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Working Papers / Documents de travail

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WP 2023 - Nr 22

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Abstract

In this paper, we examine rebalancing strategies for long-term institutional investors. Specifically, we test the difference in risk-adjusted performances between stock-bond portfolios based on buy-and-hold, periodic and threshold rebalancing strategies. Using the Norwegian Sovereign Wealth Fund (SWF) as a benchmark and an econometric approach based on a bootstrap test of Sharpe ratios difference, we show that the optimal rebalancing differs across economic and financial cycles. Furthermore, we find that the optimal strategy is periodic rebalancing except during recessions and crises when the buy-and-hold approach is best, thus calling into question the hypothesis of the countercyclical behavior of SWFs. Our results are robust to alternative performance measures, asset allocations, investment horizons, rebalancing rule, nonnormal and non-iid returns, transaction costs and time sampling. Finally, our findings promote the consideration of macroprudential rules to improve the Santiago Principles and a specific monitoring framework targeted at SWFs.

Keywords: *Portfolio Rebalancing; Financial Stability; Bootstrap Test; Institutional Investors.*

*The authors thank Bertrand Candelon, Serge Darolles, Campbell Harvey, William Sharpe and seminar participants at the 5th Quantitative Finance and Financial Econometrics conference (QFFE 2023, Marseille), the 6th International Conference on Econometrics and Statistics (EcoSta 2023, Tokyo) and the 11th Conference on Economic and Financial Adjustments (UECE 2023, Lisbon) for their helpful comments. The project that led to this publication has received funding from the French government under the "France 2030" investment plan managed by the French National Research Agency (reference: ANR-17-EURE-0020) and from the Excellence Initiative of Aix-Marseille University - A*MIDEX. This research was performed as part of a research program titled "Risk Management, Investment Strategies and Financial Stability" under the aegis of the Europlace Institute of Finance, a joint initiative with insti7. The usual disclaimers apply.

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1. Introduction

In this paper, we examine rebalancing strategies for a long-term institutional investor. Specifically, we test the difference in modified Sharpe ratios between bootstraped stock-bond portfolios based on buy-and-hold, periodic and threshold rebalancing strategies using the econometric approach of Ardia and Boudt (2015). This comparative analysis considers a global sample, as well as the phases of economic and financial cycles separately. Both innovations enable us to revisit the recent contributions on long-term institutional investor rebalancing (i.a., Dichtl et al., 2016; Rattray et al., 2020).

Among long-term institutional investors, we are interested in sovereign wealth funds (SWFs) for two reasons. First, as argued by Chambers et al. (2021), SWFs are an attractive model for long-horizon investors, as they have considerable freedom regarding how to invest their assets: they have no explicit financial liability. Second, SWFs are interesting from a regulatory and financial stability perspective because of their large size and the size of their participations. This point is crucial, as the investment behavior of SWFs during the COVID-19 pandemic has called into question their role as liquidity providers and volatility dampeners (Bortolotti and Fotak, 2020). Then, among SWFs, we choose to base our empirical analysis on the Norwegian Government Pension Fund Global (GPFG) not only because of its size but also for its *"coherent and compelling approach to managing long-term pools of assets"* (Chambers et al., 2021).

Without anticipating our results, we find that the optimal rebalancing differs across economic and financial cycles. Furthermore, we find that the optimal rebalancing option is periodic rebalancing except during recessions and crises when the buy-and-hold option is best, thus calling into question the hypothesis of the countercyclical behavior of SWFs. Our findings promote the consideration of macroprudential rules to improve the Santiago Principles and a specific monitoring framework targeted at SWFs. Our results are robust to alternative performance measures, asset allocations, investment horizons, rebalancing rule, nonnormal and non-iid returns, transaction costs and time sampling.

Our contribution to the literature is twofold. On the one hand, we contribute to the portfolio management literature. Focusing on long-term institutional investors, we compare rebalancing strategy options with an innovative empirical approach. Our innovation focuses on method and data: (i) we revisit the recent literature using a test of modified Sharpe ratios difference instead of comparing traditional Sharpe ratio statistic estimates only, and (ii) we use GPFG data returns separating recession/expansion and crisis/noncrisis periods instead of sampling time periods only. Our results advocate for an adaptative rebalancing strategy rather than a mechanical rebalancing, i.e., a rebalancing strategy conditioned to the economic and financial cycles. In addition, we contribute to the macroprudential policy and financial stability literature. Indeed, we revisit the literature about the role played by SWFs in financial stability. Our findings contrast with previous works and call into question the hypothesis of the countercyclical behavior of SWFs.

The rest of this paper is organized as follows. Section 2 reviews the literature on long-term investor rebalancing strategies, with a particular emphasis on those related to institutional investors, and among them, SWFs. Insights into the role played by SWFs in financial stability are also provided. Section 3 offers a review of the econometric methodology of the resampling procedure and the performance measures used to compare the different investment strategies. Section 4 describes the dataset and the main empirical results, whereas Section 5 is dedicated to robustness checks. Finally, Section 6 highlights some policy implications, and Section 7 concludes the paper.

2. Related literature

2.1. Optimal rebalancing for long-term investors

As originally shown by Samuelson (1969) and Merton (1969), portfolio rebalancing is one of the pillars of any long-term investment strategy. Indeed, financial market fluctuations induce variations in asset prices, which in turn lead to changes in portfolio asset allocation. In their seminal work, Perold and Sharpe (1988) point out the importance of choosing the appropriate dynamic strategies to manage these fluctuations. The authors define rebalancing as the process of returning the weights of a portfolio's asset allocations to its initial weights defining the strategic allocation. In addition, they document several investment strategies, including buy-and-hold and rebalancing strategies, and their respective impact on stock-bond portfolio performances. Furthermore, they examine the impact of each dynamic strategy relative to different market conditions. Since then, the literature on stock-bond portfolios has been enriched with numerous theoretical and empirical contributions. Campbell and Viceira (2002) resumes the consumption and portfolio choice for long-term investors with different utility functions and with time-varying market conditions.

Considering the practical importance of the issue to investors, a large body of empirical research has investigated the effects of rebalancing. Since the 2000s, the empirical literature has sought to investigate the optimal rebalancing frequency or a no-trade interval around desired portfolio weights, but no clear consensus actually emerges from these studies (Buetow et al., 2002; Smith and Desormeau, 2006; McLellan and Kinlaw, 2009). However, various results depend on the methodological approach, including the performance measures used, time horizons, geographical locations and time periods considered, as well as whether transaction costs are taken into account. Some papers find that a rebalancing strategy outperforms a buy-and-hold strategy (Harjoto and Jones, 2006; Bolognesi et al., 2013), whereas other papers conclude that a buy-and-hold strategy outperforms in a strongly trending market (Plaxco and Arnott, 2002).

2.2. Institutional long-term investors: the case of sovereign wealth funds

Among long-term investors, institutional investors have recently been at the center of the literature on rebalancing. Compared to retail investors, the large investment opportunities, weaker transaction costs and access to investment insights of institutional investors make them interesting examples with which to examine strategic asset allocations. Focusing on long-term institutional investors, Sun et al. (2006) show that under certain circumstances, some rebalancing strategies are significantly better than others. Along these lines, recent contributions have examined the rebalancing impact on portfolio performance. Dichtl et al. (2013) compare the performance of different rebalancing strategies, including periodic, threshold, and range rebalancing, using historical stock and bond data returns. One of their contributions is to report both Sharpe ratio estimates and statistical significance levels. Alternatively, Almadi et al. (2014) investigate the effects of periodic rebalancing frequency on portfolio performance using a set of performance measure estimates (i.e., maximum drawdowns and Calmar ratios). Dichtl et al. (2014) extend their previous work using Sortino ratios and Omega measures, as well as different asset allocations (Dichtl et al., 2016). Rattray et al. (2020) revisit these empirical findings by examining the impact of different rebalancing strategies during financial turmoil.

Among others, sovereign wealth funds (SWFs) are long-term institutional investors that have been of particular interest because they are free of nonfinancial constraints, such as financial liability or regulation (Chambers et al., 2021). Surprisingly – and probably due to the lack of data on SWFs – the literature about SWF rebalancing is scarce. In a report prepared for the Norwegian's Ministry of Finance, Ang et al. (2014) describe the rebalancing guidelines in the mandate given to Norges Bank Investment Management (NBIM). The authors argue that this mandate causes this SWF to act countercyclically to maintain optimal portfolio weights. According to them, the adoption of a rebalancing rule adds value over time, as it limits overreaction and impulsive changes in its asset allocation. This observation is in line with Beck and Fidora (2008), who examine the potential impact of portfolio rebalancing on financial stability using GPFG data returns.

2.3. Sovereign Wealth Funds and Financial Stability

The view that SWFs play a stabilizing role in the financial system by growing and developing the economy is widely accepted (Beck and Fidora, 2008; Ciarlone and Miceli, 2016; Benedictow and Boug, 2017). In this line, Gomes (2008) argues that SWFs are long-term investors with countercyclical behavior, providing liquidity and reducing market volatility. He concedes that potential threats exist (e.g., lack of transparency, protectionism or size); however, according to the author, it is unlikely to destabilize financial markets. Sun and Hesse (2009) focus on SWFs' potential for destabilization related to investment or divestment. Investigating SWFs' announcements, they find no consecutive impact on stock markets. Then, examining the potential impact of Norwegian SWF portfolio rebalancing on asset prices, Beck and Fidora (2008) find that such an impact poses no threat to financial stability. Ciarlone and Miceli (2016) generalize their findings, giving evidence that even during the global financial crisis, SWFs followed their investment strategy by investing or rebalancing their assets to the countries and sectors most affected by the crisis.

However, the perception of the role of SWFs in the financial system has changed recently (Megginson and Gao, 2020; Bahoo et al., 2020). Since 2014, commodity prices have decreased, reducing the revenues of some producing countries that have set up SWFs. Additionally, the rise of protectionism has helped halt the development of SWFs. Finally, the COVID-19 pandemic revealed the negative impact that SWFs could have on financial stability. Indeed, during the March-April 2020 stock market crash, some SWFs diverged from their long-term investment strategy. Bortolotti and Fotak (2020) highlight the fact that some SWFs have favored domestic investments to support the national economy and have financed strategic sectors such as pharmaceutical research. According to the authors, this procyclical behavior has revealed the potential threat that an SWF can represent for financial stability.

3. Econometric methodology

3.1. Resampling procedure

Until the late 2010s, most of the existing studies on rebalancing were based on historical analyses only. However, rebalancing is a dynamic trading strategy, which means that its performance is highly path dependent (Sharpe, 2010). Hence, estimating the impact of rebalancing based on historical analyses could lead to data snooping issues because the results could be more influenced by specific characteristics of the underlying sample period rather than by the corresponding considered rebalancing algorithm (White, 2000). To avoid this potential issue, we implement a history-based simulation approach based on GPFG stocks and bonds data returns, as in NBIM (2018). This econometric approach enables us to report statistical significance levels under realistic market conditions, as in Dichtl et al. (2013).

Specifically, we use a circular moving-block-bootstrap allowing for overlapping blocks. Furthermore, we opt for pairwise resampling to maintain the cross-sectional dependency structure of stocks, bond returns and risk-free rates. This approach, related to Kunsch (1989) and Politis and Romano (1991) and recently used by Fong (2013), can produce biased estimates related to the block size. To overcome potential bias, we use different block sizes as advocated by Cogneau and Zakamouline (2013), whereas Dichtl et al. (2016) use blocks of random size as an alternative. Therefore, in the main results, the block size is determined following the rule put forth by Hall et al. (1995) (i.e., $l \in \{n^{1/3}, n^{1/4}, n^{1/5}\}$, with l being the block size and n being the number of observations); then, in a dedicated robustness check, the block size is determined by the investment horizon (i.e., $l \in \{h^{1/3}, h^{1/4}, h^{1/5}\}$, with l being the block size and h being the horizon), as in Dichtl et al. (2013). As in NBIM (2018), we block-bootstrap 1,000 20-year samples of equity and bond returns to which we apply the alternative rebalancing rules. Performance measure (e.g., Sharpe ratios) estimates are computed by averaging across the simulated samples.

In summary, this econometric framework enables us to mimic realistic stock-bond portfolios to evaluate the performances of alternative rebalancing rules. In addition to avoiding data snooping issues, bootstrapping returns enable (i) the estimation of the significance of Sharpe ratio estimates and (ii) control of the impact of the investment horizon. From this point, we depart from the literature, as we are interested in estimating these performances depending on the phases of economic and financial cycles. In summary, we separately examine all recession and expansion periods (resp. crisis and noncrisis periods) determined by OECD (resp. IMF) dummies. Therefore, our approach is different from the time-sampling analysis of Rattray et al. (2020), as we aggregate data returns from different time periods. We also use this time-sampling approach as a final robustness check to verify that our findings are driven by economic and financial cycles rather than by specific periods.

3.2. Performance measures

This approach necessarily implies revisiting the econometric methodology used in the literature. First, following the recent contributions in the field, our main results are based on Sharpe ratios to evaluate the performance of rebalancing, defined as follows:

$$S_i = \frac{\mu_i - r_f}{\sigma_i}, \tag{1}$$

where μ_i and σ_i are the mean return and volatility of portfolio i, respectively. In addition to the traditional Sharpe ratio, we also use a modified Sharpe ratio to be robust to nonnormal returns. Indeed, our investigations include left-tailed events such as financial crises, and the traditional Sharpe ratio is not the best indicator designed for such periods. Alternatively, several modified Sharpe ratios coexist in the literature, i.e., Favre and Galeano (2002), Gregoriou and Gueyie (2003) and Bali et al. (2013). We choose the measure put forth by Gregoriou and Gueyie (2003), as suggested in Candelon et al. (2021), which is defined as follows:

$$mS_i = \frac{\mu_i - r_f}{mVaR_i^{\alpha\%}}, \tag{2}$$

where μ_i and $mVaR_i^{\alpha\%}$ are the mean return and the $1-\alpha$ % Cornish-Fisher's approximation of the value-at-risk of the portfolio i, respectively, and r_f is the risk-free rate. Other performance measures used in the literature (e.g., the Sortino ratio, the Omega measure, the Jensen's α, the Levy-Tobin multiperiod Sharpe ratio and centiles of the drawdown) are also estimated, and the results are reported in the robustness checks section. Second, instead of comparing the Sharpe ratios related to each rebalancing rule as in Dichtl et al. (2014), we use the tests put forth by Ledoit and Wolf (2008) and Ardia and Boudt (2015) to properly infer the differences between the Sharpe ratios and the modified Sharpe ratios, respectively. More formally, under normal returns, Ledoit and Wolf (2008) introduce the following test for equality of Sharpe ratios:

$$H_0 : \Delta \equiv S_A - S_B = 0, \tag{3}$$

where S_A and S_B are the Sharpe ratios of portfolios A and B, respectively. However, under nonnormal returns, Ardia and Boudt (2015) argue that testing for equality of modified Sharpe ratios boils down to the following:

$$H_0 : \Delta_m \equiv mS_A - mS_B = 0, \tag{4}$$

where mS_A and mS_B are the modified Sharpe ratios of portfolios A and B, respectively.

Ledoit and Wolf (2008) and Ardia and Boudt (2015) both recommend a bootstrap method to compute the associated p-values because stock and bond returns are generally not iid. Specifically, they resample with replacement blocks of fixed size $l \geq 1$ to generate bootstrapped pairs of returns, following the circular block-bootstrap of Politis and Romano (1994). Moreover, they both propose constructing a symmetric studentized bootstrap confidence interval to improve inference accuracy. Therefore, for each bootstrapped pair $(r^{*b}_{t,A}, r^{*b}_{t,B})$, the bootstrap test statistic is computed as follows:

$$\hat{\tau}^{*b}_{A-B} = \frac{\hat{\Delta}^{*b}_{A-B} - \hat{\Delta}_{A-B}}{s(\hat{\Delta}^{*b}_{A-B})}, \tag{5}$$

where $*b$ denotes the estimators computed on the $b-th$ bootstrap dataset. Following Ledoit and Wolf (2008), we test $H0 : \Delta = 0$ (resp. $H0 : \Delta_m = 0$) by inverting a bootstrap confidence interval. In other words, we construct a two-sided bootstrap confidence interval with nominal level $1 - \alpha$ for Δ (resp. Δ_m), defined as follows:

$$CI = [\hat{\tau}^{*b}_{A-B[\alpha/2\times 1000]}, \hat{\tau}^{*b}_{A-B[(1-\alpha)/2\times 1000]}]. \tag{6}$$

If this interval does not contain zero, then $H0$ is rejected at nominal level α. Compared to the classic approach used by Ardia and Boudt (2015), the advantage of their indirect approach is that one can simply resample from the historical returns.[1]

4. Empirical analysis

Our objective is to examine rebalancing options for long-term institutional investors across economic and financial cycles and to revisit their respective consequences on financial stability. Among the investors most likely to have an impact on financial stability, sovereign wealth funds are at the heart of supervisors' attention. Because of their large size, the size of their participations and their political liabilities and because their behavior can influence other investors, sovereign wealth funds' activity during financial crises has been the subject of close scrutiny. Among potential SWFs, we choose to focus on the Norwegian GPFG for three reasons. First, the GPFG is the world's largest sovereign wealth fund, and it is considered a model for long-term institutional investors in terms of good financial performance, low management costs and high liquidity. Second, the GPFG has clear governance and is free of political liabilities; thus, its investment behavior is unbiased. Third, the GPFG is transparent and is known for high standards of ethical behavior, so the data are publicly available and reliable. In summary, the Norwegian GPFG is a relevant institutional portfolio benchmark providing the necessary historical data returns and hindsight to compare rebalancing strategy performances. See Chambers et al. (2021) for an extensive discussion about the choice of Norway as a reference.

4.1. Data

Data about financial performance and strategic asset allocation are reported from December 1998 and made public by one of the Norges Bank subsidiaries (i.e., Norges Bank Investment Management - NBIM), under the aegis of the Norwegian Ministry of Finance. IMF and OECD recession dummies are used to proxy financial and economic cycles, respec-

[1] The details of the bootstrap procedure are described in Appendix B.

tively. [2] Following Bauer et al. (2022), we use the US one-month T-bill rate as a proxy for the risk-free interest rate. Table 1 indicates the variables description and sources.

Table 1: Description of the dataset

Variable	Description	Code	Source
Stocks returns	Investment equities	Rs	NBIM
Bonds returns	Investment fixed income	Rb	NBIM
Risk free rate	US 1-month T-bill	Rf	Kenneth French's website
Financial cycles	Dummy for stock market crises	CRI	IMF
Business cycles	Dummy for recessions	REC	OECD

Notes: This table provides each variable's name, description, code and source. The dataset covers the Norwegian SWF over the period 1998 to 2021.

Norwegian's SWF was a 60/40 stock-bond portfolio from 2007 to 2017. Since then, the strategic allocation has shifted to a 70/30 strategic allocation. Data on portfolio allocation are available at a quarterly frequency, whereas performance data are provided at a monthly frequency starting from December 1998. Table 2 reports the descriptive statistics of the portfolio returns.

Table 2: Descriptive statistics

	Stocks returns	Bonds returns
Mean	0.00682	0.00371
St. Dev.	0.04237	0.00958
Median	0.01249	0.00411
Min	-0.16776	-0.03370
Max	0.12776	0.03082
Kurtosis	4.71872	3.90307
Skewness	-0.80050	-0.29938
Obs.	287	287

Notes: This table provides each variable's name, description, code and source. The panel dataset covers the Norwegian SWF over the period 1998 to 2021.

It is worth noting that the portfolio returns appear not to be normally distributed. The nonnormality of returns will be a point of attention in the remainder of this paper. Last

[2]See Candelon et al. (2020) and Hasse and Lajaunie (2022) for further details about alternative data sources.

but not least, the portfolio returns are reported in a currency basket as in NBIM's financial reports. This currency basket is computed as a weighted combination of the currencies in the fund's benchmark index. [3]

4.2. Main results

The results displayed in Table 3 report the risk-adjusted performances of a stock-bond portfolio with different investment strategies. Specifically, these two tables report the Sharpe ratio (SR) and the modified Sharpe ratio (mSR) of several stock-bond portfolios built from GPFG stock and bond bootstrapped returns. As in Dichtl et al. (2016), this empirical analysis was performed for nine different strategic allocations, i.e., for an allocation to stocks from 10% to 90%. We only report the results related to the 60/40 stock-bond portfolio for the sake of brevity. However, we report results related to a 70/30 stock-bond portfolio as robustness checks (see Section 5.2), and other results are available upon request. Following Dichtl et al. (2016) and NBIM (2018), estimates are computed by averaging across the bootstrapped samples, whereas confidence intervals are constructed as percentile intervals according to Efron and Tibshirani (1998). We consider three distinctive rebalancing classes: (i) buy-and-hold rebalancing, (ii) threshold rebalancing (2% and 4%), and (iii) periodic rebalancing (monthly, quarterly and semiannual). If there is no rebalancing period, then rebalancing reduces to a buy-and-hold strategy. In contrast, periodic rebalancing is characterized by a reallocation to the initial portfolio weights at the end of each predetermined period. The choice of the no-trade band for rebalancing (2% and 4%) is based on the rebalancing policy followed by the NBIM. The results in Table 3 are displayed for the global sample but also for recession (resp. crisis) and expansion (resp. noncrisis) periods. Figure 1 illustrates the percentage allocated to stocks for a monthly, quarterly, semiannual, target 2%, target 4% rebalanced and a buy-and-hold portfolio.

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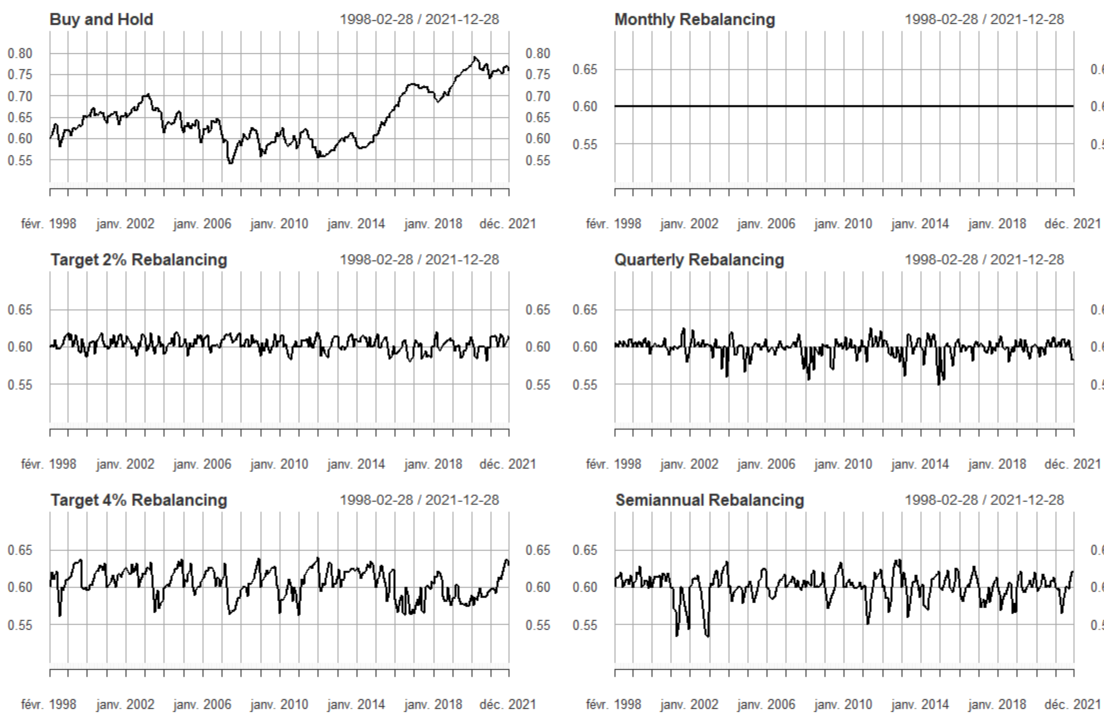
[3] See NBIM's website for further details: `https://www.nbim.no/en/the-fund/returns/methodology-for-the-calculation-of-returns/`

Figure 1: Allocation to Stocks for several Investment Strategies, GPFG, 1998–2021



Notes: This figure illustrates the percentage allocated to stocks for a monthly, quarterly, semiannual, target 2%, target 4% rebalanced and a buy-and-hold portfolio. In each case, at the start 60% of capital is allocated to stocks and 40% to bonds. We use monthly stock and bond returns data from February 1998 to December 2021.

The results indicate that both the Sharpe ratios and the modified Sharpe ratios exhibit qualitatively similar results, indicating that they are robust to violations of the normality assumption. In addition, they also indicate that the results related to economic and financial cycles are qualitatively similar. In summary, we find that the optimal investment strategy is periodic rebalancing except during recessions and crises when the buy-and-hold approach is best (resp. during expansion and noncrisis periods when periodic rebalancing is best).

Table 3: Comparing performances - Optimal rebalancing

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
			Global			
SR	0.148***	0.162***	**0.164*** **	0.163**	0.163***	**0.164*** **
mSR	0.082***	0.090***	**0.091*** **	0.090**	0.090***	0.090***
			Recession periods			
SR	**0.048* **	-0.013	-0.009	-0.015	-0.013	-0.011
mSR	**0.028* **	-0.008	-0.006	-0.009	-0.008	-0.006
			Expansion periods			
SR	0.336***	0.357***	0.356***	**0.358*** **	0.358***	0.357***
mSR	0.170***	**0.179*** **	0.178***	**0.179*** **	0.178***	0.178***
			Crisis periods			
SR	**-0.103*** **	-0.375***	-0.375***	-0.375***	-0.375***	-0.374***
mSR	**-0.067*** **	-0.295***	-0.295***	-0.296***	-0.296***	-0.294***
			Noncrisis periods			
SR	0.341***	0.376***	0.376***	**0.378*** **	**0.378*** **	0.377***
mSR	0.172***	0.186***	0.186***	**0.187*** **	**0.187*** **	**0.187*** **

Notes: This table enables the comparison of the Sharpe ratios and modified Sharpe ratios of different 60/40 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing. The results are computed using R 3.6.0 (R Core Team, 2020) and *DiversificationR* (*v0.1.0*; Hasse (2021) package. The full reproducible code is available on CRAN. Labels $***$, $**$ and $*$ indicate significance at 99%, 95% and 90% levels, respectively.

Tables 4 and 5 report the results of the statistics of the Sharpe ratios and modified Sharpe ratios differences, as well as their levels of significance. Using test from Ledoit and Wolf (2008) and Ardia and Boudt (2015) allows us to make inferences about the comparison of rebalancing options. The results indicate common findings for the global sample, where quarterly rebalancing exhibits a significantly better performance than the other strategies. The results also indicate differences across economic and financial cycles. Indeed, the results reported in Tables 4 and 5 indicate that the buy-and-hold strategy is the best during financial crises and the worst during noncrisis and expansion periods.

The results reported in Table 5 are qualitatively similar to those displayed in Table 4. The findings clearly indicate that a buy-and-hold strategy performs significantly better during financial crises, whereas this strategy significantly underperforms all the other rebalancing strategies otherwise.

Table 4: Testing difference of Sharpe ratios - Optimal rebalancing

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
			Global			
Buy & Hold		-0.006	-0.006	-0.004	**-0.010***	**-0.009***
2%			0.000	**0.002***	**-0.003*****	**-0.003****
4%				0.002	-0.003	-0.002
Monthly					**-0.005*****	**-0.004*****
Quarterly						0.001
Semiannual						
			Recession periods			
Buy & Hold		0.016	0.015	0.018	0.016	0.020
2%			-0.001	0.001	0.000	0.004
4%				0.002	0.000	**0.005***
Monthly					-0.001	0.003
Quarterly						0.004
Semiannual						
			Expansion periods			
Buy & Hold		**-0.026*****	**-0.023****	**-0.025****	**-0.025*****	**-0.027*****
2%			0.002	0.000	0.000	-0.002
4%				-0.001	-0.002	**-0.004***
Monthly					0.000	-0.002
Quarterly						**-0.002*****
Semiannual						
			Crisis periods			
Buy & Hold		**0.036***	**0.035***	**0.038***	**0.040****	**0.041****
2%			-0.001	0.001	0.003	0.005
4%				0.002	0.004	0.006
Monthly					0.002	0.003
Quarterly						0.001
Semiannual						
			Noncrisis periods			
Buy & Hold		**-0.047*****	**-0.044****	**-0.047*****	**-0.049*****	**-0.048*****
2%			0.003	0.000	-0.002	-0.001
4%				-0.003	**-0.004***	-0.004
Monthly					-0.002	-0.001
Quarterly						0.000
Semiannual						

Notes: This table enables the comparison of the Sharpe ratios of different 60/40 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing. Significance levels of the statistic are computed via a studentized circular block-bootstrap as in Ledoit and Wolf (2008). The results are computed using R 3.6.0 (R Core Team, 2020) and *PeerPerformance* (*v2.2.5*; Ardia et al. (2021) package. The full reproducible code is available on CRAN. Labels $***$, $**$ and $*$ indicate significance at 99%, 95% and 90% levels, respectively.

Table 5: Testing difference of modified Sharpe ratios - Optimal rebalancing

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
				Global		
Buy & Hold		-0.009	-0.008	-0.008	**-0.014****	-0.011
2%			0.001	0.002	**-0.005*****	-0.001
4%				0.000	**-0.006***	-0.003
Monthly					**-0.006*****	-0.003
Quarterly						0.003
Semiannual						
				Recession periods		
Buy & Hold		0.013	0.012	0.014	0.013	0.016
2%			0.000	0.000	0.000	0.003
4%				0.001	0.000	**0.004****
Monthly					0.000	0.002
Quarterly						0.003
Semiannual						
				Expansion periods		
Buy & Hold		-0.023	-0.018	-0.027	-0.025	-0.028
2%			0.005	-0.004	-0.002	-0.005
4%				**-0.009*****	-0.007	**-0.010****
Monthly					0.002	0.000
Quarterly						-0.003
Semiannual						
				Crisis periods		
Buy & Hold		**0.017***	**0.017***	**0.017***	**0.018***	**0.018****
2%			0.000	0.000	0.001	0.002
4%				0.000	0.001	0.002
Monthly					0.000	0.000
Quarterly						0.000
Semiannual						
				Noncrisis periods		
Buy & Hold		**-0.096*****	**-0.096*****	**-0.096*****	**-0.100*****	**-0.097*****
2%			0.000	0.000	-0.004	-0.001
4%				0.000	-0.005	-0.001
Monthly					-0.004	-0.001
Quarterly						0.003
Semiannual						

Notes: This table enables the comparison of the modified Sharpe ratios of different 60/40 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing. Significance levels of the statistic are computed via a studentized circular block-bootstrap as in Ardia and Boudt (2015). The results are computed using R 3.6.0 (R Core Team, 2020) and *PeerPerformance* (*v2.2.5*; Ardia et al. (2021)) package. The full reproducible code is available on CRAN. Labels $***$, $**$ and $*$ indicate significance at 99%, 95% and 90% levels, respectively.

5. Robustness checks

As a robustness check, we replicate this empirical study in five steps. First, we use alternative performance measures. Specifically, we use the multiperiod Sharpe ratio, the Sortino ratio, the Omega ratio, the Jensen's α and several centiles of the drawdowns distribution to compare the performances of different rebalancing strategies (see Table 6 and Table 7) as in Dichtl et al. (2014) and Rattray et al. (2020). Second, we use an alternative asset allocation; in line with Dichtl et al. (2016), we replicate our results using a 70/30 stock–bond portfolio (see Table 8). Third, we replicate our results including transaction costs as in Ang et al. (2014), Dichtl et al. (2016) and NBIM (2018), i.e., 0.01% for stocks and 0.005% for bonds (see Table 9). Fourth, we use an alternative investment horizon (see Table 10). Following Dichtl et al. (2013), we replicate our results with a different investment horizon, i.e., 10 years, using a similar bootstrap procedure. Fifth, we restrict the initial data sample to four temporal subsamples from 1998 to 2009 (resp. from 1999 to 2014) and from 2009 to 2021 (resp. from 2014 to 2021) (see Table 11). Indeed, the results could be related to heterogeneous returns over the period 1998-2021, potentially biasing the impact of economic and financial cycles. Finally, we use an alternative rebalancing rule: Rattray et al. (2020)'s strategic rebalancing. Compared to the previous results based on an ex post technique, this rebalancing strategy is based on a trend-following signal.

5.1. Alternative performance measures

Compared to the previous results based on Sharpe and modified Sharpe ratios, the results in Table 6 are based on alternative performance measures used in the recent literature, namely, the Sortino and Omega ratios (Dichtl et al., 2016). We also report the Jensen's alpha and the Levy-Tobin multiperiod Sharpe ratio to deepen our empirical analysis.[4] These results are qualitatively similar; rebalancing enhances risk-adjusted portfolio performance

[4]The definitions of these performance measures are summarized in Appendix A.

except during recession and financial crises, when the buy-and-hold approach performs better.

Table 6: Comparing performances - Optimal rebalancing - Alternative performance measures

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
			Global			
Multiperiod SR	1.487	1.521	1.522	1.512	1.540	**1.544**
Sortino	0.255	0.266	0.267	0.271	**0.271**	0.263
Omega	0.943	0.946	0.944	0.950	**0.954**	0.943
Jensen's α	-3.51e-04	-1.82e-04	-1.70e-04	-2.25e-04	**-9.75e-05**	-1.37e-04
			Recession periods			
Multiperiod SR	**-0.150**	-0.220	-0.211	-0.231	-0.221	-0.267
Sortino	**0.046**	0.029	0.030	0.024	0.029	0.027
Omega	**0.745**	0.740	0.742	0.733	0.741	0.738
Jensen's α	**-3.58e-04**	-6.59e-04	-6.26e-04	-6.93e-04	-6.58e-04	-7.90e-04
			Expansion periods			
Multiperiod SR	2.389	2.700	2.681	2.700	2.698	**2.707**
Sortino	0.666	0.718	0.711	**0.723**	0.720	0.717
Omega	1.197	1.338	1.330	**1.343**	1.340	1.340
Jensen's α	1.98e-04	4.40e-04	4.16e-04	4.24e-04	4.34e-04	**4.71e-04**
			Crisis periods			
Multiperiod SR	**-3.861**	-4.434	-4.405	-4.454	-4.477	-4.487
Sortino	**-0.412**	-0.433	-0.435	-0.438	-0.435	-0.435
Omega	**0.693**	0.663	0.670	0.655	0.657	0.661
Jensen's α	**1.27e-03**	1.73e-03	1.72e-03	1.79e-03	1.83e-03	1.91e-03
			Noncrisis periods			
Multiperiod SR	2.022	2.549	2.520	2.553	**2.556**	2.550
Sortino	0.564	0.649	0.636	0.650	**0.651**	0.648
Omega	1.041	1.226	1.220	1.230	**1.235**	1.230
Jensen's α	1.49e-04	9.10e-04	8.92e-04	9.09e-04	**9.58e-04**	9.37e-04

Notes: This table enables the comparison of performance measures of different 60/40 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing. The results are computed using R 3.6.0 (R Core Team, 2020).

Then, the results in Table 7 are based on the drawdown approach of Rattray et al. (2020). In addition, we also compute several centiles of the drawdown to deepen our analysis. Unlike previous estimates, these ratios are calculated from historical data and not from simulations, as this approach would not be relevant for measures such as the maximum drawdown. These results are qualitatively similar; rebalancing enhances risk-adjusted portfolio performance except during recession and financial crises, when the buy-and-hold approach performs better.

5.2. Alternative asset allocations: 70/30 stock-bond portfolios

Compared to the previous results based on a 60/40 stock-bond portfolio, the results in Table 8 are based on an alternative asset allocation, as in Dichtl et al. (2016). Among asset

Table 7: Comparing performances - Optimal rebalancing - Alternative performance measures

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
			Global			
DD 75c	1.112	1.114	1.122	1.112	**1.111**	1.114
DD 90c	1.475	1.453	1.455	1.464	**1.439**	1.447
MDD	**3.069**	3.109	3.160	3.100	3.100	3.100
			Recession periods			
DD 75c	**1.273**	1.286	1.294	1.285	1.279	1.300
DD 90c	**1.694**	1.737	1.777	1.738	1.746	1.735
MDD	**3.074**	3.109	3.094	3.135	3.135	3.100
			Expansion periods			
DD 75c	1.078	1.074	1.067	1.071	1.073	**1.069**
DD 90c	1.292	1.258	1.259	**1.253**	1.254	1.257
MDD	2.171	1.962	1.990	1.905	**1.899**	1.970
			Crisis periods			
DD 75c	**1.853**	1.872	1.872	1.871	1.889	1.889
DD 90c	**2.252**	2.503	2.427	2.499	2.557	2.507
MDD	**3.469**	3.836	3.836	3.940	4.051	3.836
			Noncrisis periods			
DD 75c	1.069	1.047	1.047	1.047	**1.046**	**1.046**
DD 90c	1.270	1.220	1.220	1.223	**1.216**	1.220
MDD	3.069	2.972	3.069	**2.970**	**2.970**	**2.968**

Notes: This table enables the comparison of performance measures of different 60/40 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing. The results are computed using R 3.6.0 (R Core Team, 2020).

allocation, we choose to focus on a 70/30 stock–bond portfolio referring to the current Norwegian SWF asset allocation. These results are qualitatively similar; rebalancing enhances risk-adjusted portfolio performance except during recession and financial crises, when the buy-and-hold approach performs better.

Table 8: Comparing performances - Optimal rebalancing - Alternative asset allocations

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
			Global			
SR	0.147	0.150	0.154	0.152	**0.154**	0.150
mSR	0.082	0.084	0.086	0.085	**0.085**	0.083
			Recession periods			
SR	**-0.001**	-0.010	-0.009	-0.014	-0.010	-0.011
mSR	**-0.001**	-0.006	-0.006	-0.009	-0.006	-0.006
			Expansion periods			
SR	0.334	0.345	0.344	**0.346**	0.345	0.344
mSR	0.169	0.173	0.173	**0.174**	0.173	0.173
			Crisis periods			
SR	**-0.395**	-0.408	-0.408	-0.413	-0.411	-0.409
mSR	**-0.316**	-0.330	-0.330	-0.335	-0.333	-0.331
			Noncrisis periods			
SR	0.339	0.360	0.360	0.362	**0.363**	0.361
mSR	0.171	0.180	0.180	0.180	**0.181**	0.180

Notes: This table enables the comparison of the Sharpe ratios and modified Sharpe ratios of different 70/30 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing. The results are computed using R 3.6.0 (R Core Team, 2020) and *DiversificationR* (*v0.1.0*; Hasse (2021) package. The full reproducible code is available on CRAN.

5.3. Transaction costs

In our main analysis, we follow Bauer et al. (2022), who argue that in the specific case of the Norwegian SWF, transaction costs can be omitted in performance analysis. However, Dichtl et al. (2016) and NBIM (2018) opt for the inclusion of transaction costs (e.g., 0.01% for stocks and 0.005% for bonds). Hence, for robustness purposes, we take a step further. We replicate our results incorporating the same transaction costs. The results in Table 9 are qualitatively similar to those obtained without transaction costs; rebalancing enhances risk-adjusted portfolio performance except during recession and financial crises, when the buy-and-hold approach performs better.

Table 9: Comparing performances - Optimal rebalancing - Transaction costs

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
			Global			
SR	0.157	0.162	0.163	**0.165**	0.166	0.161
mSR	0.087	0.090	0.090	**0.091**	0.092	0.089
			Recession periods			
SR	**-0.001**	-0.011	-0.009	-0.015	-0,011	-0,011
mSR	**-0.001**	-0.006	-0.006	-0.009	-0.007	-0.007
			Expansion periods			
SR	0.334	0.345	0.343	**0.346**	0.344	0.344
mSR	0.169	0.173	0.172	**0.174**	0.173	0.173
			Crisis periods			
SR	**-0.376**	-0.397	-0.397	-0.402	-0.400	-0.398
mSR	**-0.296**	-0.318	-0.317	-0.324	-0.332	-0.319
			Noncrisis periods			
SR	0.343	0.377	0.375	0.378	**0.379**	0.377
mSR	0.172	0.186	0.186	**0.187**	**0.187**	**0.187**

Notes: This table enables the comparison of the Sharpe ratios and modified Sharpe ratios of different 60/40 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing. The results are computed using R 3.6.0 (R Core Team, 2020) and *DiversificationR* (*v0.1.0*; Hasse (2021) package. The full reproducible code is available on CRAN.

5.4. Alternative investment horizons

We then replicate our main results considering a different investment horizon, i.e., 10 years. As argued by Dichtl et al. (2013), the optimal rebalancing strategy can differ for shorter investment horizons, especially for periodic rebalancing. However, it could also have an impact on the performance of the other strategies. The results reported in Table 10 are qualitatively similar to those obtained previously, indicating that rebalancing enhances risk-adjusted portfolio performance except during recession and financial crises, when the buy-and-hold approach performs better.

5.5. Time sampling

The results in Table 11, which reports estimates on two time subsamplings, are different from those described previously. Focusing on the period from 1998 to 2009 (resp. from 2009 to 2021), the results indicate that our main findings about optimal rebalancing across economic and financial cycles are not driven by a time-trend effect or a specific time period. Indeed, we find the same results before and after the Global Financial Crisis. Then, focusing

Table 10: Comparing performances - Optimal rebalancing - Alternative investment horizon

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
			Global			
SR	0.152	0.166	**0.169**	0.164	0.164	**0.169**
mSR	0.085	0.092	**0.093**	0.091	0.090	**0.093**
			Recession periods			
SR	**0.000**	-0.013	-0.013	-0.014	-0.012	-0.012
mSR	**0.000**	-0.008	-0.008	-0.009	-0.008	-0.007
			Expansion periods			
SR	0.346	0.359	0.357	**0.361**	0.360	0.358
mSR	0.174	0.179	0.178	**0.180**	**0.180**	0.179
			Crisis periods			
SR	**-0.254**	-0.374	-0.375	-0.376	-0.376	-0.373
mSR	**-0.182**	-0.294	-0.296	-0.297	-0.296	-0.293
			Noncrisis periods			
SR	0.357	0.378	0.378	0.378	**0.380**	0.379
mSR	0.178	0.187	0.187	0.187	**0.188**	0.187

Notes: This table enables the comparison of the Sharpe ratios and modified Sharpe ratios of different 60/40 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing with an alternative 10 years investment horizon. The results are computed using R 3.6.0 (R Core Team, 2020) and *DiversificationR* (*v0.1.0*; Hasse (2021) package. The full reproducible code is available on CRAN.

on the period from 1998 to 2014 (resp. from 2014 to 2021), we find that the results are still the same before and after the crude oil plunge that occurred in 2014. In summary, our main results are not impacted by time sampling.

5.6. Alternative rebalancing rule: Strategic rebalancing

Compared to the previous results based on an ex post technique, the results in Table 12 are based on strategic rebalancing as defined by Moskowitz et al. (2012) and Rattray et al. (2020). Unlike previous estimations, rebalancing is conditioned by a trend-following signal. Specifically, we use a momentum signal that is defined as :

$$mom_{t-1}(12) = \frac{\sum_{i=1}^{12} \tilde{R}_{t-i}}{\sigma_{t-1}\sqrt{12}}, \tag{7}$$

where $\tilde{R}_{t-i}$ is the return over the past 12 months and σ_{t-1} is the standard deviation of the past 12 monthly returns. So the rebalancing rules are the same but rebalancing is delayed if stock markets are in a negative trend. Most of these results are qualitatively similar to the results reported in Tables 4 and 5; rebalancing enhances risk-adjusted portfolio

Table 11: Comparing performances - Optimal rebalancing - Subsampling

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
				Global		
SR	0.157	0.163	0.164	0.165	**0.166**	0.161
mSR	0.087	0.090	0.090	0.091	**0.092**	0.089
				Subsample 1998 - 2009		
SR	0.056	0.066	0.068	0.067	**0.069**	0.064
mSR	0.033	0.039	0.040	0.039	**0.040**	0.037
				Subsample 2009 - 2021		
SR	0.265	0.278	0.278	**0.279**	0.277	0.277
mSR	0.139	0.145	0.145	**0.145**	0.144	0.144
				Subsample 1998 - 2014		
SR	0.120	0.129	0.131	0.127	**0.132**	0.131
mSR	0.068	0.073	0.074	0.072	**0.074**	**0.074**
				Subsample 2014 - 2021		
SR	0.246	**0.256**	0.250	0.253	0.255	0.255
mSR	0.130	**0.135**	0.132	0.133	0.134	0.134

Notes: This table enables the comparison of the Sharpe ratios and modified Sharpe ratios of different 60/40 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing. The results are computed using R 3.6.0 (R Core Team, 2020) and *DiversificationR* (*v0.1.0*; Hasse (2021) package. The full reproducible code is available on CRAN.

performance except during financial crises, when the buy-and-hold approach performs better. Contrasting with previous results reported in Table 3, rebalancing enhances risk-adjusted portfolio performance during recessions. However, this difference is driven by the fact that the signal is negative for 58% of periods.

Table 12: Comparing performances - Optimal rebalancing

	No rebalancing	Threshold rebalancing		Periodic rebalancing		
	Buy & Hold	2%	4%	Monthly	Quarterly	Semiannual
				Global		
SR	0.153	0.172	**0.173**	0.170	0.172	0.170
mSR	0.085	**0.095**	**0.095**	0.093	**0.095**	0.094
	Recession periods - momentum signalis negative for 58% of periods					
SR	-0.014	-0.011	-0.013	-0.010	-0.010	**-0.007**
mSR	-0.009	-0.007	-0.008	-0.006	-0.006	**-0.004**
	Expansion periods - momentum signalis negative for 10% of periods					
SR	0.337	0.351	0.348	0.350	0.350	**0.352**
mSR	0.170	**0.176**	0.175	0.175	0.175	**0.176**
	Crisis periods - momentum signalis negative for 77% of periods					
SR	**-0.409**	-0.425	-0.425	-0.425	-0.425	-0.410
mSR	**-0.331**	-0.348	-0.348	-0.349	-0.348	-0.332
	Noncrisis periods - momentum signalis negative for 17% of periods					
SR	0.339	0.372	0.369	0.372	**0.374**	**0.374**
mSR	0.171	**0.185**	0.183	0.184	**0.185**	**0.185**

Notes: This table enables the comparison of the Sharpe ratios and modified Sharpe ratios of different 60/40 stock-bond portfolios between buy-and-hold, periodic and threshold rebalancing using the strategic allocation approach of Rattray et al. (2020). The results are computed using R 3.6.0 (R Core Team, 2020) and *DiversificationR* (*v0.1.0*; Hasse (2021) package. The full reproducible code is available on CRAN.

6. Policy implications

Since 2008, the Santiago Principles have included four objectives that have been endorsed by International Forum of Sovereign Wealth Funds (IFSWF) members. Among these principles and practices objectives, the Santiago Principles ensure that SWFs (i) *"invest on the basis of economic and financial risk and return-related considerations"* and that they (ii) *"help maintain a stable global financial system"*. [5] Our findings indicate that these two objectives are conflicting.

On the one hand, as long-term institutional investors without any liabilities, SWFs are expected to behave as countercyclical investors. Consequently, SWFs are expected to rebalance their portfolio accordingly, e.g., by buying stocks and selling bonds during times of stock market turmoil and vice versa. From this perspective, SWFs play a positive role in

[5] See IFSWF's website for further details: `https://www.ifswf.org/santiago-principles-landing/santiago-principles`

financial stability, providing liquidity and reducing market volatility. On the other hand, our results indicate that such countercyclical behavior is suboptimal. Indeed, we find that the best rebalancing option during recessions/financial crises is the buy-and-hold strategy, while periodic rebalancing is best otherwise. Therefore, from a financial standpoint, SWFs should not behave countercyclically during macroeconomic stress periods. This is where the conflict between the two objectives arises. Our findings shed new light on some SWFs' behavior during the COVID-19 pandemic. In addition to the implicit liabilities identified by Bortolotti and Fotak (2020) as a brake on countercyclical rebalancing, financial considerations could also be a cause of this behavior.

In summary, our findings advocate complementing the existing Santiago Principles by including a macroprudential dimension. Indeed, the fourth objective, i.e., *"to have in place a transparent and sound governance structure that provides for adequate operational controls, risk management, and accountability"*, is microprudential by definition, similar to the regulatory framework for both investment funds (van der Veer et al., 2017) and banks (Aiyar et al., 2015; de Haan et al., 2019). Several macroprudential principles and practices could be considered, such as the setup of a countercyclical liquidity buffer to reduce the liquidity risk of SWFs (Ahnert, 2016) or the self-imposition of a rebalancing rule depending on the business cycle (Argyropoulos et al., 2023).

Macroprudential principles also require efficient supervision (Cerutti et al., 2017). The Santiago Principles include the objective to *"comply with all applicable regulatory and disclosure requirements in the countries in which they invest"*. This objective should be revisited to promote the inclusion of SWFs in the stress tests developed by the International Monetary Fund and the World Bank. [6] Such a practice would help to evaluate the potential systemic impact of SWFs on the global financial system (Hasse, 2022).

[6] See IMF's website for further details about the Financial Sector Assessment Program (FSAP): `https://www.imf.org/en/About/Factsheets/Sheets/2023/financial-sector-assessment-program-FSAP`.

7. Conclusion

In this paper, we examine rebalancing options for long-term institutional investors across economic and financial cycles, and we revisit their respective consequences on financial stability. Using historical stock and bond data returns of the GPFG, we build different simulated stock-bond portfolios with varying investment strategies. By means of simulations, we test the difference in Sharpe ratios of these portfolios to compare the performance induced by different rebalancing strategies. Our investigations cover different asset allocations and investment horizons, as well as alternative performance measures. We find that the optimal rebalancing strategy is periodic rebalancing except during recessions and financial crises, when the buy-and-hold approach is best.

The implications based on our findings are twofold. First, an investment policy that does not take into account economic and financial cycles is suboptimal, even for a long-term investor without financial liabilities. Therefore, an adaptative rebalancing policy should be preferred over a calendar- or threshold-based rule rebalancing policy. Second, the hypothesis of the countercyclical behavior of SWFs contrasts with our findings. During financial turmoil, SWFs could be a threat rather than a hope for financial stability. Hence, our findings advocate complementing existing systemic risk supervision by including SWFs. In addition, several macroprudential rules could also be considered to improve the Santiago Principles, such as the setup of a countercyclical liquidity buffer or the self-imposition of a rebalancing rule depending on the business cycle.

Finally, our findings call for further research. As our work is restricted to a portfolio-level analysis, it would also be interesting to extend our investigations to an asset-level examination. Such a development could highlight the procyclical behavior of SWFs via their investments and disinvestments across industrial sectors (Bortolotti and Fotak, 2020) and geographical locations (Fischer et al., 2021). Another limitation of our research is related to the unavailability of monthly cash flows of the GPFG. This lack of information prevents to take into account the rebalancing via the cash inflows and outflows, thus calling for further investigations.

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Appendix A: Definitions of alternative performance measures

Sortino ratio

The Sortino and Price (1994)'s ratio, also known as the Sortino ratio, addresses one of the limitations of the Sharpe ratio by isolating downside volatility (i.e., financial risk associated with losses) from total volatility. More formally, the Sortino ratio is the expected value of the excess return divided by the downside deviation.

$$Sortino(L) = \frac{E(R) - L}{\sqrt{VAR[R - L]^{-}}}, \tag{8}$$

where R is the asset return and L is the minimum acceptable return.

Omega measure

The Keating and Shadwick (2002)'s ratio, also known as the Omega performance measure, is based on the expected return level L. It takes into account both weighted potential gains and losses. Specifically, the Omega performance measure is the expected value of gains above level L divided by the expected value of losses below level L. More formally, Kazemi et al. (2004) define the Omega performance measure as:

$$Omega(L) = \frac{exp[(R - L)]^{+}}{exp[(L - R)]^{+}}, \tag{9}$$

where $[(R - L)]^{+}$ is the expected value of the gains above the threshold L and $[(L - R)]^{+}$ is the expected value of losses below the threshold L.

Multiperiod Sharpe ratio

The multiperiod Sharpe ratio proposed in Levy (1972), also known as the Levy-Tobin multiperiod Sharpe ratio is :

$$Multiperiod\, SR = \frac{(1+\mu)^n - (1+R_f)^n}{\sqrt{(\sigma^2 + (1-\mu)^2)^n - (1+\mu)^{2n}}}, \tag{10}$$

where μ is the expected return of the one-period investment, σ is the standard deviation of this investment, R_f is the riskless interest rate and n is the number of periods.

Appendix B: Bootstrap-based test for (modified) Sharpe ratios equality

Ledoit and Wolf (2008) recommend a bootstrap method to test equality of Sharpe ratios between two portfolios. Specifically, they advocate using the circular block-bootstrap of Politis and Romano (1991) to take into account the finite sample properties of the return distribution and the potential autocorrelation and heteroskedasticity. In this line, Ardia and Boudt (2015) use the same approach to test equality of modified Sharpe ratios.

This method follows several steps:

- (B1) Create three circularized vectors of returns by placing the series of the historical stock returns r_s, bond returns r_b and risk-free rate r_f, respectively, one after the other (e.g., juxtapose the time series h times) so $r_{c,i} = (r_{i,1}, ..., r_{i,T}, ..., r_{i,1}, ..., r_{i,T})$, with $i \in \{s, b, f\}$ and $r_{c,i}$ being a $T \times h$ vector (Politis and Romano, 1991).
- (B2) Create a multivariate empirical distribution function, $EF_i(t)$, with $i \in \{s, b, f\}$ from the circularized historical stock and bond returns $r_{c,s}$, $r_{c,b}$ and $r_{c,f}$, respectively.
- (B3) Draw bootstrapped returns $(r^{*b}_{i,1}, ..., r^{*b}_{i,T})$ in $EF_i(t)$. Note that we do not perform wild bootstrap calculations but instead draw blocks (in both dimensions, cross-knit and time) to preserve the cross-sectional dependence of the returns and their dynamic properties. With respect to this last dimension, we consider blocks of 4 periods (Hall et al., 1995) so each block is a 4×3 matrix.
- (B4) Under the bootstrapped pseudo-returns, compute the portfolios returns r^{*b}_p, then estimate the (modified) Sharpe ratio difference Δ^{*b} and Δ^{*b}_m, respectively.
- (B5) Calculate the studentized statistics τ^{*b} and τ^{*b}_m and save them.
- (B6) Repeat the last (B3-B5) steps a large number of times (e.g., $Boo = 1000$), and build the bootstrapped distribution of the studentized (modified) Sharpe ratio statistics.

- (B7) Construct a two-sided bootstrap confidence interval with nominal level $1-\alpha$ for τ (resp. τ_m), defined as follows $CI = [\hat{\tau}^{*b}_{[\alpha/2\times 1000]}, \hat{\tau}^{*b}_{[(1-\alpha)/2\times 1000]}]$ (resp. $CI = [\hat{\tau}^{*b}_{m,[\alpha/2\times 1000]}, \hat{\tau}^{*b}_{m,[(1-\alpha)/2\times 1000]}]$). The null of equality is rejected at a $\alpha\%$ level if this interval does not contain 0.