.0894 ***	0.0247	0.0327 ***	0.0181	0.0236 ***	0.0484	0.0553 ***
	Y-BAH	0.0202	0.0527 ***	0.0133	0.0414 ***	0.0469	0.0926 ***	0.0260	0.0341 ***	0.0173	0.0230 ***	0.0461	0.0548 ***
	M-Q	-0.0100	-0.0030 ***	-0.0049	-0.0005 ***	-0.0123	-0.0036 ***	-0.0091	-0.0070 ***	-0.0036	-0.0021 ***	-0.0109	-0.0083 ***
	M-Y	-0.0140	0.0015	-0.0069	0.0049	-0.0198	-0.0009 *	-0.0119	-0.0064 ***	-0.0040	-0.0006 ***	-0.0113	-0.0050 ***
	Q-Y	-0.0061	0.0068	-0.0033	0.0066	-0.0099	0.0050	-0.0025	0.0004	-0.0004	0.0015	-0.0004	0.0033
7 years	M-BAH	0.0209	0.0548 ***	0.0269	0.0439 ***	0.0473	0.0719 ***	0.0159	0.0247 ***	0.0141	0.0199 ***	0.0360	0.0443 ***
	Q-BAH	0.0271	0.0615 ***	0.0292	0.0473 ***	0.0568	0.0864 ***	0.0250	0.0336 ***	0.0171	0.0229 ***	0.0472	0.0552 ***
	Y-BAH	0.0271	0.0650 ***	0.0238	0.0487 ***	0.0579	0.1029 ***	0.0269	0.0355 ***	0.0160	0.0217 ***	0.0465	0.0552 ***
	M-Q	-0.0099	-0.0038 ***	-0.0048	-0.0007 ***	-0.0148	-0.0073 ***	-0.0099	-0.0080 ***	-0.0036	-0.0023 ***	-0.0123	-0.0099 ***
	M-Y	-0.0173	0.0000	-0.0067	0.0059	-0.0343	-0.0041 ***	-0.0127	-0.0086 ***	-0.0034	-0.0004 ***	-0.0130	-0.0080 ***
	Q-Y	-0.0087	0.0058	-0.0027	0.0074	-0.0151	0.0001	-0.0036	0.0000 ***	-0.0001	0.0018	-0.0009	0.0019
10 years	M-BAH	0.0152	0.0665 ***	0.0249	0.0372 ***	0.0429	0.0661 ***	0.0123	0.0225 ***	0.0099	0.0169 ***	0.0292	0.0390 ***
	Q-BAH	0.0216	0.0705 ***	0.0277	0.0407 ***	0.0543	0.0779 ***	0.0218	0.0319 ***	0.0131	0.0201 ***	0.0424	0.0519 ***
	Y-BAH	0.0169	0.0793 ***	0.0227	0.0394 ***	0.0531	0.0948 ***	0.0253	0.0356 ***	0.0136	0.0204 ***	0.0447	0.0550 ***
	M-Q	-0.0087	-0.004 ***	-0.0043	-0.0013 ***	-0.0128	-0.0100 ***	-0.0103	-0.0083 ***	-0.0038	-0.0026 ***	-0.0139	-0.0119 ***
	M-Y	-0.0137	0.0004	-0.0046	0.0045	-0.0295	-0.0060 ***	-0.0152	-0.0106 ***	-0.0052	-0.0019 ***	-0.0181	-0.0128 ***
	Q-Y	-0.0062	0.0059	-0.0008	0.0065	-0.0117	0.0008	-0.0055	-0.0015 ***	-0.0012	0.0005	-0.0044	-0.0008 **

Table XIII

Calculated Confidence Intervals: Sharpe Ratios (Threshold and Range Rebalancing)

Panel A shows the confidence intervals for Sharpe ratios of threshold rebalancing for a 5, 7, and 10-year investment horizon, respectively. Panel B presents the confidence intervals for Sharpe ratios of range rebalancing for the same investment horizons. All strategies are based on a 60% stocks and 40% bonds asset allocation with a threshold of 5%. Transaction costs are quoted at 15 bps per roundtrip. BAH denotes buy-and-hold, Y yearly rebalancing, Q quarterly rebalancing, and M monthly rebalancing. For each two strategies that are compared, the lower and upper boundary of the corresponding confidence interval is calculated. 10 million simulations with a fixed block length of 6 are performed. Repeated simulations reveal that the results are stable. Threshold rebalancing involves a reallocation to the target weights, while rebalancing to range requires a reallocation to the nearest edge of the predefined no-trade region. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Threshold Rebalancing

		Rolling Window Approach						Bootstrap Approach					
	Strategies	USA		United Kingdom		Germany		USA		United Kingdom		Germany	
5 years	M-BAH	0.0159	0.0485 ***	0.0171	0.0441 ***	0.0475	0.0881 ***	0.0197	0.0272 ***	0.0137	0.0199 ***	0.0415	0.0499 ***
	Q-BAH	0.0187	0.054 ***	0.0187	0.0461 ***	0.0557	0.0985 ***	0.0208	0.0285 ***	0.0149	0.0212 ***	0.0424	0.0507 ***
	Y-BAH	0.0216	0.0546 ***	0.0157	0.0482 ***	0.0440	0.0938 ***	0.0205	0.0290 ***	0.0128	0.0187 ***	0.0394	0.0488 ***
7 years	M-BAH	0.0257	0.0618 ***	0.0281	0.0517 ***	0.0573	0.0889 ***	0.0178	0.0285 ***	0.0147	0.0213 ***	0.0403	0.0511 ***
	Q-BAH	0.0301	0.0639 ***	0.0283	0.0498 ***	0.0628	0.0968 ***	0.0200	0.0306 ***	0.0157	0.0219 ***	0.0436	0.0543 ***
	Y-BAH	0.0273	0.0751 ***	0.0249	0.0576 ***	0.0588	0.1007 ***	0.0224	0.0332 ***	0.0147	0.0218 ***	0.0440	0.0553 ***
10 years	M-BAH	0.0192	0.0741 ***	0.0295	0.0461 ***	0.0518	0.0850 ***	0.0146	0.0255 ***	0.0122	0.0191 ***	0.0353	0.0447 ***
	Q-BAH	0.0205	0.0718 ***	0.0264	0.0428 ***	0.0566	0.0847 ***	0.0186	0.0289 ***	0.0135	0.0206 ***	0.0393	0.0491 ***
	Y-BAH	0.0185	0.0855 ***	0.0241	0.0457 ***	0.0552	0.0893 ***	0.0218	0.0327 ***	0.0131	0.0199 ***	0.0397	0.0502 ***

Table XIII – *Continued*

Panel A: Range Rebalancing													
		Rolling Window Approach						Bootstrap Approach					
	Strategies	USA		United Kingdom		Germany		USA		United Kingdom		Germany	
5 years	M-BAH	0.0172	0.0468 ***	0.0136	0.0417 ***	0.0539	0.0953 ***	0.0152	0.0213 ***	0.0104	0.0148 ***	0.0341	0.0416 ***
	Q-BAH	0.0171	0.0457 ***	0.0141	0.0408 ***	0.0488	0.0904 ***	0.0147	0.0206 ***	0.0090	0.0131 ***	0.0312	0.0390 ***
	Y-BAH	0.0131	0.0376 ***	0.0081	0.0295 ***	0.0365	0.0736 ***	0.0121	0.0177 ***	0.0067	0.0107 ***	0.0243	0.0323 ***
7 years	M-BAH	0.0264	0.0702 ***	0.0231	0.0490 ***	0.0591	0.1008 ***	0.0127	0.0213 ***	0.0092	0.0150 ***	0.0331	0.0431 ***
	Q-BAH	0.0263	0.0689 ***	0.0219	0.0486 ***	0.0619	0.0997 ***	0.0132	0.021 ***	0.0081	0.0135 ***	0.0321	0.0417 ***
	Y-BAH	0.0182	0.0605 ***	0.0136	0.0380 ***	0.0451	0.0921 ***	0.0110	0.0181 ***	0.0060	0.0108 ***	0.0264	0.0361 ***
10 years	M-BAH	0.0222	0.0789 ***	0.0171	0.0392 ***	0.0601	0.0967 ***	0.0161	0.0248 ***	0.0106	0.0163 ***	0.0361	0.0463 ***
	Q-BAH	0.025	0.0771 ***	0.0147	0.0383 ***	0.0567	0.0975 ***	0.0166	0.0249 ***	0.0101	0.0156 ***	0.0357	0.0456 ***
	Y-BAH	0.0157	0.0722 ***	0.0111	0.0282 ***	0.0430	0.0901 ***	0.0155	0.0231 ***	0.0086	0.0135 ***	0.0320	0.0409 ***