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

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Demand for socially responsible investment (SRI) has seen 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 paper 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 favorable 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 plan, 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 corporate governance (CG) rated firms and 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 corporate governance (CG) rated firms and 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 corporate governance (CG) rated firms and weak ones.

2. Brief Literature Review

Modern Portfolio Theory introduced by Markowitz in 1952 [3] has revolutionized the investment management landscape and provided an understanding of portfolio diversification, for example [4-11]. While it is based solely on the so-called diversification benefit (rather than because of better governance in 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 remaining 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 relies on the idea of diversification, for example, that high-quality assets can reduce the risk of a portfolio, it is important to ensure that the diversification benefits are realized. While prior studies in CG and firm performance have documented a positive relationship between CG and investment performance, this general suggests that strong CG practice leads to sound investment and financing decisions among firms and thus considered favorable 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.

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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:

\[
\begin{align*}
\max & \quad SR = \frac{\mu_p - r_f}{\sigma_p}, \\
\text{subject to} & \quad \sum_{i=1}^{N} w_i = 1 \quad \text{and} \quad l_i < w_i < u_i,
\end{align*}
\]

where:
- \( SR \) denotes the Sharpe ratio;
- \( \mu_p \) is mean return of the portfolio;
- \( r_f \) indicates risk free rate;
- \( \sigma_p \) 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

\begin{center}
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|}
\hline
 \( w_i \) & 0.01 & 0.02 & 0.03 & 0.04 & 0.05 & 0.06 & 0.07 & 0.08 & 0.09 \\
\hline
\end{tabular}
\end{center}

Source: Compiled by the authors

\begin{center}
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|}
\hline
 \( w_i \) & 0.10 & 0.11 & 0.12 & 0.13 & 0.14 & 0.15 & 0.16 & 0.17 & 0.18 \\
\hline
\end{tabular}
\end{center}

Source: Compiled by the authors

Tab. 1: T25 portfolio correlation matrix

| Source: Compiled by the authors |
| --- |

Tab. 2: B25 portfolio correlation matrix

| 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...
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).

Table 3: Portfolio performance

| Metrics                  | Top 25 In-sample | Top 25 Out-of-sample | Bottom 25 In-sample | Bottom 25 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 comparison.

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 suggests significant investment in companies with stronger CG, might 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 formally 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 the research 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 market 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 CG (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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