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Optimal portfolios vis-à-vis corporate governance ratings: some UK evidence

Abstract
Socially responsible investments may offer investors higher returns because of the perceived lower risk and thus associated cost (monitoring, litigation, etc.), although it might also be less profitable as posited by proponents of the Efficient Market Hypothesis where higher risk is compensated with higher returns. Corporate governance (CG) - one of the key components in socially responsible investing - has been extensively studied for evaluating its relationship with firm performance. In this paper, we extend prior literature by exploring the investment performances of two distinct portfolios built using strong versus weak corporate governance firms. We contribute by investigating the value of corporate governance (or lack thereof) in formulating portfolios. Using London Stock Exchange data for the period January 2012 through June 2018 and both ends of the quartile spectrum from 2017 Good Governance Report, we optimize each portfolio based on their Sharpe criterion.
Our findings offer some practical and theoretical implications. Investors who are conscious about CG and attempt to maximize Sharpe measure by investing in strong governance firms may face lower portfolio risk by foregoing higher returns. Whereas reduction in value-at-risk midway onwards appears to suggest investment in companies with strong CG would less likely to fail in the long run. Volatility and downside volatility results tell similar story. Indeed, from the agency theoretical perspective, companies with strong CG would lead to lower agency cost (and risk) and better firm performance.
We find profitable outcomes for both portfolios, although out-of-sample, weak governance portfolio dominates in terms of several key performance metrics.
Keywords: Portfolio Optimization; Corporate Governance; Sharpe Ratio; Information Ratio; Maximum Drawdown; Sortino Ratio; Value-at-Risk
JEL Classifications: G3; G11; C60
Acknowledgment: *Dr. Safwan Mohd Nor has been awarded as RHB Islamic Endowed Scholar in Finance at University of Malaysia Terengganu, which is the first industry-sponsored endowed academic position at the university. The author would like to thank RHB Islamic Bank Berhad for the financial support in publishing this paper (Grant Number: 53276).*
DOI: https://doi.org/10.21003/ea.V170-10

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Зіставлення оптимальності портфелів з рейтингами корпоративного управління: практика Сполученого Королівства

Анотація
Соціально відповідальні інвестиції можуть бути більш вигідними, що обумовлено меншими ризиками й передбачуваними витратами. Разом із тим такі інвестиції можуть бути менш прибутковими, оскільки, на думку прихильників гіпотези ефективного ринку, високий ступінь ризику компенсується більш високою прибутковістю. Корпоративному управлінню як одному з ключових компонентів соціально відповідального інвестування представниками наукових кіл було приділено достатньо уваги для оцінки його впливу на роботу фірм. Дана робота також є внеском у вивчення досліджуваного питання з огляду на те, що автори статті визначили дієвість двох різних видів портфелів, побудованих на принципах роботи фірм, що практикують різний ступінь корпоративного управління.
Автори статті врахували цінність корпоративного управління, а також можливість його незастосування в процесі розробки портфелів.
Використавши дані Лондонської фондової біржі, а також квартальні показники доповіді про ефективне управління за 2017 рік, автори дослідження оптимізували кожен із двох видів портфелів, узявши за основу критерій Шарпа. Результати дослідження показують, що обидва види портфелів можуть приносити прибуток. Слід, однак, відзначити, що в цілому портфель зі «слабким» корпоративним управлінням є пріоритетним з урахуванням деяких ключових характеристик.
Ключові слова: оптимізація портфеля; корпоративне управління; коефіцієнт Шарпа; інформаційне співвідношення; максимальний дроудаун; коефіцієнт Сортіно; управління ризиками.

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Сопоставление оптимальности портфелей с рейтингами корпоративного управления: практика Соединенного Королевства

Аннотация. Социально ответственные инвестиции могут быть более выгодными, что обусловлено меньшими рисками и более прогнозируемыми издержками. Вместе с тем такие инвестиции могут быть менее прибыльными, поскольку, по мнению сторонников гипотезы эффективного рынка, высокая степень риска компенсируется более высокой доходностью. Корпоративному управлению как одному из ключевых компонентов социально ответственного инвестирования представителями научных кругов было уделено достаточное внимание в контексте оценки его влияния на работу фирм. Данная работа также является вкладом в изучение исследуемого вопроса, так как авторы статьи определили действенность двух различных видов портфелей, построенных на принципах работы фирм, практикующих различную степень корпоративного управления. Авторы статьи учли ценность корпоративного управления, а также возможность его отсутствия в процессе разработки портфелей. Используя данные Лондонской фондовой биржи за период с января 2012 года по июнь 2018 года, а также крайние квартальные показатели доклада об эффективном управлении за 2017 год, авторы исследования оптимизировали каждый из двух видов портфелей, взяв за основу критерий Шарпа. Результаты исследования показывают, что оба вида портфелей могут приносить прибыль. Следует, однако, отметить, что в целом портфель со «слабым» корпоративным управлением является приоритетным с учетом некоторых ключевых характеристик.
Ключевые слова: оптимизация портфеля; корпоративное управление; коэффициент Шарпа; информационное соотношение; максимальный дроудаун; коэффициент Сортино; управление рисками.

1. Introduction

Demand for socially responsible investment (SRI) has seen a tremendous growth. It is a big business. As reported in Forbes and The Edge Markets, such funds account for over USD 23 trillion in global assets under management [1-2]. Numerous mutual funds have been developed with socially responsible objectives. In this connection, indices have been built for gauging such quality among companies, including the KLD Global Sustainability Index, the FTSE4Good Index for Global Portfolios and the ASEAN CG Scorecard. Key to the SRI principle is the use of environmental, social and governance (ESG) factors in making investment decisions. The emphasis of our paper is on corporate governance (CG), which is the most significant area of the three (as extrapolated from Scopus database based on abstract, keyword and title on each relationship with firm performance and/or stock returns). However, debate continues about the benefits of incorporating these non-financial factors in stock selection or portfolio formation process. Moreover, existing literature focuses on simple firm performance measures (e.g. Tobin's Q, return on equity, earnings per share, etc.) and pays little attention to the use of sophisticated evaluation metrics.

In this article, we provide evidence on the effect (or lack thereof) of good CG practice on investment performance using portfolio optimization approach. A considerable number of previous studies documented a positive relationship between CG and investment performance. This generally suggests that strong CG practice leads to sound investment and financing decisions among firms and thus considered favourable by investors. With this in mind, we develop two distinct portfolios based on strong CG-rated firms and weak ones, both optimized on the basis of their reward to variability as denoted by the Sharpe ratio.

Rather than testing CG as an optimization criterion, e.g. objective function or decision variable in finding a capital allocation plane, we attempt to evaluate and validate if portfolio based on strong governance firms can outperform that of weak ones. This has direct implication for Modern Portfolio Theory and investors who wish to gain acceptable risk-return trade-off but is also concerned with SRI based on firm-level CG practice. While prior studies in CG and firm performance focus on standard firm performance measures, we contribute by exploring more sophisticated portfolio metrics, including downside volatility, value-at-risk, Sharpe ratio, Sortino ratio, information ratio and maximum drawdown.

2. Brief Literature Review

Modern Portfolio Theory introduced by Markowitz in 1952 [3] has revolutionized the investment management landscape and propagates multitudinous studies on portfolio diversification, for example [4-11]. While it is based solely on risk and return, other qualitative or quantitative factors for building an investment portfolio can likewise be considered important. In 1972, Moskowitz highlights the need for selecting socially responsible investment [12]. While theoretically CG is considered to drive good firm performance, stock or portfolio returns and optimal weights, as shown from several studies [13-15], some argue otherwise [16-17]. Accordingly, there is no consensus for such linkages, with existing empirical research remains inconclusive. The value of CG within portfolio management context is thus debatable and explored in this paper.

3. The purpose of this article is to compare the investment performance of two distinct portfolios, each built on the basis of either good or bad CG rated firms. Because the idea of portfolio diversification chiefly depends on market efficiency and the best asset allocation along the Pareto optimal front that can yield highest return for a given level of risk (or lowest risk given return), we formulate our portfolios of stocks in the London Stock Exchange i.e. a developed stock market and thus deemed efficient, and explore their merits using a variety of performance metrics. We utilize CG quartiles as described in the recent 2017 Good Governance Report (GGR) by the Institute of Directors (2017) [18] to discriminate between top (Q1) and bottom (Q4) CG companies. Accordingly, we optimize each portfolio from both ends of the spectrum by maximizing its Sharpe ratio in-sample for out-of-sample analysis.

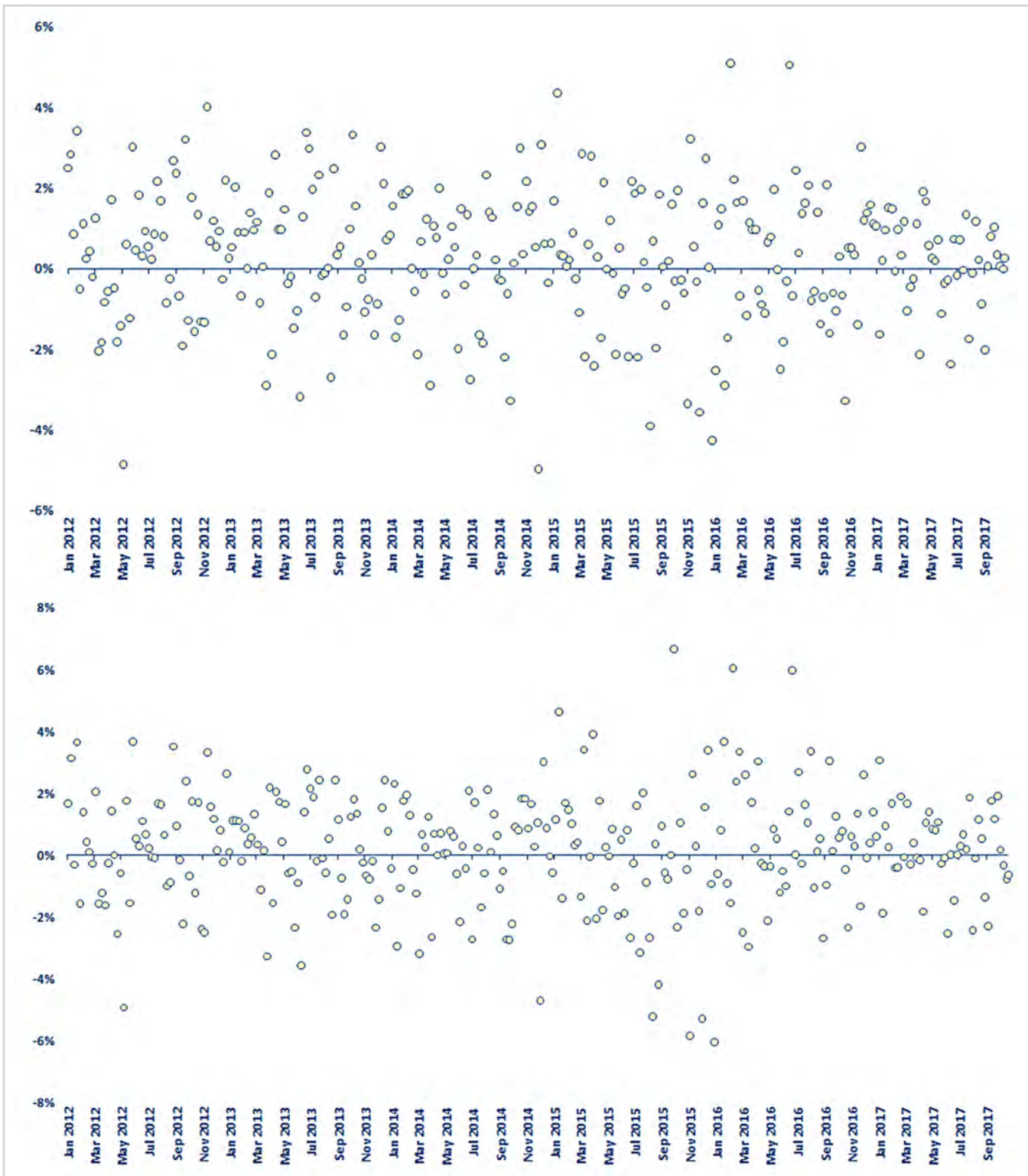
4. Results

The GGR ranks 103 largest companies listed on the London Stock Exchange as of 31 March 2017. The top quartile consists of 25 companies although the bottom one comprises of 28. To alleviate disparity and potential outperformance of one portfolio over another due to higher N and greater diversification benefit (rather than because of better governance in the sample), we eliminate three firms and only include the lowest 25 firms in Q4. Accordingly, we form two distinct equally-sized portfolios: Top 25 (Q1) and Bottom 25 (Q4).

In exploring out-of-sample investment outcome between Top 25 (T25) and Bottom 25 (B25) portfolios, we partition the whole sample into two non-overlapping subperiods. We reserve 90% for training i.e. optimizing the distinct sample portfolios while the remaining data is maintained for testing. As such, in-sample period spans 1 January 2012 to 31 October 2017, while out-of-sample period is from 1 November 2017 to 30 June 2018. The in-/out-of-sample window reflects announcement date of the 2017 GGR in October, allowing our simulation to realistically incorporate such event while mitigating look-ahead bias. Weekly stock prices are extracted from Thomson Reuters Eikon database. Figure 1 shows the best and worst CG portfolios during the in-sample period. As can be seen, the log returns for weak CG constituents are more

dispersed which generally suggests higher uncertainty among them. Table 1 and 2 show the correlation matrices for T25 and B25 portfolios, respectively.

As computed from Table 1 and Table 2, average correlations of only 0.23 (0.29) for the T25 (B25) portfolio indicate that overall component stocks are weakly correlated and thus investment pool of these firms provide diversification benefit in reducing non-systematic risk. Nonetheless, although these figures show potential advantage for asset allocation, prior literature documents that estimation error can present itself when dealing with portfolio optimization problem [6-7]. One way to allay such error is by setting upper and lower bound constraints when optimizing the allocation of each asset or stock [6], and we apply this for each individual stock in both quartile portfolios. From the practical viewpoint too, it is unwise to allocate excessively small (large) portion of capital into an individual stock. This can have negative implications towards portfolio structure, risk exposure, trading (monitoring) cost, etc. Hence, similar



Note: Top (bottom) chart denotes the log returns of the T25 (B25) portfolio during the in-sample period.

Fig. 1: **Portfolio returns**
Source: Computed and elaborated by the authors

to [6-8], we set a limit of 1% floor and 10% ceiling constraints. Our portfolio optimization problem can be described as:

$$\max\ SR = \frac{\mu_p - r_f}{\sigma_p}\ , \tag{1}$$

$$\text{subject to}\ \sum_{i=1}^{N} w_i = 1\ \text{ and }\ l_i < w_i < u_i\ , \tag{2}$$

where:
SR denotes the Sharpe ratio;
μ_p is mean return of the portfolio;
r_f indicates risk free rate;
σ_p represents portfolio volatility;
w_i is the weight of stock i;
l_i is the lower bound of 1%;
u_i is the upper bound of 10% for each stock.

We assume zero risk free rate since our portfolios are fully invested in stocks and no attempt is made to allocate excess cash elsewhere. Our portfolios are dynamic. Weights

Tab. 1: **T25 portfolio correlation matrix**

1.00																								
0.31	1.00																							
0.19	0.54	1.00																						
0.31	0.28	0.08	1.00																					
0.16	0.31	0.17	0.37	1.00																				
0.41	0.33	0.17	0.57	0.31	1.00																			
0.37	0.29	0.11	0.63	0.32	0.59	1.00																		
0.33	0.39	0.28	0.25	0.07	0.31	0.20	1.00																	
0.27	0.50	0.43	0.31	0.28	0.41	0.32	0.28	1.00																
0.17	0.15	0.13	0.29	0.10	0.26	0.19	0.11	0.18	1.00															
0.31	0.38	0.36	0.46	0.26	0.51	0.48	0.30	0.45	0.24	1.00														
0.28	0.44	0.45	0.11	0.19	0.25	0.17	0.23	0.37	0.14	0.32	1.00													
0.18	0.35	0.29	0.19	0.16	0.31	0.17	0.25	0.38	0.09	0.28	0.39	1.00												
0.20	0.40	0.38	0.16	0.21	0.30	0.18	0.21	0.32	0.19	0.22	0.39	0.38	1.00											
0.09	0.04	0.04	0.25	0.19	0.15	0.18	0.00	0.08	0.15	0.12	0.08	0.12	-0.01	1.00										
0.36	0.68	0.53	0.39	0.34	0.41	0.41	0.34	0.50	0.24	0.47	0.45	0.38	0.32	0.12	1.00									
0.04	-0.03	-0.12	0.21	0.14	0.12	0.15	-0.08	0.04	0.06	0.04	-0.12	-0.04	-0.07	0.48	-0.02	1.00								
0.20	0.35	0.22	0.25	0.17	0.39	0.27	0.25	0.38	0.20	0.34	0.27	0.22	0.26	0.15	0.39	0.09	1.00							
0.27	0.24	0.14	0.12	0.15	0.21	0.15	0.20	0.21	0.09	0.21	0.18	0.16	0.20	0.04	0.27	0.05	0.29	1.00						
0.16	0.39	0.32	0.29	0.17	0.26	0.31	0.28	0.36	0.17	0.29	0.24	0.12	0.23	0.09	0.35	0.02	0.23	0.12	1.00					
0.16	0.23	0.20	0.24	0.14	0.24	0.21	0.26	0.18	0.29	0.32	0.12	0.14	0.19	0.07	0.30	0.06	0.15	0.04	0.25	1.00				
0.23	0.50	0.39	0.40	0.36	0.42	0.38	0.27	0.53	0.19	0.43	0.27	0.30	0.31	0.07	0.51	0.05	0.35	0.29	0.32	0.25	1.00			
0.06	0.23	0.16	0.08	0.06	0.04	0.11	0.03	0.16	0.08	0.16	0.23	0.14	0.18	-0.08	0.22	-0.05	0.08	-0.03	0.13	0.09	0.09	1.00		
0.17	0.25	0.28	0.16	0.06	0.31	0.22	0.14	0.27	0.17	0.26	0.42	0.23	0.29	0.13	0.28	-0.09	0.24	-0.01	0.26	0.07	0.07	-0.01	1.00	
0.34	0.20	0.07	0.66	0.34	0.56	0.62	0.16	0.30	0.20	0.37	0.07	0.18	0.16	0.17	0.33	0.19	0.18	0.10	0.24	0.26	0.36	0.05	0.10	1.00

Source: Compiled by the authors

Tab. 2: **B25 portfolio correlation matrix**

1.00																								
0.34	1.00																							
0.34	0.45	1.00																						
0.06	0.16	0.37	1.00																					
0.17	0.29	0.16	0.15	1.00																				
0.50	0.49	0.34	0.41	0.42	1.00																			
0.54	0.27	0.42	0.30	0.32	0.59	1.00																		
0.55	0.32	0.43	0.18	0.31	0.29	0.43	1.00																	
0.43	0.44	0.58	0.35	0.45	0.55	0.46	0.39	1.00																
0.74	0.41	0.28	0.06	0.52	0.57	0.57	0.49	0.57	1.00															
0.18	0.32	0.51	0.46	0.29	0.56	0.36	0.36	0.59	0.25	1.00														
0.63	0.29	0.50	0.13	0.29	0.40	0.62	0.54	0.45	0.63	0.29	1.00													
0.32	0.33	0.10	-0.05	0.09	0.02	0.00	0.15	0.34	0.27	0.16	0.29	1.00												
0.28	0.48	0.36	-0.07	0.20	0.34	0.31	0.28	0.39	0.44	0.22	0.41	0.21	1.00											
0.04	0.36	0.17	0.22	0.27	0.42	0.35	0.14	0.44	0.26	0.25	0.32	0.31	0.50	1.00										
0.35	0.42	0.20	0.17	0.18	0.54	0.27	0.13	0.42	0.32	0.15	0.25	0.18	0.53	0.54	1.00									
0.25	0.34	0.37	0.44	0.21	0.52	0.45	0.32	0.23	0.18	0.11	0.32	-0.05	0.26	0.35	0.26	1.00								
-0.11	0.30	0.42	0.12	0.26	0.13	0.25	0.40	0.24	0.05	0.39	0.26	-0.19	0.35	0.27	0.14	0.08	1.00							
0.17	0.26	0.41	0.16	0.35	0.32	0.37	0.14	0.45	0.24	0.44	0.14	0.16	0.08	0.16	0.18	0.17	0.36	1.00						
0.68	0.36	0.21	0.03	0.46	0.50	0.51	0.53	0.47	0.71	0.16	0.64	0.26	0.45	0.37	0.39	0.27	-0.03	0.06	1.00					
0.37	-0.05	0.28	0.09	0.02	0.37	0.24	0.10	0.21	0.26	0.32	0.21	-0.02	0.40	0.05	0.38	0.03	-0.02	-0.01	0.25	1.00				
0.03	0.31	0.13	0.19	0.16	0.53	0.25	0.06	0.36	0.16	0.35	0.09	0.16	0.36	0.50	0.46	0.26	0.20	0.10	0.19	0.33	1.00			
-0.04	0.12	0.26	0.16	0.09	0.32	0.52	0.12	0.37	0.03	0.48	0.09	0.09	0.21	0.37	-0.02	0.26	0.23	0.31	0.04	0.15	0.45	1.00		
0.26	0.09	0.28	0.18	0.39	0.51	0.39	0.39	0.45	0.41	0.30	0.43	0.11	0.21	0.46	0.25	0.37	0.17	0.25	0.56	0.11	0.51	0.27	1.00	
0.29	0.00	0.49	0.17	0.18	0.33	0.38	0.29	0.51	0.17	0.46	0.31	0.13	0.46	0.31	0.23	0.24	0.24	0.27	0.42	0.52	0.34	0.42	0.48	1.00

Source: Compiled by the authors

are continuously rebalanced at each interval (weekly) to return to their optimal proportions.

By maximizing the risk-return trade-off in Equation 1, we generate the efficient frontiers as exhibited in Figure 2. It is obvious that portfolio of firms with strong CG outperforms that with weak CG. Put another way, T25-based sets of portfolios would yield higher returns for any level of risk (and lower risk for any given return) as compared to those constructed from B25 firms. Because risk in this context is defined as standard deviation, i.e. total risk, we also explore value-at-risk via block bootstrapping of the portfolio log returns to increase precision, by running over 20,000 simulations based on empirical distribution. The result is shown in Figure 3.

Briefly stated, we expect greater value-at-risk for B25 portfolio as time and confidence level increase. However, the outcome for T25 portfolio is quite striking; lower risk is expected over longer period. There are two possible explanations. First, such outcome may suggest strong properties of CG in mitigating risk and thus potential losses for long-term investment, consistent with the timeframe for CG-based fundamental analysis. Second (and an alternative) viewpoint might

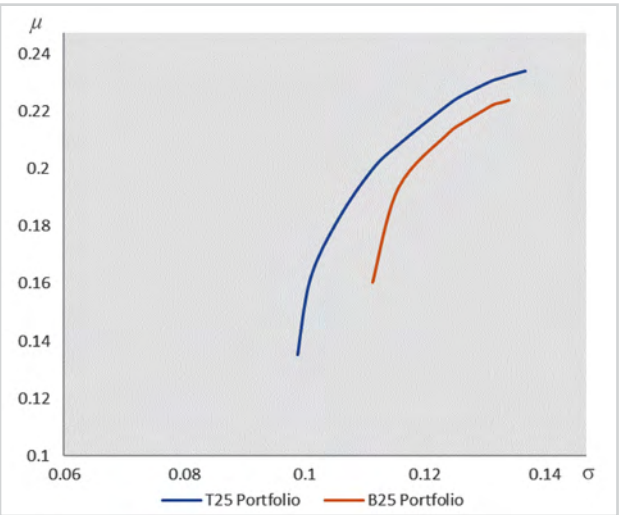
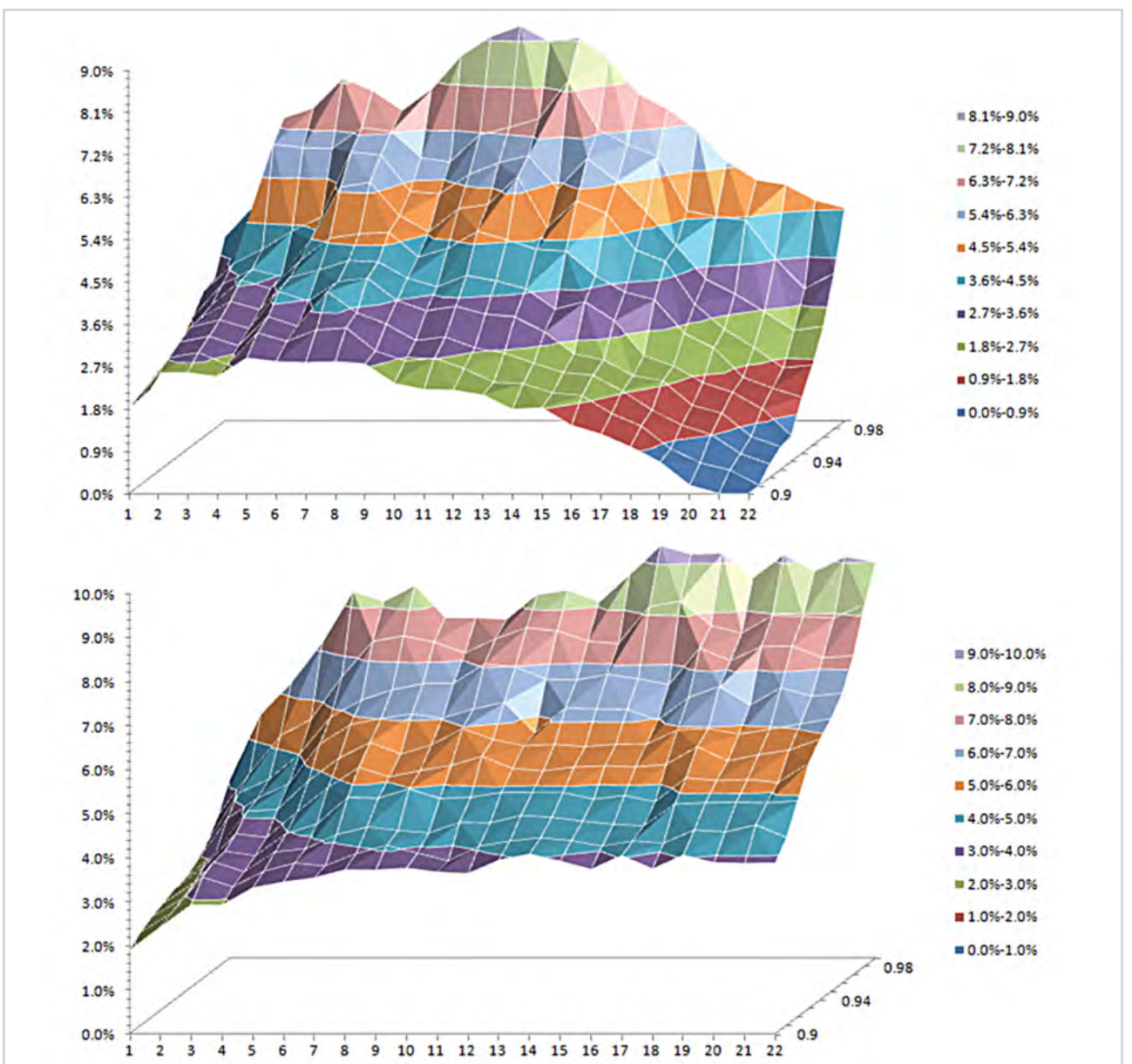


Fig. 2: **Efficient frontiers**
Source: Computed and elaborated by the authors



Note: Top (bottom) chart represents the T25 (B25) portfolio. The three axes for each chart portray VaR, period and confidence level, respectively.

Fig. 3: **Portfolio value-at-risk**
Source: Elaborated by the authors

suggest that the results are based on the empirical distribution which does not consider fat tails and asymmetry in return distribution and thus does not accurately reflect value-at-risks of the portfolios. In any event, expected value-at-risk for T25 is noticeably lower as compared to B25 portfolio. For example, based on the whole simulation period and at 0.01 significance level, T25 (B25) portfolio is exposed to 4.54% (9.01%) value-at-risk.

Table 3 displays the in-sample and out-of-sample outcome for both portfolios. It is apparent that T25 outperforms B25 portfolio in-sample, while out-of-sample analysis favours the latter despite some outperformance from the good governance-based portfolio. In the holdout period, the strong CG portfolio is exposed to lower volatility (12.26%), downside volatility (12.84%) and value-at-risk (3.23%). For the remaining metrics however, the weak CG portfolio produces better performance with higher Sharpe (0.58), Sortino (0.51) and information (0.52) ratios, although maximum drawdowns (around 7%) are very similar (identical figures in the table are due to rounding).

Tab. 3: **Portfolio performance**

	Top 25		Bottom 25	
Metrics	In-sample	Out-of-sample	In-sample	Out-of-sample
Excess return	0.2112*	0.0511	0.1646	0.0815**
Volatility	0.1171*	0.1226**	0.1232	0.1394
Downside volatility	0.1241*	0.1284**	0.1290	0.1406
Value-at-risk	0.0244*	0.0323**	0.0256	0.0363
Sharpe ratio	1.80*	0.42	1.34	0.58**
Information ratio	1.75*	0.36	1.27	0.52**
Sortino ratio	1.65*	0.34	1.22	0.51**
Maximum drawdown	0.10*	0.07	0.17	0.07*

Note: The table depicts in-sample (1 January 2012 to 31 October 2017) and out-of-sample (1 November 2017 to 30 June 2018) performance for the T25 and B25 portfolios.
* (**) indicates better in-sample (out-of-sample) performance.

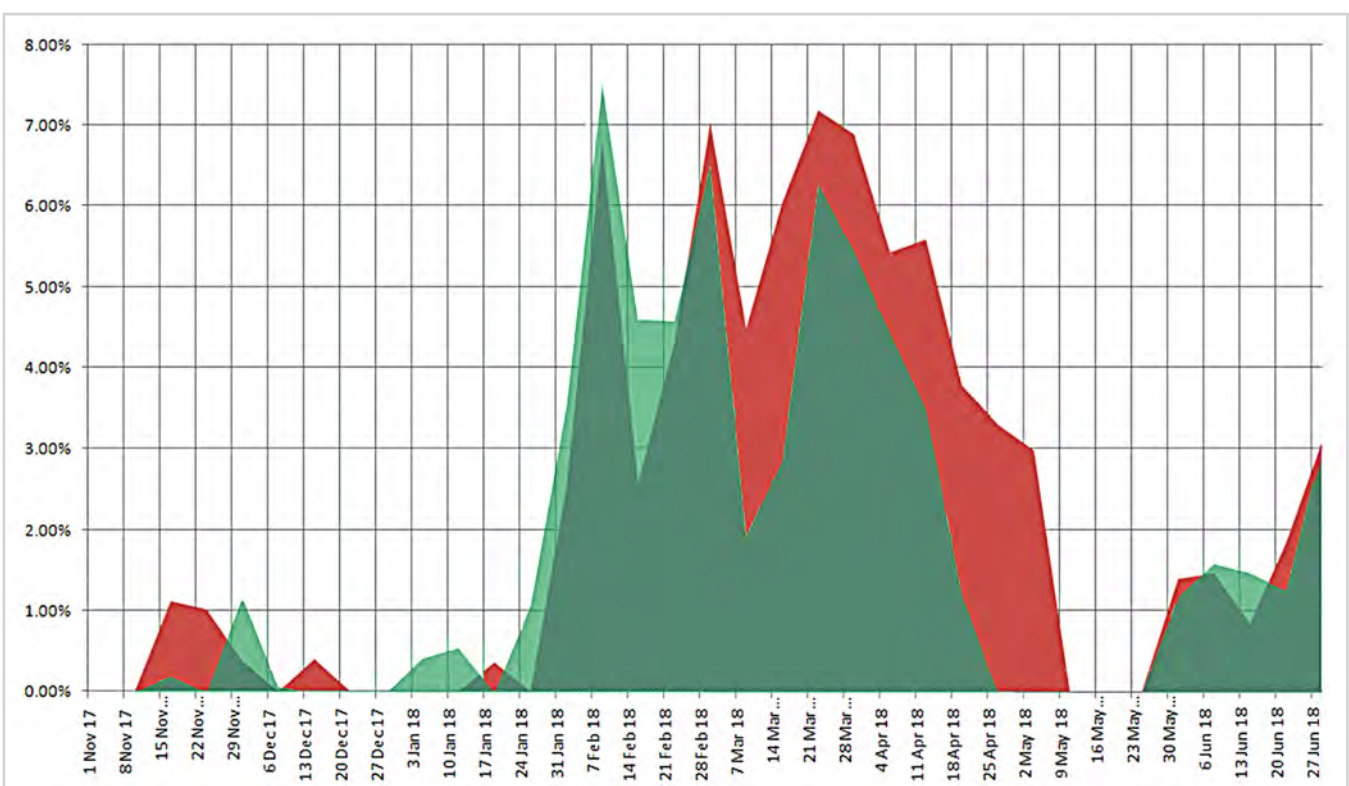
Source: Computed and elaborated by the authors

Figure 4 shows both portfolio drawdowns during the holdout sample phase. The greatest peak to valley declines for both portfolios occurs in the year 2018. Although the largest declines happen during different months, local peakedness (not in the statistical sense) appears somewhat positively correlated and concentrated throughout the January-May period. This observation is not shocking. Asia, Europe and United States markets saw episodes of massive plunges during this time - including USD 4 trillion losses in the world stock markets in just few days. Such losses were caused by US-China trade war, trade disputes, Brexit, among others, and these led to some damaging consequences on the performance of global equity markets, including London Stock Exchange. With such concerns, herding behaviour and behavioural bias of overreaction may also played parts in the selling pressure, further pushing prices (and therefore returns) down.

In a nutshell, our findings suggest that while the optimized strong CG portfolio underperforms its weak CG counterpart in many of the performance metrics, most of its discrete risks are slightly lower. Remarkably, when both returns and risk-return trade-off are considered, investment portfolio constructed from weak CG-rated components is actually superior with over 3% in return differences and better reward to variability across all key metrics.

5. Conclusion

In this article, we have constructed two distinct optimal portfolios (in-sample) based on either strong or weak CG. We have compared and contrasted their performances during in- and out-of-sample periods. In short, the strong CG portfolio outperforms the weak one in-sample, although it generally underperforms out-of-sample. Despite better results from risk-based



Note: Overlaid chart represents the T25 (green) and B25 (red) portfolios during the out-of-sample period.

Fig. 4: **Portfolio drawdowns**
Source: Analysed and described by the authors

measures in isolation, T25 portfolio yields lower return while higher risk per unit is needed to produce a unit of return, in contrast to B25 portfolio.

Our findings offer some practical and theoretical implications. Investors who are conscious about CG and attempt to maximize Sharpe measure by investing in strong governance firms may face lower portfolio risk by foregoing higher returns. Whereas reduction in value-at-risk midway onwards appears to suggest investment in companies with strong CG would less likely to fail in the long run. Volatility and downside volatility results tell similar story. Indeed, from the agency theoretical perspective, companies with strong CG would lead to lower agency cost (and risk) and better firm performance.

There are several theoretical explanations for our findings. A comparison of the two results suggests that the London Stock Exchange might not be weak-form efficient thereby refutes Modern Portfolio Theory in this market, because of the inconsistencies between risk-return trade-off. In other word, if the market is efficient, higher return is attributed to higher risk, but this is not the case in-sample (although the argument is valid out-of-sample). One possibility is such risk is not properly captured by market participants. While the developed markets have traditionally been considered efficient, some studies show that the Australian and the US markets might not be fully efficient [19-20], and similar is the case with the UK market [21]. This is in line with prior findings related to CG [16-17]. Though, focusing on a specific case study and with a relatively small sample size, caution must be applied in interpreting the theoretical inference. Our findings might not be extrapolated to other firms, CG items and specifications, portfolio selection problem, stock markets or time periods.

Our research has thrown up many areas in need of further investigation. First, there is no «one size fits all» concept whether in the current context or other fields of research. Therefore, future studies can explore different CG aspects or index in formulating optimal portfolios and comparison can be made accordingly. Indeed, as argued in [22], CG itself is abstract so incorporating construct validity in building indices can perhaps alleviate associated biases. Second, rather than using a single in-/out-of-sample window, further research can explore walk-forward optimization to ensure the most recent data and portfolio dynamics are incorporated in generating the efficient frontier. Third, we ignore trading costs in this paper which can affect our individual portfolio and/or relative outcomes. As argued by [10-11], disregarding costs is harmful to portfolio diversification. Future studies in this area can incorporate trading cost during the training and testing stages. Fourth, we simulate value-at-risk based on the empirical distribution. Further investigation can be made using other techniques, for example Cornish-Fisher expansion to account for both skewness and kurtosis in the returns. Finally, we employ popular yet simple Sharpe criterion to optimize our portfolios. More sophisticated methods such as Black-Litterman model [23-24] can thus be utilized.

Overall, our empirical findings using Sharpe measure do not suggest optimal portfolio based on strong CG constituents is more profitable in relation to its weak CG counterpart. This is not to say CG is not important; in fact it might be for socially responsible and conscious investors who look upon good CG practice itself as their investment goal. However, from the monetary perspective, one cannot expect good CG guarantees good return. Future studies can reassess its use in asset allocation by incorporating suggestions discussed earlier.

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Received 1.07.2018