



The Role of Infrastructure Assets in Portfolio Construction: A Bayesian Mean–Variance Analysis of Diversification Benefits, Macroeconomic Resilience, and a Regression-Based Evaluation of the Impact of Fund Structure.

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Abstract

This study investigates the diversification benefits of incorporating infrastructure equity and debt assets into traditional investment portfolios, employing the Bayesian mean–variance optimisation framework developed by Wang (1998). Using a comprehensive dataset of UK and global asset classes, the study constructs both constrained and unconstrained portfolios to evaluate the impact of including infrastructure on portfolio performance. The findings demonstrate that infrastructure assets can significantly enhance portfolio efficiency by improving certainty-equivalent returns and Sharpe ratios, with benefits persisting across various economic regimes, including differing interest rate, inflation, and government spending environments. Furthermore, an empirical analysis of UK-based open-ended and closed-ended infrastructure funds reveals that fund structure can materially influence outcomes, with closed-ended funds often delivering superior risk-adjusted returns. These results underscore the value of infrastructure as a strategic asset class and highlight the importance of fund structure in realising its potential benefits.

Table of Contents

ABSTRACT.....	2
INTRODUCTION	4
CHAPTER 1.....	9
1. INTRODUCTION.....	9
2. RESEARCH METHOD.....	11
3. DATA.....	15
4. RESULTS.....	19
5. EXPANDING THE BENCHMARK AND INFRASTRUCTURE IN ISOLATION.....	23
6. CONCLUSION	26
7. APPENDIX A – DATA TABLES & RESULTS	29
CHAPTER 2.....	55
OVERVIEW	55
1. ARE THE BENEFITS OF INFRASTRUCTURE ASSETS ROBUST?	56
2. INTEREST RATES	56
3. INFLATION	61
4. GOVERNMENT EXPENDITURE	63
5. EXPANDING THE BENCHMARK AND INFRASTRUCTURE IN ISOLATION.....	67
6. DISCUSSION	80
7. APPENDIX A – DATA TABLES & RESULTS	84
CHAPTER 3.....	126
1. AN EMPIRICAL ANALYSIS OF UK OPEN-ENDED AND CLOSED-ENDED INFRASTRUCTURE FUNDS.....	126
2. OPEN-END AND CLOSED-END FUNDS	126
3. RESEARCH METHOD	129
4. RESULTS.....	134
5. CONCLUSION	153
6. APPENDIX A – DATA TABLES & RESULTS	156
FINAL REMARKS.....	184
BIBLIOGRAPHY.....	188

Introduction

Infrastructure as an investment is not a new phenomenon, indeed it has been documented during the UK industrial revolution of the 18th century where significant pieces of infrastructure, such as canals and railways, which required a greater financial outlay than was possible for individual firms alone, did not rely on centralised money markets. Instead they relied on formal coalitions of local investors which were formed in order to finance the construction and operation of infrastructure assets. The local investors were a mixture of merchants, tradesmen, manufacturers and professionals who could directly observe the potential benefits of installing the canals and railways, rather than a small pool of very wealthy or distant investors. Following the successful development of these pioneering infrastructure assets this then led to the emergence of industrial hotspots to which more external investor capital could then be sought (Trew, 2010).

The asset class has developed into the more traditional sense that we see today following the increasing privatization of infrastructure assets within the sector in the 1990's. Since then, the asset class has expanded significantly with \$639bn invested in unlisted infrastructure assets under management in 2020 and is projected to rise to \$795 billion by 2025 (Murray, 2020). This growth is underpinned by a substantial funding gap in global infrastructure needs with the G20's Global Infrastructure Hub estimating a shortfall of around \$15 trillion in infrastructure investment by 2040 (Heathcote & Mulhern, 2018). Such figures underscore both the immense investment opportunities and the urgent need for capital in infrastructure worldwide.

Infrastructure assets are generally classified into social infrastructure (e.g. schools, hospitals, public facilities) and economic infrastructure (e.g. energy grids, transport networks, telecommunications, water utilities). They can further be segmented by development stage: primary (greenfield) infrastructure involves new projects in development or construction, often carrying higher risk and return potential, whereas secondary (brownfield) infrastructure refers

to established, operational assets with steady cash flows. Primary investments can offer higher returns as compensation for construction and completion risks, while secondary assets are typically favoured by investors seeking immediate yield with lower risk profiles and immediate income generation. This segmentation means that infrastructure investments can cater to different investor preferences, from growth-oriented to yield-focused.

From an investment perspective, infrastructure exhibits several appealing characteristics. Institutional investors are attracted to the asset class for its potential diversification benefits, as infrastructure returns have historically shown low correlation with traditional asset classes like public equities and bonds. Infrastructure projects often generate stable, long-term cash flows that are frequently linked to inflation (for example, via regulated utility tariffs or concession agreements), making them a potential hedge against inflation (Inderst 2010). Volatility of returns tends to be lower relative to public markets, and the assets themselves have high barriers to entry due to large capital requirements and regulatory hurdles, which can help preserve competitive advantages. Moreover, the predictable cash flows of mature infrastructure assets allow for the prudent use of leverage, giving investors the opportunity to enhance returns through gearing. Surveys of institutional investors (Prequin, 2021) consistently highlight these motivations, being inflation protection, income stability, and diversification, as key reasons for increasing allocations to infrastructure. These characteristics position infrastructure as a compelling addition to long-term investment portfolios, particularly for pension funds, endowments, and sovereign wealth funds seeking steady returns insulated to some degree from economic or business cycles.

Despite these attractive features, the academic literature on how infrastructure contributes to portfolio construction remains relatively limited. Challenges such as sparse historical data and the heterogeneous nature of infrastructure assets have constrained rigorous analysis. Unlike equities or bonds, for which long time-series and broad indices exist, many infrastructure

investments are privately held or have only very recent performance records. As a result, empirical studies on infrastructure's risk/return profile and its diversification value have been fewer in number.

This study contributes to the growing body of research by empirically examining the diversification benefits of including infrastructure in a traditional investment portfolio. The study is organised into three main chapters, each addressing a facet of this question. Chapter 1 uses a Bayesian mean–variance optimization approach to measure the impact of adding various infrastructure assets to a portfolio of traditional UK assets (equities and bonds). In this chapter I construct efficient portfolios, first in an unconstrained basis, allowing short selling and gearing and then without gearing constraints, to observe how infrastructure affects the certainty-equivalent return (CER) and other performance metrics. The analysis in Chapter 1 draws on a newly assembled dataset spanning multiple asset classes, including UK equities, UK government bonds, and a broad selection of infrastructure-related indices and funds (covering listed infrastructure equity indices, infrastructure debt funds, and active unlisted infrastructure funds). The key objective is to determine whether, and by how much, the inclusion of infrastructure can increase an investor's portfolio utility relative to traditional assets alone. I also test the persistence of any benefits when expanding the opportunity set to include international equities and bonds, thereby examining if infrastructure's value-add holds even in a globally diversified portfolio.

Chapter 2 builds upon the results of Chapter 1 by investigating the robustness of infrastructure's diversification benefits across various different economic environments. Specifically, I examine high vs. low interest rate periods, high vs. low inflation periods, and high vs low government spending periods to see if the benefits observed in Chapter 1 are sensitive to the broader macroeconomic climate. Chapter 2 also maintains the distinction between unconstrained and constrained portfolio optimisations. The results of this chapter

provide insight into how an investor's case for infrastructure may perform in different economic states of the global economy.

In Chapter 3, the focus moves from theoretical optimisation to focus on evaluating real-world fund performance. This chapter analyses historical data on UK-based open-ended (OEF) and closed-ended infrastructure funds (CEF) to determine whether the anticipated benefits of infrastructure, as identified in Chapters 1 and 2, holds up in practice. By comparing OEFs and CEFs, Chapter 3 also considers how fund structure can influence outcomes, for instance, whether the CEFs' ability to hold illiquid assets translates into higher returns relative to OEFs, or how liquidity constraints might affect an OEF's diversification properties.

Together, these chapters combined offer a multifaceted examination of infrastructure's role within investors portfolios. By using a Bayesian mean-variance optimization of diverse infrastructure indices coupled with real-world fund performance, this study bridges the gap between theoretical asset allocation and practical investment outcomes.

The findings demonstrate that the inclusion of infrastructure equity and debt significantly improves portfolio efficiency by enhancing certainty-equivalent returns and Sharpe ratios. This contributes a practical layer to the works of Bianchi et al. (2014) and Inderst (2010), who documented the low correlation of infrastructure with traditional assets. Furthermore, this research extends the work of Blanc-Brude et al. (2017) by demonstrating that these diversification benefits are not merely a product of favourable economic conditions but remains robust across differing interest rate, inflation, and government fiscal spending environments.

A primary contribution of this study is the empirical characterization of the structural impact of the investment vehicle, specifically the performance differences between OEF and CEF structures. While existing literature, such as Korniotis (2015), emphasizes the asset class resilience, this study shows that the realisation of these benefits is materially contingent upon the specific fund vehicle. The data indicates that CEFs consistently deliver superior risk-

adjusted performance and statistically significant alpha, pattern consistent with the theoretical framework that closed-ended structures can capture an illiquidity premium. This is a capacity inherently precluded for OEFs as governed by their required liquidity as a consequence of their open ended mandates.

Ultimately, the results underscore that infrastructure is not a homogeneous asset class. Rather, its potential as a strategic, inflation-hedging diversifier can be realised with good manager selection and when held within the correct investment vehicle.

Chapter 1

1. Introduction

Traditionally, investment portfolios have been constructed using a blend of equities and bonds. Increasingly, however, pension funds, endowments and limited partners have expanded their investment universe to include real estate, hedge funds and private market investments such as infrastructure and private equity (Hentov, Petrov, & Odedra, 2018). The benefits of this expanding diversification have been well documented since the publications of Grubel (1968) and Solnik (1974) and has formed the cornerstone of modern portfolio theory. More recently, however, there has been a re-examining of the benefits of diversification with Goetzmann et al in their 2005 paper noting that there is an increase in correlations over time, particularly in developed markets. This can be balanced against Hodrick and Zhang (Hodrick & Zhang, 2014) who found that by using a number of different measures that there are significant diversification benefits in developed equity markets. Alongside the benefits of diversification, private market investments, such as infrastructure, tend to benefit from their inherent illiquidity premium (Dimson & Hanke, 2004).

The primary focus of this chapter is on the diversification benefits of adding a range of infrastructure assets from a domestic UK investors perspective. I construct portfolios from a newly collected data set that spans equities, fixed income and real assets including infrastructure. The main findings of the chapter are that there are significant observable benefits when adding infrastructure assets to a benchmark of UK assets. It is also found that this benefit remains persistent when the benchmark is expanded to include international fixed income and equity assets. The diversification benefit also remains persistent when borrowing and short constraints are imposed.

One of the greatest challenges of studying infrastructure as an asset class is the limited number of indexes and the limited data history of those indexes. For investors to better understand the characteristics of any investment, it is necessary to understand the long-term risk/reward

behaviour of the asset and its inherent portfolio diversification characteristics. In the case of most publicly traded assets, this is achieved by evaluating the specific index or indexes that are constructed to track the performance of the underlying asset class. The limited number of infrastructure indexes available to evaluate over the long-term has made this process difficult and hence there is not a large body of literature specifically evaluating infrastructure as an asset class. This difficulty is compounded when reviewing infrastructure from an asset allocation framework given that portfolio selection models require a large number of data observations. This chapter addresses these empirical challenges by looking at a wide ranges of infrastructure assets including infrastructure indexes, infrastructure debt funds and active infrastructure funds. This chapter builds upon the existing research on infrastructure finance such as (Trew, 2010) and (Bianchi, Bornholt, Drew, & Howard, 2014) to evaluate the diversification benefit of adding infrastructure assets into investor portfolios. The methodology relies on the Bayesian approach of Wang (1998) which has been used extensively in the finance literature by the likes of (Li, Sarkar, & Wang, 2003), (Liu, 2016) and (Fletcher, Paudyal, & Santoso, 2018).

The empirical results in this chapter demonstrate that the inclusion of infrastructure equity and debt assets yields a significant enhancement to portfolio efficiency for a UK investor. The data reveals a statistically significant increase in both the CER and the Sharpe ratio when infrastructure is added to a traditional benchmark of domestic equities and gilts. These diversification benefits remain robust when the investment universe is expanded to include international fixed income and global equity assets. Furthermore, the gains persist even when constraints of no short selling and gearing are imposed.

This chapter contributes to the existing literature by providing a verification of the theoretical advantages proposed by Bianchi et al. (2014) and Inderst (2010). This research utilizes a newly assembled dataset that incorporates active infrastructure funds and debt instruments to offer a more comprehensive view of the performance of the asset class. By identifying that active

infrastructure funds often constitute the largest weights in an optimal constrained portfolio, this study provides novel empirical evidence consistent with the illiquidity premium framework, highlighting the potential for active management to capture risk-adjusted returns within the infrastructure sector.

2. *Research Method*

This chapter uses the mean-variance approach to examine the benefits of diversification from adding infrastructure equity and debt assets to a more traditional set of portfolio assets. I've adopted Markowitz's mean-variance framework because it provides an approach to quantify the trade-off between risk and return and is widely used in portfolio optimisation literature, allowing direct comparison with prior studies. The mean-variance approach of Markowitz (1952) assumes that investors select a $(N,1)$ vector of risky assets to:

$$\text{Max } x'u - (\gamma/2)x'Vx, \quad (1)$$

where, in equation (1), u is a $(N,1)$ vector of expected excess returns, V is a (N,N) covariance matrix of excess returns, and γ is the risk aversion level of the investor. The framework in (1) assumes that the remainder of the portfolio is invested in the risk-free asset (x_f) such that $x'e + x_f = 1$, where e is a $(N,1)$ vector of ones. This research also includes additional constraints to Equation (1) such as no short selling ($x_i \geq 0$, $i = 1, \dots, N$) and no gearing. The analysis is conducted from a U.K. perspective. This chapter considers the diversification benefits of adding the asset classes listed in the Data section to the domestic investment universe.

Diversification benefits can be measured in a number of different ways, however In this chapter I am using the mean-variance objective function noted in equation (1) as the Certainty Equivalent Return (CER) performance. In addition to the CER metric, I also evaluate performance using the Sharpe ratio. This provides a risk-adjusted return measure (ΔSharpe) that complements the risk-aversion-dependent CER, allowing me to assess diversification

benefits in terms of improved Sharpe ratios. The benefits are also then given as the increase in the CER performance of adding the Infrastructure assets to the domestic investment universe as:

$$\Delta\text{CER} = (x'u - (\gamma/2)x'Vx) - (x_b'u - (\gamma/2)x_b'Vx_b), \quad (2)$$

where x_b is a $(N,1)$ vector of weights in the benchmark portfolio which is the optimal weight in the benchmark strategy and the remaining $(N-1)$ cells are zero. N is the total number of assets and K is the number of assets in the benchmark. The ΔCER measure in Equation (2) is the increase in CER performance between holding the optimal portfolio in the benchmark assets and the optimal portfolio of the benchmark assets and the $(N-K)$ infrastructure assets. If there are no diversification benefits in adding the Infrastructure assets then the expected $\Delta\text{CER} = 0$. The CER performance measure has been used to evaluate the performance of mean–variance trading strategies in research presented by Kan and Zhou (2007), Tu and Zhou (2011), DeMiguel, Garlappi, and Uppal (2009) and Kan, Wang, and Zhou (2021).

The ΔCER measure in Equation (2) is used to compare the difference in CER performance between optimal portfolios to capture the marginal benefit of sequentially adding the assets listed above to the benchmark investment universe. This chapter estimates the ΔCER measure using one level of risk aversion, where $\gamma = 3$ as has been presented in (Tu & Zhou, 2011) for the optimal portfolio. This chapter uses the Bayesian approach utilised by (Li, Sarkar, & Wang, 2003) or more recently (Hodrick & Zhang, 2014) to estimate the increase in CER performance and to evaluate the statistical significance.

In this chapter, I also use the performance measure based on Sharpe, (1966) which is an expansion on the Treynor ratio which measures the excess return gained by an additional unit of risk. I have measured the increase in Sharpe performance by adding the list of assets noted above to the benchmark asset as:

$$\Delta\text{Sharpe} = (x'u/(x'Vx)^{1/2}) - (x_b'u/(x_b'Vx_b)^{1/2}) \quad (3)$$

If adding the additional assets does not enhance the mean-variance performance of the benchmark assets, then $\Delta\text{Sharpe} = 0$. The Sharpe performance does not depend upon the level of risk aversion unlike the ΔCER as the Sharpe performance does not control for risk aversion. Alternative approaches to examining the diversification benefits have been considered but not used. For example, Kan and Zhou (2012) provide a review of a number of different mean–variance spanning tests where the only constraint is the budget constraint. In addition, Basak, Jagannathan, and Sun (2002), Briere et al. (2013), and De Roon, Nijman, and Werker (2001) developed asymptotic mean–variance spanning and efficiency tests that allow for no short selling constraints. Li, Sarkar, and Wang (2003) highlight that using the Bayesian approach offers a number of advantages over these asymptotic tests. For example, the asymptotic tests rely on a linear approximation to a nonlinear function whereas the Bayesian approach uses the exact nonlinear function. In addition, the uncertainty of finite samples is included in the posterior distribution. Last, the Bayesian approach is easier to implement and has the ability to include a range of portfolio constraints without any added difficulty and a variety of different performance measures can be applied which will be helpful in later chapters of this study.

The Bayesian approach of Wang (1998) and Li (2003) assumes that the N asset excess returns have a multivariate normal distribution which is assumed to be appropriate for infrastructure assets. In addition to this, it assumes a non-informative prior about the expected excess returns u and the covariance matrix V . I define u_s and V_s as the sample moments of the expected excess returns and covariance matrix, and R as the (T,N) matrix of excess returns on the N assets. The posterior probability density function is given by equation (4):

$$p(u, V | R) = p(u | V, u_s, T) \cdot p(V | V_s, T), \quad (4)$$

In equation (3), $p(u | V, u_s, T)$ is the conditional distribution of a multivariate normal $(u_s, (1/T)V)$ distribution and where $p(V | V_s, T)$ is the marginal posterior distribution that has an inverse

Wishart ($TV, T-1$) distribution (Zellner, 1971). The working approximation for monthly data, alternative approaches can lead to similar portfolios as shown in Tu and Zhou (2004).

In order to approximate the posterior distribution of the ΔCER measure, this uses the Monte Carlo integration method of Wang (1998). This chapter utilises a five step approach which is conducted as follows:

1. A random V matrix is drawn from an inverse Wishart ($TV_s, T-1$) distribution.
2. Given V from step 1, a random u vector is drawn from a multivariate normal ($u_s, (1/T)V$) distribution.
3. In Step 3, I solve for the optimal portfolios for both the benchmark universe and the expanded universe including infrastructure assets. From these, I compute the Sharpe ratio for each and measure the magnitude of its change alongside ΔCER
4. Utilizing the u and V from steps highlighted in 1 and 2, the ΔCER measure from Equation (2) is estimated so that we solve the optimal portfolio first.
5. Finally, the steps from 1–4 are repeated 1000 times to generate the approximate posterior distribution of the ΔCER measure.

Following the four steps listed above, the magnitude of the diversification benefits and the statistical significance of these benefits is measured by using the posterior distribution of the ΔCER measure. Further, the average value from the posterior distribution of the ΔCER measure provides the average diversification benefits in terms of the increase in CER performance. The values of the 5th percentile of the posterior distribution of the ΔCER measure provides a statistical test of the $\Delta CER = 0$ (Hodrick & Zhang, 2014). If, by sequentially adding the assets listed above, the optimal portfolios then provide significant diversification benefits, it would then be expected to find a significant positive average ΔCER measure.

The Monte Carlo simulation method also gives the approximate posterior distribution of the optimal weights in the portfolio strategies. As shown by Britten-Jones 1999 and Kan & Smith

2008 who calculate the sampling distribution of the optimal mean–variance portfolio weights when there are no portfolio constraints. When there are portfolio constraints, in both scenarios the Bayesian method provides an approximate posterior distribution of the optimal weights. In this chapter, the posterior distribution is used to examine if the average weights in the optimal portfolios are more than two standard deviations from zero as in (Li, Sarkar, & Wang, 2003).

3. *Data*

This chapter adopts a UK perspective to evaluate the diversification benefits of adding a range of infrastructure assets alongside the traditional equity and fixed income asset classes. I chose a UK perspective as the infrastructure equity market is well developed within the UK and I am also an infrastructure equity finance professional based in the UK. All of the data is sourced from Morningstar, Inc, presented in British pounds and is the returns in excess of one month UK LIBOR. Adopting a UK perspective refers to the opportunity set available to a UK-based investor. While the universe includes global assets, all instruments are accessible to UK investors and evaluated in GBP terms. The domestic universe benchmark is comprised of the ICE Bank of America Merrill Lynch UK Gilt Total Return index and the FTSE All-share Total Return index. I chose the benchmark as it gives a broad mix of both UK equity and debt exposure. The sample period of all of the data sources is consistent between January 1999 to September 2021. A full list of the asset classes that are added to the benchmark and their groupings are given below.

Equities

1. FTSE USA Total Return Index
2. MSCI Europe ex UK Index
3. FTSE All-World Index.

Fixed Income

4. ICE Bank of America Merrill Lynch US Treasury Bill Total Return Index
5. Vanguard Long-Term Bond Index
6. Vanguard Total Bond Market Index

Real Assets

7. Alerian MLP Infrastructure Index
 8. MSCI All Country World Index Infrastructure
 9. MSCI USA Infrastructure index
 10. AMP AIT Global Infrastructure fund
 11. MainStay MacKay U.S. Infrastructure Bond Fund
 12. UPAMC Infrastructure fund
 13. Vanguard Real Estate Index Fund
-

Equities

The first equity index added is the FTSE USA Total Return index which is a market-capitalization weighted index representing the performance of US large and mid capitalisation stocks. The is the MSCI Europe ex UK Index which captures large and mid capitalisation representation across 14 Developed Markets (DM) countries in Europe. With 348 constituents, the index covers approximately 85% of the free float-adjusted market capitalization across European DM excluding the UK. Last, is the FTSE All-World Index which is a market-capitalisation weighted index representing the performance of a global basket of large and mid-capitalization, DM and Emerging Market (EM) stocks and covers 90-95% of the investable market capitalisation.

Fixed Income

The first bond index is the ICE Bank of America Merrill Lynch US Treasury Bill Total Return index which tracks the performance of US treasuries. Next is the Vanguard Long-Term Bond

index which provides a broad exposure to U.S. investment-grade bonds with maturities of more than ten years. The index targets approximately 60% of assets in corporate bonds and 40% in U.S. government bonds within that maturity range. Last is the Vanguard Total Bond Market Index which includes a broad range of investment-grade U.S.-dollar-denominated bonds with at least one year until maturity. The index weights bonds by market value, tilting the portfolio to the largest and most liquid issues. Almost 70% of the fund's assets carried a AAA credit rating as of May 2021.

Real Assets

The first real asset included in the dataset is the Alerian MLP Infrastructure index which is a market capitalization weighted composite of energy infrastructure master limited partnerships whose constituents earn the majority of their cash flows from midstream activities involving energy commodities. Next is the MSCI All Country World Index Infrastructure which captures the global opportunity set of companies that are owners or operators of infrastructure assets. Constituents cover mid and large capitalization securities across 23 DM and 25 EM countries. All index constituents are categorised into five infrastructure sectors: Telecommunications, Utilities, Energy, Transportation and Social. Next is the MSCI USA Infrastructure index which captures the opportunity set of US companies that are owners or operators of infrastructure assets. Constituents cover mid and large capitalization securities across the United States. All index constituents are categorised into five infrastructure sectors: Telecommunications, Utilities, Energy, Transportation and Social.

The next real asset is the AMP AIT Global Infrastructure fund which aims to invest mainly in listed infrastructure securities where the manager considers the underlying infrastructure assets to be stable, have strong management teams and appropriate capital structures, and are available at attractive prices. Next is the MainStay MacKay U.S. Infrastructure Bond Fund which aims to invest in high-quality taxable municipals which offer attractive income and

enhanced total return potential relative to investment-grade corporate bonds and other fixed-income sectors. The portfolio aims to have low correlation to equities due to taxable municipals providing diversification benefits. The penultimate fund is the UPAMC Infrastructure fund which aims to achieve a spread of risk and seek long-term capital appreciation through investments in companies related to economic infrastructure in Taiwan. Last is the Vanguard Real Estate Index Fund which seeks to provide a high level of income and moderate long-term capital appreciation by tracking the performance of a benchmark index that measures the performance of publicly traded equity REITs and other real estate-related investments.

[See Table 1]

Table 1 shows that there is a wide spread in the average excess returns across the assets included within this study. As expected, the standard deviation of the equity assets is greater than the fixed income assets. Within the infrastructure assets, the infrastructure indexes and infrastructure bond funds have lower standard deviations than the active infrastructure funds. Again, this would be anticipated as the active funds are taking more concentrated risk in their portfolios than indexes or infrastructure debt assets. Table 1.1 shows the correlation matrix for the monthly excess returns of the initial benchmarks and the thirteen additional indices and funds categorised in the data section. Consistent with the existing literature, infrastructure assets exhibit relatively low correlations with both the FTSE All-Share and UK Gilt indices. The low linear association observed between the assets suggests that infrastructure possesses significant potential to reduce portfolio volatility and improve risk adjusted returns. To give an example, the MainStay MacKay US Infrastructure Bond Fund demonstrates a negative correlation with the UK All-Share index, which highlights its role as a diversifier. These

empirical relationships underpin the increases in CER and Sharpe performance observed throughout the optimisation process presented below.

[See Table 1.1]

A methodological consideration regarding the dataset in Chapters 1 and 2 is that the analysis includes both passive infrastructure indices and active infrastructure funds without explicitly adjusting for fee differentials across vehicle types. In practice, management fees, expense ratios, and operational costs differ substantially between active strategies and passive index-tracking products, with active management typically carrying higher fee levels and potentially performance fees. Reviewing this fee differential could be an interesting area of future research in this space. Nevertheless, the fee differential should be considered when interpreting the chapter results.

4. *Results*

In this chapter I examine the diversification benefits of adding a number of different assets, including infrastructure, to a traditional bond and equity portfolio during the period from January 1999 to September 2021. First, I examine the CER and Sharpe performance on an unconstrained basis, next I examine the CER and Sharpe performance on a constrained. Finally, I review the optimal portfolio weights on a constrained and unconstrained basis.

ΔCER and Sharpe Performance (Unconstrained)

I begin the analysis by examining the diversification benefits of sequentially adding the asset classes listed in section 2 to the benchmark assets, on an unconstrained basis, and capturing the ΔCER performance. While each asset is sequentially added, the benchmark assets remain the same throughout. The results of this are presented in Table 2. As you can see, when short selling

is not constrained, all of the asset classes added to the benchmark assets are statistically significant at both the 5% and 10% level with all being greater than zero. Some assets in particular stick out in terms of the incremental increase in the mean when they are incrementally added. For example, FTSE USA, MSCI Europe ex UK, Alerian MLP Infrastructure, MSCI USA Infrastructure, FTSE All World and the Vanguard Total Bond Market Index all provide large incremental increases in the mean vs the other assets. This analysis suggests that each of the assets in this study provide diversification benefits with some assets providing more than others on an unconstrained basis. In addition to this, as noted in Table 2, there are sizable weights in the Alerian MLP and MSCI ACWI infrastructure assets and also sizeable short positions in the MSCI USA and MainStay MacKay US infrastructure assets when all assets are considered in the optimal portfolio weights.

[See Table 2]

A similar pattern emerges when reviewing the difference in Sharpe performance when no short selling constraints are imposed. All of the asset classes listed in section two were again added sequentially to the benchmark assets and the Sharpe performance observed. The result of this are shown in Table 3 below. Once more, all of the assets are significant at both the 5% and a 10% level with all being greater than zero. The assets which produce the largest incremental increases in the mean are FTSE USA, MSCI Europe ex UK, Alerian MLP Infrastructure, MSCI USA Infrastructure, FTSE All World and the Vanguard Total Bond Market Index.

[See Table 3]

ΔCER and Sharpe Performance (Constrained)

When the constraints of no short selling and no gearing are introduced, the benefits of diversification are not as clear across all of the asset classes within this study. By no gearing, it is meant that the portfolio weights cannot be leveraged by using borrowing at the risk free rate and therefore cannot be more than 100% at any time. No short selling means that the

investor cannot profit if the value of the asset falls. I begin the analysis on a constrained basis by examining the diversification benefits of sequentially adding the asset classes listed in section 2 to the benchmark assets and capturing the increase in CER performance. The results of this are captured in Table 4 and as you can see, the FTSE USA and MSCI Europe ex UK assets are no longer significant at a 5% level, however, they are marginally significant at the 10% level. The remainder of the asset classes are all significant at both the 5% and 10% level. Not all assets produce an increase in the mean, however, the assets with the largest incremental increase to the mean are FTSE USA, Alerian MLP Infrastructure, AMP AIT Global Infrastructure, UPAMC Infrastructure and the Vanguard Real Estate Index fund. Suggesting that investors can benefit from the diversification of these assets. If you refer to Table 4 you will note that there are sizeable positions in Alerian MLP Infrastructure, AMP AIT Global Infrastructure and UPAMC Infrastructure in terms of portfolio weights when all assets are included in the optimal portfolio calculation.

[See Table 4]

The benefits become less clear still in terms of the difference in Sharpe performance with the introduction of no short selling and no gearing. In this case, as presented in Table 5, only the Vanguard Long-Term Bond Index and Vanguard Total Bond Market Index are significant at the 5% level. There is small benefit with significance shown in the ICE BofA US Treasury Bill, MainStay MacKay US Infrastructure, UPAMC Infrastructure, Vanguard Real Estate Index, Vanguard Long-Term Bond Index and Vanguard Total Bond Market Index at the 10% level. Not all of the assets produce an increase in the mean, with FTSE USA, Alerian MLP Infrastructure, UPAMC Infrastructure and the Vanguard Real Estate Index Fund providing the largest incremental increases to the mean.

[See Table 5]

Optimal Portfolio Weights (Constrained and Unconstrained)

When it comes to examining the optimal portfolio weights I have sequentially added the asset classes listed in section 2 to the benchmark assets following the methodology from the method section on both a constrained and unconstrained basis and tabularised the results. For a full set of results in sequential order, please refer to Appendix 1, however in this section I have only presented the findings when all of the assets are included as shown in Table 6. Focusing specifically on the infrastructure assets, what is interesting is that all of the infrastructure assets constitute meaningful weights when viewed across the constrained and unconstrained optimal portfolio weights suggesting that investor can benefit from adding infrastructure assets alongside more traditional portfolio assets. On a constrained basis, the Alerian MLP Infrastructure, AMP AIT Global Infrastructure and UPAMC Infrastructure all constitute sizeable weights in the optimal portfolio. It is interesting that the three active infrastructure funds all constitute sizeable weights in the optimal constrained portfolio. On an unconstrained basis, the Alreian MLP Infrastructure, MSCI ACWI Infrastructure, AMP AIT Global Infrastructure, Mainstay Mackay US Infrastructure and UPAMC Infrastructure fund all constitute positive weightings with the MSCI USA Infrastructure fund constituting a large short position in the optimal portfolio.

[See Table 6]

It is important to note that the unconstrained portfolio optimisations in Table 6 produce extreme long and short allocations. These allocations represent theoretically generated positions arising from unconstrained mean-variance optimisation. Because it is unlikely that any institutional or retail investor could or would implement positions of this magnitude due to short-selling restrictions, leverage mandates, margin costs, and regulatory constraints, these unconstrained results should be interpreted as such. They remain informative because they isolate the underlying, unconstrained statistical interactions and joint dependencies between infrastructure assets and traditional benchmarks without constraints.

5. *Expanding the Benchmark and Infrastructure in Isolation*

In this next section of the chapter, I introduce two new scenarios while maintaining the same methodology as detailed in the Research Method section above.

Scenario 1. rather than sequentially adding assets to the benchmark and observing the Δ CER and difference in Sharpe performance along with the optimal portfolio weights, all of the infrastructure assets are added collectively as a single grouping.

Scenario 2. To expand upon scenario 1 further, the benchmark assets are then broadened to include the Vanguard Total Bond Market Index and also FTSE All-World Index. This way the benchmark is no longer constituted only by UK domiciled assets, rather, it now includes a broad mix of large and mid-cap, global equities, and also includes large, liquid AAA rated debt securities.

The purpose of the two new scenarios is to observe the benefits of adding a wide range of infrastructure assets to a UK domestic benchmark. It then also tests if this benefit extends to an expanded benchmark by adding a wide range of infrastructure assets to an internationally diversified mix of UK and global equity and fixed income assets.

Δ CER and Sharpe Performance (Unconstrained)

I begin the expanded analysis by examining the diversification benefits of adding all of the infrastructure assets detailed in the data section to the UK domestic benchmark, on an unconstrained basis, and capturing the Δ CER performance. Following this, the benchmark assets are then expanded to include a broader range of assets. The results of this are presented in Table 7 below. As you can see, when short selling and gearing are not constrained, both of

the additional scenarios are statistically significant at the 5% and 10% level. This means that there is an observable diversification benefit from adding a mix of infrastructure assets to the UK domestic benchmark and also that the benefits remains present even with an expanded benchmark.

[See Table 7]

A similar pattern emerges when reviewing the difference in Sharpe performance with no short selling and no borrowing constraints imposed, which can be seen in Table 8. Again, both of the scenarios are statistically significant at the 5% and 10% level. Albeit, the benefit is more marginal when compared to the CER performance.

[See Table 8]

Δ CER and Sharpe Performance (Constrained)

This next section looks at the Δ CER and Sharpe performance of the two new scenarios, however, the constraint of no short selling and no gearing is introduced. I begin the constrained analysis by looking at the CER Performance which can be seen in Table 9 below. As you can see, it is again observed that both of the additional scenarios are statistically significant at the 5% and 10% level. This means that there is an observable diversification benefit from adding a mix of infrastructure assets to the UK domestic benchmark and also that the benefits remains present even with an expanded benchmark and that this benefit remains evident even when no short selling and no gearing constraints are introduced.

[See Table 9]

The difference in Sharpe performance, as shown in Table 10, with the introduction of constraints on gearing and short selling, does not present as clear a benefit for the two scenarios. Neither of the two scenarios is significant at the 5% level, however, both are marginally significant at the 10% level. This indicates that there may be a small increase in Sharpe

performance as a result of adding a broad range of infrastructure assets to a UK domestic benchmark and that the benefit remains with the expansion of that benchmark.

[See Table 10]

Optimal Portfolio Weights (Constrained and Unconstrained)

In this last section of the chapter I report on the optimal portfolio weights of the two newly introduced scenarios. The results of the first scenario can be seen below in Table 11. On a constrained basis, there is a sizeable optimal portfolio weight in Alerian MLP Infrastructure, AMP AIT Global Infrastructure, UPAMC Infrastructure and Mainstay MacKay US Infrastructure. When this is coupled with the increase in CER and Sharpe performance then it is demonstrated that it can be beneficial to include infrastructure assets to a UK investment portfolio. Similarly, on an unconstrained basis, there are sizeable weights and short positions across all of the infrastructure assets. Again, when coupled with the increase in CER and Sharpe performance, there, appears to be demonstratable benefit to adding infrastructure assets to a UK portfolio when there are no constraints on short selling and gearing.

[See Table 11]

In the second new scenario, where the benchmark is expanded, the results of the optimal portfolio weights are presented in Table 12. On a constrained basis, there is a sizeable weight in Alerian MLP Infrastructure, AMP AIT Global Infrastructure and UPAMC Infrastructure. Given the sizeable portfolio weights, coupled with the increase in Δ CER and change in Sharpe performance, it is shown that even with an internationally diversified benchmark there are still measurable benefits to adding infrastructure assets to an investors portfolio on a constrained basis. Again, it is the active infrastructure funds that constitute the largest weights. On an unconstrained basis, there are significant weights and short positions in all of the infrastructure assets. Again when paired with the increase in Δ CER and change in Sharpe performance, it is observed that on an unconstrained basis there are demonstratable benefits to adding

infrastructure assets to an internationally diversified investor portfolio with the bulk of the portfolio being made up of infrastructure assets.

[See Table 12]

6. Conclusion

In this chapter I have used a newly compiled data set of international equities, fixed income and real assets in order to ascertain if there is a potential for UK investors to achieve portfolio gains through diversification into infrastructure assets. I have looked at this on both a constrained and unconstrained basis. I find that diversification into infrastructure assets, over the sample period, can cause significant increases in the Δ CER and Sharpe performance. I also find that this benefit remains persistent with the introduction of gearing and short selling constraints. Furthermore, I find that the benefit of adding infrastructure assets is not limited to investors in solely UK assets, rather, when the benchmark is extended to include international fixed income and equity securities, the gain from adding infrastructure assets remains persistent. My observed diversification benefit from adding infrastructure assets into investors portfolio is anticipated due to the long-term, inflation-linked, stable and predictable nature of the cash flows, which tend to be agnostic to the wider business and economic cycles. My analysis suggests that active infrastructure funds produce superior benefits versus the infrastructure index assets, which is an area that warrants further study.

The empirical evidence presented in this chapter provides a robust justification for the inclusion of infrastructure equity and debt within a diversified investment framework. The results of the Bayesian optimisation indicate that infrastructure assets offer significant diversification benefits for a UK based investor, characterised by a substantial increase in both the Δ CER and Sharpe performance. These gains persist under the imposition of constraints, such as the no

short selling and gearing, and remain statistically significant even when the benchmark is expanded to include global equity and fixed income securities.

These findings contribute to the existing literature by reinforcing the theoretical propositions of Inderst (2010), who argued that the unique characteristics of infrastructure provide a strategic hedge against traditional market volatility. By utilising a newly compiled dataset that includes both indices and active funds, this study extends the empirical work of Bianchi et al. (2014). The results suggest that the diversification benefit is not a byproduct of domestic market idiosyncratic risk, but rather a distinct risk premium rooted in the stable, inflation linked cash flows inherent to infrastructure projects.

An additional point of note is the observed outperformance of active infrastructure funds relative to passive infrastructure indices. This finding is consistent with the argument that active management and careful fund selection may be required to access the potential benefits associated with project complexity and the illiquidity of underlying infrastructure assets. This aligns with the observations of Blanc-Brude et al. (2017) regarding the heterogeneous nature of the asset class, suggesting that the method of implementation is as crucial as the asset allocation decision itself. This is explored further in Chapter 3.

The persistence of these benefits across diverse investment universes suggests that infrastructure possesses a low linear association with both public equities and debt assets. This reinforces the role of infrastructure as a defensive, market-agnostic asset class that can protect a portfolio from the broader business cycle. While traditional assets are often highly sensitive to immediate market sentiment, the long-term contractual nature of infrastructure provides a level of certainty that is highly valued within the mean–variance framework.

In conclusion, this chapter has demonstrated that infrastructure assets can significantly enhance portfolio utility and risk adjusted returns. The results of this chapter provide the foundation for the subsequent chapters of this study. Having established that infrastructure offers clear

benefits over the full sample period, the research will now proceed to investigate whether these advantages remain robust across different macroeconomic regimes, specifically focusing on shifting macro environments of high/low inflation, interest rates, and government expenditure.

7. *Appendix A – Data Tables & Results*

Table 1. Summary Statistics of assets included in this chapter

	Mean	Standard Deviation	Minimum	Maximum
Equities				
(Benchmark) FTSE All-Share	0.308	4.011	-15.096	12.736
FTSE USA	0.591	4.321	-12.806	11.161
MSCI Europe ex UK	0.211	5.032	-16.647	16.307
FTSE All World	0.519	4.166	-12.797	10.563
Fixed Income				
(Benchmark) ICE BofA UK Gilt	0.203	1.736	-5.82	5.87
ICE BofA US Treasury Bill	0.052	2.508	-8.15	10.03
Vanguard Long-Term Bond Index	0.490	3.733	-8.37	18.59
Vanguard Total Bond Market Index	0.278	2.675	-7.38	10.96
Real Assets				
Alerian MLP Infrastructure	0.989	6.593	-46.54	45.03
MSCI ACWI Infrastructure	0.252	3.924	-14.05	13.32
MSCI USA Infrastructure	0.227	4.395	-14.10	17.57
AMP AIT Global Infrastructure	0.671	5.230	-19.51	26.42
MainStay MacKay US Infrastructure	0.208	2.721	-8.46	10.06
UPAMC Infrastructure	1.092	7.993	-27.13	38.78
Vanguard Real Estate Index	0.868	5.877	-24.62	26.90

This table presents the summary statistics of monthly excess returns (%) for all of the assets listed in the data section over the sample period. The summary statistics includes the mean, standard deviation, minimum, and maximum values (%).

Table 1.1 Correlation Matrix of Monthly Excess Returns

	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15
(1) ICE BofA UK Gilt Index	1														
(2) FTSE All-Share Index	-0.108	1													
(3) FTSE USA Index	-0.007	0.796	1												
(4) MSCI Europe ex UK Index	-0.047	0.881	0.794	1											
(5) FTSE All-World Index	-0.033	0.892	0.956	0.904	1										
(6) ICE BofA US Treasury Bill Index	0.287	-0.083	0.262	-0.006	0.143	1									
(7) Vanguard Long-Term Bond Index	0.705	-0.05	0.18	0.03	0.126	0.697	1								
(8) Vanguard Total Bond Market Index	0.518	-0.083	0.23	0.001	0.135	0.928	0.898	1							
(9) Alerian MLP Infrastructure Index	-0.093	0.429	0.425	0.299	0.416	0.059	0.058	0.064	1						
(10) MSCI ACWI Infrastructure Index	0.139	0.717	0.789	0.772	0.821	0.268	0.313	0.298	0.333	1					
(11) MSCI USA Infrastructure Index	0.182	0.504	0.7	0.481	0.64	0.41	0.394	0.421	0.356	0.838	1				
(12) AMP AIT Global Infrastructure Fund	0.139	0.575	0.566	0.615	0.64	-0.004	0.178	0.084	0.358	0.559	0.412	1			
(13) MainStay MacKay US Infra Bond Fund	0.496	-0.109	0.201	-0.024	0.102	0.92	0.877	0.985	0.064	0.265	0.385	0.061	1		
(14) UPAMC Infrastructure Fund	-0.006	0.423	0.497	0.444	0.539	0.141	0.065	0.103	0.251	0.393	0.286	0.297	0.072	1	
(15) Vanguard Real Estate Index Fund	0.199	0.504	0.6	0.532	0.603	0.179	0.295	0.245	0.328	0.499	0.465	0.551	0.212	0.309	1

This table presents the correlation coefficients for the monthly excess returns of the fifteen assets included in Chapter 1 from January 1999 to September 2021. All returns are calculated in British pounds and represent the return in excess of one month UK LIBOR. Numbers (1) through (15) in the column headers correspond to the respective asset classes listed in the row headers. The correlation coefficients provide the empirical foundation for the Bayesian mean–variance optimisation utilised in this study.

Table 2. CER Performance (Unconstrained Basis)

CER Performance Unconstrained					
Assets	Mean	Sdev	5%	10%	Med
FTSE USA	0.2631	0.2460	0.0069	0.0232	0.1922
MSCI Europe ex UK	0.5230	0.3519	0.0913	0.1476	0.4421
Alerian MLP Infrastructure	0.7393	0.4000	0.1838	0.2710	0.6847
MSCI ACWI Infrastructure	0.8891	0.4486	0.2620	0.3621	0.8426
MSCI USA Infrastructure	1.2079	0.5156	0.4711	0.5846	1.1422
ICE BofA US Treasury Bill	1.2557	0.5135	0.5542	0.6664	1.1736
FTSE All World	1.5568	0.5947	0.6653	0.8388	1.5169
AMP AIT Global Infrastructure	1.6172	0.5872	0.7327	0.9307	1.5656
MainStay MacKay US Infrastructure	1.7531	0.6279	0.8376	1.0254	1.6719
UPAMC Infrastructure	1.8844	0.6309	0.9527	1.1154	1.8133
Vanguard Real Estate Index	1.9889	0.6415	1.0851	1.2436	1.9002
Vanguard Long-Term Bond Index	2.1079	0.6707	1.1014	1.2700	2.0510
Vanguard Total Bond Market Index	3.1761	0.9187	1.8355	2.0221	3.0859

This table presents the CER performance, equation (2), of sequentially adding the assets listed to the benchmark, which remains constant, on an unconstrained basis i.e. short selling and gearing is permitted. Full details of the assets are given in the Data section.

Table 3. Sharpe Performance (Unconstrained Basis)

Sharpe Performance Unconstrained					
Assets	Mean	Sdev	5%	10%	Med
FTSE USA	0.0432	0.0567	0.0014	0.0042	0.0341
MSCI Europe ex UK	0.0778	0.0603	0.0152	0.0245	0.0712
Alerian MLP Infrastructure	0.1041	0.0575	0.032	0.0449	0.0991
MSCI ACWI Infrastructure	0.1204	0.0581	0.0445	0.0557	0.1163
MSCI USA Infrastructure	0.1523	0.0563	0.065	0.0783	0.1497
ICE BofA US Treasury Bill	0.1586	0.0556	0.0712	0.0907	0.1535
FTSE All World	0.1847	0.0589	0.0877	0.1087	0.1802
AMP AIT Global Infrastructure	0.1894	0.0567	0.0991	0.1172	0.1862
MainStay MacKay US Infrastructure	0.203	0.0567	0.1089	0.1287	0.199
UPAMC Infrastructure	0.2131	0.0573	0.1231	0.1417	0.2102
Vanguard Real Estate Index	0.2230	0.0553	0.1309	0.1479	0.2212
Vanguard Long-Term Bond Index	0.2311	0.0574	0.1363	0.1583	0.2297
Vanguard Total Bond Market Index	0.3037	0.0625	0.1974	0.2192	0.3015

This table presents the Sharpe performance of sequentially adding the assets listed to the benchmark, which remains constant, on an unconstrained basis i.e. short selling and gearing is permitted.

Table 4. CER Performance (Constrained Basis)

CER Performance Constrained					
Assets	Mean	Sdev	5%	10%	Med
FTSE USA	0.1345	0.1257	0.0000	0.0026	0.1033
MSCI Europe ex UK	0.1378	0.1221	0.0000	0.0036	0.1094
Alerian MLP Infrastructure	0.3145	0.2077	0.0376	0.0762	0.2863
MSCI ACWI Infrastructure	0.3204	0.2162	0.0390	0.0713	0.2821
MSCI USA Infrastructure	0.3431	0.2266	0.0560	0.0885	0.3028
ICE BofA US Treasury Bill	0.3220	0.2126	0.0396	0.0756	0.2888
FTSE All World	0.3270	0.2260	0.0341	0.0720	0.2909
AMP AIT Global Infrastructure	0.3678	0.2214	0.0658	0.1026	0.3407
MainStay MacKay US Infrastructure	0.3548	0.2088	0.0638	0.1032	0.3315
UPAMC Infrastructure	0.4575	0.2353	0.1153	0.1605	0.4416
Vanguard Real Estate Index	0.5218	0.2381	0.1569	0.2161	0.5064
Vanguard Long-Term Bond Index	0.5408	0.2292	0.1842	0.2559	0.5309
Vanguard Total Bond Market Index	0.5415	0.2286	0.2089	0.2720	0.5214

This table presents the CER performance of sequentially adding the assets listed to the benchmark, which remains constant, on an constrained basis i.e. short selling and gearing is not permitted.

Table 5. Sharpe Performance (Constrained Basis)

Sharpe Performance Constrained					
Assets	Mean	Sdev	5%	10%	Med
FTSE USA	0.0217	0.0450	-0.0117	-0.0043	0.0146
MSCI Europe ex UK	0.0214	0.0467	-0.0150	-0.0053	0.0154
Alerian MLP Infrastructure	0.0480	0.0433	-0.0135	-0.0009	0.0426
MSCI ACWI Infrastructure	0.0492	0.0448	-0.0107	-0.0013	0.0427
MSCI USA Infrastructure	0.0521	0.0438	-0.0132	-0.0022	0.0472
ICE BofA US Treasury Bill	0.0506	0.0452	-0.0108	0.0005	0.0451
FTSE All World	0.0517	0.0443	-0.0095	0.0000	0.0469
AMP AIT Global Infrastructure	0.0574	0.0467	-0.0115	-0.0001	0.0548
MainStay MacKay US Infrastructure	0.0582	0.0461	-0.0074	0.0023	0.0566
UPAMC Infrastructure	0.0712	0.0464	-0.0028	0.0093	0.0706
Vanguard Real Estate Index	0.0832	0.0480	-0.0024	0.0129	0.0839
Vanguard Long-Term Bond Index	0.0896	0.0493	0.0104	0.0274	0.0902
Vanguard Total Bond Market Index	0.0896	0.0486	0.0133	0.0260	0.0918

This table presents the Sharpe performance of sequentially adding the assets listed to the benchmark, which remains constant, on an constrained basis i.e. short selling and gearing is not permitted.

Table 6 Portfolio weights – all assets

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Equities				
FTSE All Share Total Return Index (Benchmark)	0.0021	0.0241	-0.2969	1.6231
FTSE USA	0.0306	0.1026	2.1789	2.6261
MSCI Europe ex UK	0.0001	0.0034	-2.3218	1.4183
FTSE All World	0.0019	0.0213	1.2621	4.2065
Fixed Income				
ICE Bank of America UK Gilt Index (Benchmark)	0.0155	0.0705	0.1012	2.0030
ICE BofA US Treasury Bill	0.0000	0.0000	-16.7025	4.7400
Vanguard Long-Term Bond Index	0.1559	0.2078	-5.7706	2.6076
Vanguard Total Bond Market Index	0.0025	0.0261	31.0530	8.9067
Real Assets				
Alerian MLP Infrastructure	0.2667	0.2336	0.4758	0.3966
MSCI ACWI Infrastructure	0.0005	0.0085	0.8016	1.7556
MSCI USA Infrastructure	0.0016	0.0201	-1.7620	1.2076
AMP AIT Global Infrastructure	0.0929	0.1719	0.0669	0.6088
MainStay MacKay US Infrastructure	0.0000	0.0013	-8.5587	5.0089
UPAMC Infrastructure	0.2256	0.1981	0.3601	0.3459
Vanguard Real Estate Index	0.2035	0.2305	0.2348	0.5120

This table presents the optimal portfolio weights on a constrained and unconstrained basis. Each asset listed in the data section is sequentially added to the benchmark assts and the tables are then listed in order.

Table 7 CER Performance (Unconstrained Basis)

CER Performance Unconstrained					
Assets					
	Mean	Sdev	5%	10%	Med
Infrastructure Assets	0.9327	0.4405	0.3160	0.4140	0.8637
Expanded Benchmark	1.2351	0.5262	0.5106	0.5939	1.1638

This table presents the CER performance on an unconstrained basis i.e. short selling and gearing is permitted. The first line is the UK domestic benchmark with all of the infrastructure assets in this chapter added as a group. The second line, expands upon the first line by adding global equity and debt assets to the benchmark.

Table 8 Sharpe Performance (Unconstrained Basis)

Sharpe Performance Unconstrained					
Assets					
	Mean	Sdev	5%	10%	Med
Infrastructure Assets	0.1261	0.0576	0.0503	0.0626	0.1203
Expanded Benchmark	0.1327	0.0566	0.0572	0.0719	0.1266

This table presents the Sharpe performance on an unconstrained basis i.e. short selling and gearing is permitted. The first line is the UK domestic benchmark with all of the infrastructure assets in this chapter added as a group. The second line, expands upon the first line by adding global equity and debt assets to the benchmark.

Table 9 CER Performance (Constrained Basis)

CER Performance Constrained					
Assets					
	Mean	Sdev	5%	10%	Med
Infrastructure Assets	0.4577	0.2429	0.0965	0.1588	0.4400
Expanded Benchmark	0.349	0.2226	0.0526	0.0842	0.3175

This table presents the CER performance on a constrained basis i.e. short selling and gearing is not permitted. The first line is the UK domestic benchmark with all of the infrastructure assets in this chapter added as a group. The second line, expands upon the first line by adding global equity and debt assets to the benchmark.

Table 10 Sharpe Performance (Constrained Basis)

Sharpe Performance Constrained					
Assets					
	Mean	Sdev	5%	10%	Med
Infrastructure Assets	0.0707	0.0484	-0.0041	0.0092	0.0677
Expanded Benchmark	0.0482	0.0459	-0.0081	0.0024	0.0414

This table presents the Sharpe performance on a constrained basis i.e. short selling and gearing is not permitted. The first line is the UK domestic benchmark with all of the infrastructure assets in this chapter added as a group. The second line, expands upon the first line by adding global equity and debt assets to the benchmark.

Table 11 Optimal Portfolio Weights (Infrastructure Assets)

Portfolio Weights				
	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
ICE Bank of America UK Gilt Index (Benchmark)	0.0802	0.1632	2.2598	1.3834
FTSE All Share Total Return Index (Benchmark)	0.0116	0.0681	0.1575	0.8729
Infrastructure				
Alerian MLP Infrastructure	0.3507	0.2532	0.6768	0.3673
MSCI ACWI Infrastructure	0.004	0.0361	-0.5365	1.3166
MSCI USA Infrastructure	0.0088	0.0551	-0.3502	0.9241
AMP AIT Global Infrastructure	0.1947	0.238	0.4795	0.5102
MainStay MacKay US Infrastructure	0.0661	0.1479	0.4164	1.0253
UPAMC Infrastructure	0.2821	0.2129	0.4559	0.2896

This table presents the optimal portfolio weights on both a constrained and unconstrained basis when adding only the infrastructure assets to a UK benchmark.

Table 12 Optimal Portfolio Weights (Expanded Benchmark)

Portfolio Weights				
	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
ICE Bank of America UK Gilt Index (Benchmark)	0.0617	0.1456	2.1944	1.4900
FTSE All Share Total Return Index (Benchmark)	0.004	0.0338	-1.1783	1.4004
Vanguard Total Bond Market Index (Benchmark)	0.0965	0.1851	10.4607	4.6785
FTSE All World (Benchmark)	0.033	0.109	2.1739	1.6467
Infrastructure				
Alerian MLP Infrastructure	0.3477	0.2603	0.806	0.4006
MSCI ACWI Infrastructure	0.0019	0.0285	-0.8832	1.3912
MSCI USA Infrastructure	0.0071	0.0484	-0.8939	0.9659
AMP AIT Global Infrastructure	0.1689	0.2209	0.2158	0.5548
MainStay MacKay US Infrastructure	0.0014	0.0247	-9.7028	4.4354
UPAMC Infrastructure	0.2772	0.2117	0.2046	0.3140

This table presents the optimal portfolio weights on both a constrained and unconstrained basis when adding only the infrastructure assets to an expanded benchmark which now includes the Vanguard Total Bond Market Index and the FTSE All World Index.

8. *Appendix B – Additional Results*

Table 13. *FTSE USA Total Return Index*

Portfolio Weights	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.3414	0.3197	2.2100	1.1966
FTSE All Share Total Return Index (Benchmark)	0.0332	0.1207	-0.4996	0.8439
FTSE USA	0.6190	0.3307	1.4127	0.7969

Table 13 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework. The "Constrained" column represents allocations where short-selling and gearing are prohibited, whereas the "Unconstrained" column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds from January 1999 to September 2021.

Table 14. MSCI Europe ex UK Index

Portfolio Weights				
	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.3178	0.3131	2.3510	1.2394
FTSE All Share Total Return Index (Benchmark)	0.0313	0.1201	0.8909	1.1838
FTSE USA	0.6400	0.3256	1.8898	0.8221
MSCI Europe ex UK	0.0041	0.0412	-1.5950	0.9493

Table 14 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for the period from January 1999 to September 2021

Table 15. Alerian MLP Infrastructure Index

Portfolio Weights

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.2046	0.2420	2.4112	1.2057
FTSE All Share Total Return Index (Benchmark)	0.0114	0.0698	0.4055	1.2100
FTSE USA	0.3196	0.2970	1.5671	0.8525
MSCI Europe ex UK	0.0039	0.0383	-1.2540	0.9412
Alerian MLP Infrastructure	0.4595	0.2831	0.5670	0.3621

This table presents the optimal portfolio weights on a constrained and unconstrained basis. Each asset listed in the data section is sequentially added to the benchmark assts and the tables are then listed in order.

Table 16. MSCI All Country World Index Infrastructure

Portfolio Weights

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.1964	0.2412	2.8235	1.2709
FTSE All Share Total Return Index (Benchmark)	0.0135	0.0801	0.3185	1.2193
FTSE USA	0.3259	0.3073	2.0441	0.9644
MSCI Europe ex UK	0.0050	0.0428	-0.8154	0.9947
Alerian MLP Infrastructure	0.4515	0.2846	0.5891	0.3694
MSCI ACWI Infrastructure	0.0052	0.0390	-1.1404	0.9795

This table presents the optimal portfolio weights on a constrained and unconstrained basis. Each asset listed in the data section is sequentially added to the benchmark assts and the tables are then listed in order.

Table 17 MSCI USA Infrastructure index

Portfolio Weights

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.1815	0.2286	3.0117	1.3227
FTSE All Share Total Return Index (Benchmark)	0.0130	0.0715	0.3944	1.2246
FTSE USA	0.3010	0.2864	2.8132	1.0330
MSCI Europe ex UK	0.0040	0.0346	-1.8965	1.1869
Alerian MLP Infrastructure	0.4835	0.2823	0.6918	0.3838
MSCI ACWI Infrastructure	0.0047	0.0467	1.0380	1.5539
MSCI USA Infrastructure	0.0106	0.0613	-2.0097	1.1563

This table presents the optimal portfolio weights on a constrained and unconstrained basis. Each asset listed in the data section is sequentially added to the benchmark assts and the tables are then listed in order.

Table 18 FTSE All-World Index

Portfolio Weights

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.2049	0.2520	3.2508	1.2840
FTSE All Share Total Return Index (Benchmark)	0.0057	0.0462	-1.1266	1.4727
FTSE USA	0.2435	0.2815	-0.1247	2.3301
MSCI Europe ex UK	0.0035	0.0432	-2.9930	1.3389
Alerian MLP Infrastructure	0.4574	0.2802	0.6511	0.3722
MSCI ACWI Infrastructure	0.0041	0.0339	0.5927	1.6768
MSCI USA Infrastructure	0.0065	0.0478	-1.5477	1.1633
ICE BofA US Treasury Bill	0.0119	0.0659	-1.0799	1.0788
FTSE All World	0.0621	0.1682	5.6523	3.4827

Table 18 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for the period from January 1999 to September 2021.

Table 19. AMP AIT Global Infrastructure fund

Portfolio Weights

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.1343	0.2089	3.0611	1.3745
FTSE All Share Total Return Index (Benchmark)	0.0028	0.0294	-0.9554	1.4913
FTSE USA	0.1845	0.2520	0.0331	2.2392
MSCI Europe ex UK	0.0003	0.0053	-3.0570	1.3522
Alerian MLP Infrastructure	0.4022	0.2825	0.6134	0.4027
MSCI ACWI Infrastructure	0.0020	0.0225	0.6384	1.6008
MSCI USA Infrastructure	0.0084	0.0582	-1.6241	1.1413
ICE BofA US Treasury Bill	0.0105	0.0631	-0.9774	1.1171
FTSE All World	0.0263	0.1102	5.2822	3.4060
AMP AIT Global Infrastructure	0.2261	0.2563	0.2378	0.5602

This table presents the optimal portfolio weights on a constrained and unconstrained basis. Each asset listed in the data section is sequentially added to the benchmark assts and the tables are then listed in order.

Table 20 MainStay MacKay U.S. Infrastructure Bond Fund

Portfolio Weights

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.1147	0.1955	1.7766	1.7183
FTSE All Share Total Return Index (Benchmark)	0.0051	0.0518	-0.7690	1.5121
FTSE USA	0.1831	0.2487	0.3502	2.3281
MSCI Europe ex UK	0.0024	0.0331	-2.9564	1.2923
Alerian MLP Infrastructure	0.3941	0.2646	0.5150	0.3838
MSCI ACWI Infrastructure	0.0017	0.0195	0.3910	1.6597
MSCI USA Infrastructure	0.0038	0.0315	-1.4521	1.1723
ICE BofA US Treasury Bill	0.0000	0.0003	-4.0346	2.6742
FTSE All World	0.0281	0.1122	4.9292	3.5413
AMP AIT Global Infrastructure	0.1999	0.2362	0.1356	0.5597
MainStay MacKay US Infrastructure	0.0665	0.1552	3.3216	2.6338

This table presents the optimal portfolio weights on a constrained and unconstrained basis. Each asset listed in the data section is sequentially added to the benchmark assts and the tables are then listed in order.

Table 21 UPAMC Infrastructure fund

Portfolio Weights

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.0853	0.1678	1.5330	1.6847
FTSE All Share Total Return Index (Benchmark)	0.0023	0.0241	-0.4740	1.4926
FTSE USA	0.0788	0.1740	0.8543	2.3998
MSCI Europe ex UK	0.0002	0.0067	-2.7945	1.4132
Alerian MLP Infrastructure	0.3339	0.2478	0.4752	0.3820
MSCI ACWI Infrastructure	0.0005	0.0132	0.4277	1.7136
MSCI USA Infrastructure	0.0045	0.0334	-1.4077	1.1895
ICE BofA US Treasury Bill	0.0000	0.0000	-4.6254	2.6712
FTSE All World	0.0070	0.0527	3.5432	3.8297
AMP AIT Global Infrastructure	0.1720	0.2262	0.2170	0.5903
MainStay MacKay US Infrastructure	0.0516	0.1281	3.8953	2.6369
UPAMC Infrastructure	0.2626	0.2118	0.3328	0.3349

This table presents the optimal portfolio weights on a constrained and unconstrained basis. Each asset listed in the data section is sequentially added to the benchmark assts and the tables are then listed in order.

Table 22 Vanguard Real Estate Index Fund

Portfolio Weights

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.0508	0.1248	1.2457	1.6292
FTSE All Share Total Return Index (Benchmark)	0.0006	0.0073	-0.4645	1.5264
FTSE USA	0.0418	0.1319	0.8671	2.3906
MSCI Europe ex UK	0.0003	0.0064	-2.8727	1.4337
Alerian MLP Infrastructure	0.2937	0.2364	0.4606	0.3846
MSCI ACWI Infrastructure	0.0005	0.0085	0.6621	1.6754
MSCI USA Infrastructure	0.0037	0.0328	-1.4981	1.1757
ICE BofA US Treasury Bill	0.0000	0.0000	-4.5243	2.7664
FTSE All World	0.0034	0.0361	3.2773	3.8321
AMP AIT Global Infrastructure	0.1047	0.1808	0.1274	0.6027
MainStay MacKay US Infrastructure	0.0407	0.1206	3.7638	2.6471
UPAMC Infrastructure	0.2384	0.2085	0.3424	0.3402
Vanguard Real Estate Index	0.2204	0.2409	0.3627	0.4999

This table presents the optimal portfolio weights on a constrained and unconstrained basis. Each asset listed in the data section is sequentially added to the benchmark assts and the tables are then listed in order.

Table 23 Vanguard Long-Term Bond Index

Portfolio Weights

	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.0159	0.0759	0.8100	2.0146
FTSE All Share Total Return Index (Benchmark)	0.0024	0.0305	-0.5652	1.5267
FTSE USA	0.0303	0.1038	1.0423	2.5121
MSCI Europe ex UK	0.0000	0.0015	-2.7996	1.3642
Alerian MLP Infrastructure	0.2668	0.2361	0.4542	0.3838
MSCI ACWI Infrastructure	0.0008	0.0165	0.5721	1.5916
MSCI USA Infrastructure	0.0022	0.0266	-1.5747	1.1751
ICE BofA US Treasury Bill	0.0000	0.0000	-4.1354	3.0190
FTSE All World	0.0021	0.0276	3.2185	4.0315
AMP AIT Global Infrastructure	0.0815	0.1566	0.0868	0.5940
MainStay MacKay US Infrastructure	0.0018	0.0278	2.4236	3.9174
UPAMC Infrastructure	0.2275	0.2042	0.3298	0.3371
Vanguard Real Estate Index	0.1981	0.2354	0.3401	0.4944
Vanguard Long-Term Bond Index	0.1681	0.2169	1.0099	1.8600

This table presents the optimal portfolio weights on a constrained and unconstrained basis. Each asset listed in the data section is sequentially added to the benchmark assts and the tables are then listed in order.

Table 24 Vanguard Total Bond Market Index

Portfolio Weights				
	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
ICE Bank of America UK Gilt Index (Benchmark)	0.0155	0.0705	0.1012	2.0030
FTSE All Share Total Return Index (Benchmark)	0.0021	0.0241	-0.2969	1.6231
FTSE USA	0.0306	0.1026	2.1789	2.6261
MSCI Europe ex UK	0.0001	0.0034	-2.3218	1.4183
Alerian MLP Infrastructure	0.2667	0.2336	0.4758	0.3966
MSCI ACWI Infrastructure	0.0005	0.0085	0.8016	1.7556
MSCI USA Infrastructure	0.0016	0.0201	-1.7620	1.2076
ICE BofA US Treasury Bill	0.0000	0.0000	-16.7025	4.7400
FTSE All World	0.0019	0.0213	1.2621	4.2065
AMP AIT Global Infrastructure	0.0929	0.1719	0.0669	0.6088
MainStay MacKay US Infrastructure	0.0000	0.0013	-8.5587	5.0089
UPAMC Infrastructure	0.2256	0.1981	0.3601	0.3459
Vanguard Real Estate Index	0.2035	0.2305	0.2348	0.5120
Vanguard Long-Term Bond Index	0.1559	0.2078	-5.7706	2.6076
Vanguard Total Bond Market Index	0.0025	0.0261	31.0530	8.9067

Table 24 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for the period from January 1999 to September 2021

Chapter 2

Overview

This chapter expands upon the analysis of Chapter 1 by testing the robustness of the observed diversification benefits of infrastructure across distinct macroeconomic environments. While Chapter 1 established the general efficacy of infrastructure as a diversifying asset class over the full sample period, this research now investigates whether these performance enhancements persist during specific economic regimes defined by periods of high/low interest rates, inflation, and government expenditure.

The chapter utilises the same Bayesian mean–variance framework as previously established, but segments the data to isolate three categories of high and low macroeconomic states. This segmented approach allows for an assessment of how infrastructure assets respond to the macroeconomic state, by measuring the change in the CER and Sharpe metrics under these states. By partitioning the sample period, the analysis aims to determine if the market-agnostic nature of infrastructure cash flows provides a consistent hedge or if the diversification benefit is sensitive to particular economic conditions.

The analysis is organised into dedicated sections for each macroeconomic factor, allowing for an individual evaluation of how infrastructure returns interact with the three macroeconomic states. The chapter concludes with a discussion that situates these findings within the existing empirical literature.

1. Are the benefits of infrastructure assets robust?

The previous chapter has shown that UK investors can achieve benefits through diversification into infrastructure assets. I find that diversification into infrastructure assets, over the sample period, can cause significant increases in the CER and Sharpe performance. I also find that this benefit remains persistent with the introduction of gearing and short selling constraints. Furthermore, I find that the benefit of adding infrastructure assets is not limited solely to a UK benchmark, rather, when the benchmark is extended to include international fixed income and equity securities, the gain from adding infrastructure assets remains persistent. My observed diversification benefit from adding infrastructure assets into investors' portfolio was anticipated due to the long-term, inflation-linked, stable and predictable nature of the cash flows, which tend to be agnostic to the wider business and economic cycles Gatti (2008). In this chapter, I aim to test if these anticipated diversification benefits remain present and robust in three different macroeconomic environments. The macroeconomic environments I have chosen are those which I would anticipate to have the biggest impact on infrastructure related asset returns. My reasons for choosing these macroeconomic environments and the result of this analysis are presented below.

2. Interest Rates

Due to the stable, predictable and contractual nature of infrastructure cash flows, the preferred valuation methodology employed by infrastructure investors is the Discounted Cash Flow (DCF) methodology. As a result of this, valuations and returns are highly dependent on the discount factor which, in turn, is highly sensitive to the underlying interest rate. The discount factor is built up using the underlying risk-free interest rate and then a premium is added for factors specific to the asset such as if the investment is greenfield or brownfield or if there is any volume or demand based revenues. All else being equal, if you hold an infrastructure asset, and the underlying interest rate increases, the value of your asset will decrease due to the rising

discount factor. Conversely, if you hold an infrastructure asset and the underlying interest rate decreases, then all else being equal, you would expect the valuation to increase as a result of the decreasing discount factor (Delmon, 2021). In reality, in my experience the pass through of interest rates on discount factors is not as clean as this predominantly for two reasons. One, infrastructure funds tend to be raised in vintages, with defined investment windows and target return requirements which can make them less dynamic to changes in underlying interest rate movements (Hopkins, 2018). Two, the assets tend to be valued on a quarterly basis and therefore do not react to short term movements.

Interest rates increasing, decreasing valuations, and vice versa is the dominant maxim regarding infrastructure valuations. However, I believe that the reality is slightly more complex than this. If you apply second level thinking as advocated by the likes of Howard Marks then you will need to consider more specific details about the infrastructure investment before reaching that conclusion (Marks, 2011). For example, given the scale of most infrastructure investments and the level of debt that is involved, almost all infrastructure investments will be required to hold significant cash balances (Delmon, 2021). If you own an infrastructure investment with significant cash balances and you hold to maturity. The IRR will increase as a result of the higher interest rate earned on the cash balances. Often the debt will be fixed for the length of the concession with currency or interest rate risks hedged or swapped, however, this is not always the case, and if it is the case, the pass thorough is not always perfect, therefore, floating debt increases could negatively affect your valuation due to the impact on future cash flows (Weber, Staub-Bisang, & Alfen, 2016). Interest rates can also affect your valuation when it comes to refinancing assumptions. This is due to the risks involved in an infrastructure project being very different during the construction phase vs when the asset has been in operation for a number of years or decades. Investors will often assume higher borrowing costs during construction, which can be refinanced at lower premiums once the investment is in

operations, delivering potentially significant benefits to equity (Delmon, 2021). To provide an example local to myself, the Edinburgh Tram project cost more than double the original estimate, with a much smaller scope and was delivered twelve years later than originally planned which highlights the increased risk profile of infrastructure assets during construction (Edinburgh Tram Inquiry, 2023). Due to the change in risk profile once the asset is in operations, then any future refinancing assumptions will be impacted by future interest rate forecasts and any delays to project completion could also impact this.

From an asset pricing perspective, the sensitivity of real asset valuations to discount rates is rooted in standard duration theory (Macaulay, 1938), where long-dated cash flow profiles exhibit heightened sensitivity to interest rate changes. In the empirical infrastructure literature, Newell and Peng (2008) evaluate the role of infrastructure in investment portfolios, highlighting that listed infrastructure carries notable exposure to interest rate risk due to high leverage. Furthermore, segmenting asset returns into regimes based on interest rate thresholds follows the regime-shifting portfolio choice framework established by Ang and Bekaert (2002).

My overall point regarding interest rates is that the standard maxim that when an underlying interest rates increase, mechanically, the infrastructure asset valuations decrease is insufficient to accurately describe the asset class dynamics. If you own an existing infrastructure asset and are planning to hold until maturity then very often increasing interest rates can be beneficial to your returns whether you are an infrastructure debt or equity holder. In addition, increasing interest rates, increasing the underlying discount factor will increase the future expected returns of new investments. If you are an infrastructure investor, the impact of interest rates will depend on a number of factors including if your asset is in construction or operations, if you're a debt or equity holder, floating or fixed instruments are employed, if you are planning to buy and hold or trade in the short term.

Given the above, I have chosen to look at the impact of infrastructure investment returns, using the same methodology as outlined in Chapter 1, however, this time the data set is segmented into two macroeconomic states based on high and low interest rates. I have done this by taking the Bank of England published 3-Month London Interbank Offered Rate during my sample period and calculated the mean. Any investment data periods when the Bank of England interest rate is higher than the mean are classed as high interest periods. Conversely, any investment data periods when the Bank of England interest rate is below the mean is considered to be a low interest period. Across all three macroeconomic states evaluated in this chapter, it is important to acknowledge an inherent limitation of this regime classification approach regarding look-ahead bias. Defining high and low macroeconomic states based on the full-sample mean utilises information across the entire sample period. An investor operating in real time would not have known this distinction in the moment, save for extreme macroeconomic regimes such as the post-financial crisis zero-interest-rate environment. Even in such unusual cases, a real-time investor cannot anticipate the duration of the regime or the ultimate multi-decade sample average. Consequently, this sample-splitting technique represents a backward-looking, empirical classification designed to evaluate asset performance conditionally across historical economic environments, rather than a real-time predictive asset allocation strategy. While this look-ahead element reflects a standard constraint of ex-post historical regime analysis, it does not invalidate the findings, as the primary objective is to test the structural robustness of infrastructure's diversification properties across distinct macroeconomic conditions. Because these are in-sample tests, one interesting extension to this work would be to look at out-of-sample tests that could address these issues

The results of this analysis are presented below. As can be seen, the results indicate that in both high and low interest rate environments, adding infrastructure assets improves the change in CER and Sharpe performance (both significant at 5%). Notably, the optimal portfolio weights

shift: in low-rate periods, infrastructure equity funds (e.g., UPAMC, AMP AIT) take on larger weights, whereas in high-rate periods, the weight of infrastructure debt funds increases. This suggests that the type of infrastructure assets in an optimal portfolio can depend on the interest rate regime. The persistence of positive ΔCER in both regimes confirms that the diversification benefit is robust to interest rate fluctuations.

[See Tables 1-6]

3. *Inflation*

Besides interest rates, another macroeconomic factor that has a significant impact on the expected returns of infrastructure investments is inflation. Investors who allocate to infrastructure will often cite the inherent inflation hedge as the reason for doing so (Mckinsey 2019). The reason why inflation impacts infrastructure cash flows is that the cash flows are linked to inflation indexes, typically the Consumer Price Index (CPI). The revenue stream of an availability-based infrastructure investment will increase by a pre-determined CPI measure for the length of the concession, provided that the asset is available for use. On the contrary, the expenses will also be linked to a pre-determined inflation measure. The major ongoing expenses of an infrastructure investment are the ongoing SPV costs associated with managing the investment, which is subcontracted via a long-term Management Services Agreement (MSA), and the ongoing Operations and Maintenance (O&M) which will be managed via a O&M agreement. Both of these agreements will be linked to inflation (Delmon, 2021).

For a demand-based infrastructure investment, the revenue streams will also tend to be linked to inflation and therefore the revenue streams will be highly dependent on demand, however, there may be more discretion of the management team to increase revenues by less than inflation. For example, the owner of a toll road, a demand-based asset, may decide to keep ticket prices lower than an increase in inflation in order to maximise revenues by avoiding pricing out users of the asset. Contractual mismatches can cause a detriment to returns if your MSA and O&M contracts are mechanically linked to inflation but your revenues are not. If your costs increase by inflation but your revenues are unable to increase by the same amount, over many years or decades this can begin to cause a detriment to returns. Some demand based infrastructure investments can have a contractually set minimum demand order in order to provide a quasi-availability like cash flow stream. For example, a power station may set a minimum annual demand from the offtake at the bidding phase, or a desalination plant could

set a minimum acre feet of water delivery per year. By including a minimum demand for demand-based investments, this greatly improves the stability and reliability of future cash flows (Weber, Staub-Bisang, & Alfen, 2016).

For infrastructure assets that are still in construction, long-term inflation assumptions will be less of a concern, however, there may be concerns regarding short term inflation spikes or for more specific cost components of inflation such as labour costs or building material costs. For example, following the global reopening of economies after the 2019/2020 coronavirus pandemic, there was a significant spike in building material costs, inflation and labour costs. Short, sharp, unexpected fluctuations such as this can have a negative impact on investment returns. For infrastructure debt investors, besides the exceptions noted above, increasing inflation will tend to be positive for returns, due to the increase in revenue providing more income being available for debt service. Due to the fact that infrastructure concessions contractually last for a long time, often decades, and that the future revenue streams are linked to inflation, fixed or highly visible and forecastable with fixed costs that are also known make it particularly attractive to long-term investors while also protecting against inflation.

Given the above, I have chosen to look at the impact of infrastructure investment returns, using the same methodology as outlined in Chapter 1, however, this time the data set is segmented into two macroeconomic states based on high and low inflation rates. The theoretical framework for evaluating an asset's capacity to hedge inflation originates from the classic Fisher (1930) hypothesis, extended empirically to financial assets by Fama and Schwert (1977). In the asset-liability management literature, Amenc, Martellini, and Ziemann (2009) demonstrate that real asset allocations provide significant long-term inflation-hedging benefits for liability-driven investors.

I have done this by taking the Office for National Statistics (ONS) actual CPI figures during my sample period and calculated the mean. Any investment data periods when the ONS CPI

rate is higher than the mean are classed as high inflation periods. Conversely, any investment data periods when the ONS CPI rate is below the mean is considered to be a low inflation period. The results of this analysis are presented below.

The results demonstrate that under both high and low inflation regimes, the inclusion of infrastructure yields a positive ΔCER and an improvement in the Sharpe ratio, although the magnitude of the Sharpe enhancement is relatively lower during periods of high inflation. In high inflation environments, optimal portfolios exhibit a distinct tilt towards inflation linked infrastructure assets, most notably the Alerian MLP Infrastructure and UPAMC Infrastructure. Conversely, in low inflation periods, the allocation is more broadly distributed across the various infrastructure sub sectors.

Crucially, the diversification gains remain statistically significant at the 5% level in both instances, which suggests that the fundamental benefits of infrastructure are not eroded by inflationary pressures. This resilience is likely attributable to the fact that many infrastructure cash flows, including toll road fees and utility tariffs, are contractually linked to inflation indices. This finding reinforces the established characterisation of infrastructure as an effective inflation hedge, providing a stable risk premium that is decoupled from the volatility typically associated with traditional asset classes during inflationary spikes.

[See Tables 7-12]

4. *Government Expenditure*

Infrastructure is critical for economic and social development. At the most fundamental level, people need access to clean, safe drinking water, and power for lighting and heating their homes. Roads and railways then allow people to get to and from work in order to provide for their families. Transport infrastructure, such as sea ports and airports, allows firms to reach the markets they need to trade their goods and services, including across international boundaries.

In these ways, and many more, infrastructure is vital to quality of life and economic development. Even with these social and economic benefits inherent in infrastructure investment, there is still often a tendency for governments to under-invest in infrastructure.

The global infrastructure spending gap remains a pressing concern, with the stark contrast between the burgeoning demand for both sustainable and resilient infrastructure and the available financial resources. Globally, the need for infrastructure investment is forecast to reach USD 94 trillion by 2040, and a further USD 3.5 trillion will be required to meet the UN SDGs for electricity and water. This is 19 percent higher than would be delivered under current trends, and is an average of USD 3.7 trillion per year. To meet this investment need, the world will need to increase the proportion of GDP it dedicates to infrastructure to 3.5 percent, compared to the 3.0 percent expected under current trends, creating a substantial gap in meeting the world's infrastructure requirements. Closing this gap not only calls for increased public investment but also emphasises the pivotal role of private sector engagement and innovative financing mechanisms (Economics, 2017)

As shown in figure 1 below, the infrastructure investment gap is largest in the Americas. However, it is persistent throughout all regions of the globe. Countries all over the world need to invest heavily in infrastructure to meet the needs of their citizens and underpin productivity throughout their economies.

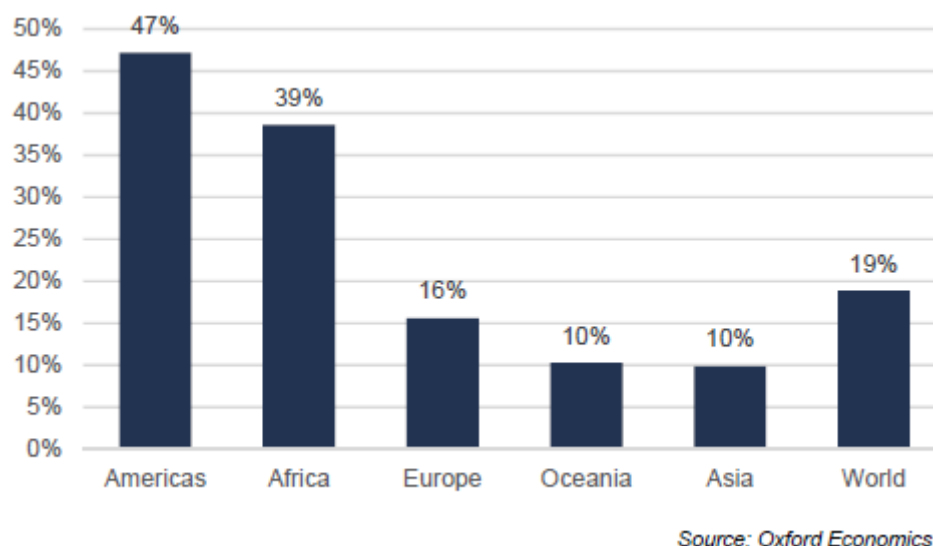


Figure 1 Infrastructure Spending Gap by Geography

Steps have been taken to close the gap. For example, in 2021, the United States issued the US Bipartisan Infrastructure Law, which introduced USD 550 billion in new spending, with USD 284 billion allocated to surface transportation. Similar global initiatives include the United Kingdom’s National Infrastructure Strategy and the European Union’s NextGen program. In fact, in 2022, G20 central governments set aside almost USD 1 trillion for infrastructure investment according to Deloitte (Deloitte, 2023). It’s important to acknowledge that aggregating public spending across the sample period groups structurally distinct fiscal periods together. To give notable examples, the post-Global Financial Crisis fiscal stimulus and the COVID-19 pandemic related spending. While both periods represent high fiscal expenditure relative to the sample mean, their underlying economic mechanisms differ fundamentally. In addition, neither episode would necessarily result in significantly increased infrastructure based spending. Consequently, while government expenditure serves as a practical macro proxy for overall fiscal stance, its aggregate nature does not isolate targeted infrastructure capital expenditure from emergency fiscal support. Further analysing the data to target specific infrastructure spending and contraction could be an interesting area for further research.

The relationship between public infrastructure expenditure and private market returns is supported by macroeconomic theory (Aschauer, 1989) and confirmed by modern empirical synthesis (Bom & Ligthart, 2014; Abiad et al., 2016), establishing that public capital investment enhances private sector productivity and expands capital formation opportunities. In public finance, government expenditure interacts with private capital allocations via the crowding-in effect (Eden & Kraay, 2014; Boehm, 2020), where public infrastructure lowers private operating costs and complements private capital to stimulate aggregate investment.

My expectation is that during periods of increased infrastructure spending by governments then the returns on infrastructure will increase. Given this expectation, I have chosen to look at the impact of infrastructure investment returns, using the same methodology as outlined in Chapter 1, however, this time the data set is segmented into two macroeconomic states based on high and low rates of government spending. I have done this by taking the Office for National Statistics (ONS) actual Government expenditure as a percentage of Gross Domestic Product (GDP) during my sample period and calculated the mean. Any investment data periods when the ONS Government expenditure as a percentage of GDP rate is higher than the mean are classed as high spending periods. Conversely, any investment data periods when the ONS Government expenditure as a percentage of GDP rate is below the mean is considered to be a low spending period. The results of this analysis are presented below.

The diversification effect of infrastructure investment persists across both high and low government spending environments. The empirical analysis indicates that the ΔCER remains positive and significant at the 5% level regardless of whether government expenditure is above or below the long-term average. However, the Sharpe improvements in the low-spending scenario are only marginally significant at the 10% level. The optimal portfolio weights suggest a cyclical shift in implementation. During periods of high government spending, the mix leans

toward infrastructure funds such as UPAMC Infrastructure. In contrast, during low-spending periods, assets such as Alerian MLP Infrastructure and the AMP AIT Global Infrastructure fund continue to add measurable value. This robustness across fiscal regimes underscores that infrastructure assets confer diversification benefits that are independent of broader government expenditure trends.

An evaluation of the results under high government spending reveals that the empirical data does not fully support my original hypothesis that fiscal expansion increases infrastructure's risk-adjusted diversification benefits in all cases. While unconstrained metrics remain significant, the constrained Δ Sharpe under high government spending fails to achieve statistical significance. These results underscore the key distinction between absolute returns and relative portfolio diversification. These findings demonstrate that while infrastructure provides persistent gains in Δ CER across fiscal cycles, its incremental Sharpe ratio benefits are most pronounced when broader public fiscal stimulus is absent.

[See Tables 13-18]

5. *Expanding the Benchmark and Infrastructure in Isolation*

In this next section of the chapter, I introduce two new scenarios while maintaining the same methodology as detailed in the Research Method in Chapter 1 and as above.

Scenario 1. rather than sequentially adding assets to the benchmark and observing the CER and Sharpe performance along with the optimal portfolio weights, all of the infrastructure assets are added collectively as a single grouping.

Scenario 2. To expand upon scenario 1 further, the benchmark assets are then broadened to include the Vanguard Total Bond Market Index and also FTSE All-World Index. This way the benchmark is no longer constituted only by UK domiciled assets, rather, it now includes a

broad mix of large and mid-cap, global equities, and also includes large, liquid AAA rated debt securities.

The purpose of the two new scenarios is to observe the benefits of adding a wide range of infrastructure assets to a UK domestic benchmark. It then also tests if this benefit extends to an expanded benchmark by adding a wide range of infrastructure assets to an internationally diversified mix of UK and global equity and fixed income assets. And whether the benefits remain present and robust in six different macroeconomic environments.

ΔCER and Sharpe Performance (Unconstrained) – High and Low Interest Rates

I begin the expanded analysis by examining the diversification benefits of adding all of the infrastructure assets detailed in the data section to the UK domestic benchmark, on an unconstrained basis, and capturing the CER performance. Following this, the benchmark assets are then expanded to include a broader range of assets. In addition, I have segmented the data into two macroeconomic states based on high and low interest rates. I have done this by taking the Bank of England published 3-Month London Interbank Offered Rate during my sample period and calculated the mean. Any investment data periods when the Bank of England interest rate is higher than the mean are classed as high interest periods. Conversely, any investment data periods when the Bank of England interest rate is below the mean is considered to be a low interest period. It should be noted, a limitation of applying a full-sample mean threshold to interest rates in my sample period stems from the prolonged structural regime shift triggered by post-Global Financial Crisis Quantitative Easing. Because UK interest rates were compressed near the zero lower bound for a substantial portion of the sample period, applying the arithmetic mean effectively functions as a pre- and post-GFC segmentation of the analysis. While this reflects the historical reality of the data history, treating the post-GFC period as a monolithic "low rate" state means that the estimates heavily reflect the unique liquidity and asset-price dynamics of the QE era. If it had been possible for my study to be extended to more

recent years then the switching of interest rate states could have been studied. With the recent increase in interest rates and the consequent fall in infrastructure investment trust premiums, this would be an interesting extension to the research in future.

The results of this are presented in Table 19 below. As you can see, when short selling and gearing are not constrained, all of these additional scenarios are statistically significant at the 5% and 10% level. This means that there is an observable diversification benefit from adding a mix of infrastructure assets to the UK domestic benchmark and also that the benefits remains present even with an expanded benchmark on a unconstrained basis in both a high and low interest rate environment.

[See Table 19]

A similar pattern emerges when reviewing the Sharpe performance with no short selling and no borrowing constraints imposed, which can be seen in Table 20. Again, both of the scenarios are statistically significant at the 5% and 10% level. Albeit, the benefit is more marginal when compared to the CER performance.

[See Table 20]

ΔCER and Sharpe Performance (Constrained) – High and Low Interest Rates

This next section looks at the CER and Sharpe performance of the two new scenarios, however, the constraint of no short selling and no gearing is introduced. By no gearing, it is meant that the portfolio weights cannot be leveraged by using debt and therefore cannot be more than 100% at any time. No short selling means that the investor cannot profit if the value of the asset falls. Again, in this section of the analysis, I have segmented the data into two macroeconomic states based on high and low interest rates. I begin the constrained analysis by looking at the CER Performance which can be seen in Table 21 below. As you can see, it is again observed that both of the additional scenarios are statistically significant at the 5% and 10% level. This means that there is an observable diversification benefit from adding a mix of infrastructure

assets to the UK domestic benchmark and also that the benefits remains present even with an expanded benchmark and that this benefit remains evident even when no short selling and no gearing constraints are introduced. Additionally, the benefit remains present in both a high and low interest rate environment.

[See Table 21]

A less robust pattern emerges when reviewing the Sharpe performance with no short selling and no borrowing constraints imposed, which can be seen in Table 22. Both of the high interest rate scenarios are statistically significant at the 5% and 10% level. Albeit, the benefit is more marginal when compared to the CER performance. However, the same cannot be said for the low interest rate scenarios which are not significant.

[See Table 22]

Optimal Portfolio Weights (Constrained and Unconstrained) – High Interest Rates

In this next section of the chapter I report on the optimal portfolio weights of the two newly introduced scenarios in the high interest rate environment. The results of the first scenario can be seen below in Table 23. On a constrained basis, there is a sizeable optimal portfolio weight in Alerian MLP Infrastructure, AMP AIT Global Infrastructure, UPAMC Infrastructure and Mainstay MacKay US Infrastructure. When this is coupled with the increase in CER and Sharpe performance then it is demonstrated that it can be beneficial to include infrastructure assets to a UK investment portfolio. Similarly, on an unconstrained basis, there are sizeable weights and short positions across all of the infrastructure assets with the exception of the UPAMC Infrastructure fund. Again, when coupled with the increase in CER and Sharpe performance, there, appears to be demonstratable benefit to adding infrastructure assets to a UK portfolio when there are no constraints on short selling and gearing in the high interest rate environment.

[See Table 23]

In the second scenario, where the benchmark is expanded, in the high interest rate environment, the results of the optimal portfolio weights are presented in Table 24 below. On a constrained basis, there is a sizeable weight in Alerian MLP Infrastructure, AMP AIT Global Infrastructure and UPAMC Infrastructure. Given the sizeable portfolio weights, coupled with the increase in CER and Sharpe performance, it is shown that even with an internationally diversified benchmark there are still measurable benefits to adding infrastructure assets to an investor's portfolio on a constrained basis in a high interest rate environment. Again, it is the active infrastructure funds that constitute the largest weights. On an unconstrained basis, there are significant weights and short positions in all of the infrastructure assets. Again when paired with the increase in CER and Sharpe performance, it is observed that on an unconstrained basis there are demonstrable benefits to adding infrastructure assets to an internationally diversified investor portfolio in a high interest rate environment.

[See Table 24]

Optimal Portfolio Weights (Constrained and Unconstrained) – Low Interest Rates

Next, I report on the optimal portfolio weights of the two newly introduced scenarios in the low interest rate environment. The results of the first scenario can be seen below in Table 25. On a constrained basis, there is a sizeable optimal portfolio weight in Alerian MLP Infrastructure, MSCI USA Infrastructure, UPAMC Infrastructure, AMP AIT Global Infrastructure. When this is coupled with the increase in CER and Sharpe performance then it is demonstrated that it can be beneficial to include infrastructure assets to a UK investment portfolio also in a low interest rate environment. Similarly, on an unconstrained basis, there are sizeable weights and short positions across all of the infrastructure assets. Again, when coupled with the increase in CER and Sharpe performance, there appears to be demonstrable benefit to adding infrastructure assets to a UK portfolio when there are no constraints on short selling and gearing in the low interest rate environment.

[See Table 25]

In the second scenario, where the benchmark is expanded, in the low interest rate environment, the results of the optimal portfolio weights are presented in Table 26 below. On a constrained basis, there is a sizeable weight in Alerian MLP Infrastructure, MSCI USA Infrastructure, AMP AIT Global Infrastructure and UPAMC Infrastructure. Given the sizeable portfolio weights, coupled with the increase in CER and Sharpe performance, it is shown that even with an internationally diversified benchmark there are still measurable benefits to adding infrastructure assets to an investors portfolio on a constrained basis in a low interest rate environment. Again, it is the active infrastructure funds that constitute the largest weights. On an unconstrained basis, there are significant weights and short positions in all of the infrastructure assets with the exception of Alerian MLP Infrastructure which has a marginal weighting. Again when paired with the increase in CER and Sharpe performance, it is observed that on an unconstrained basis there are demonstratable benefits to adding infrastructure assets to an internationally diversified investor portfolio in a low interest rate environment.

[See Table 26]

ΔCER and Sharpe Performance (Unconstrained) – High and Low Inflation Rates

I follow on the expanded analysis by examining the diversification benefits of adding all of the infrastructure assets detailed in the data section to the UK domestic benchmark, on an unconstrained basis, and capturing the CER performance. Following this, the benchmark assets are then expanded to include a broader range of assets. In addition, I have segmented the data into two macroeconomic states based on high and low inflation rates. I have done this by taking the Office for National Statistics (ONS) actual CPI figures during my sample period and calculated the mean. Any investment data periods when the ONS CPI rate is higher than the mean are classed as high inflation periods. Conversely, any investment data periods when the ONS CPI rate is below the mean is considered to be a low inflation. The results of this are

presented in Table 27 below. As you can see, when short selling and gearing are not constrained, all of these additional scenarios are statistically significant at the 5% and 10% level. This means that there is an observable diversification benefit from adding a mix of infrastructure assets to the UK domestic benchmark and also that the benefits remains present even with an expanded benchmark on a unconstrained basis in both a high and low inflationary rate environment.

[See Table 27]

A similar pattern emerges when reviewing the Sharpe performance with no short selling and no borrowing constraints imposed, which can be seen in Table 28. Again, both of the scenarios are statistically significant at the 5% and 10% level. Albeit, the benefit is more marginal when compared to the CER performance. It is therefore observed that on an unconstrained basis there is a benefit to adding infrastructure investments in both a high and low inflation rate environment.

[See Table 28]

ΔCER and Sharpe Performance (Constrained) – High and Low Inflation Rates

This next section looks at the CER and Sharpe performance of the two new scenarios, however, the constraint of no short selling and no gearing is introduced. By no gearing, it is meant that the portfolio weights cannot be leveraged by using debt and therefore cannot be more than 100% at any time. No short selling means that the investor cannot profit if the value of the asset falls. Again, in this section of the analysis, I have segmented the data into two macroeconomic states based on high and low inflation rates. I begin the constrained analysis by looking at the CER Performance which can be seen in Table 29 below. As you can see, it is again observed that both of the additional scenarios are statistically significant at the 5% and 10% level. This means that there is an observable diversification benefit from adding a mix of infrastructure assets to the UK domestic benchmark and also that the benefits remains present even with an

expanded benchmark and that this benefit remains evident even when no short selling and no gearing constraints are introduced. Additionally, the benefit remains present in both a high and low inflation rate environment.

[See Table 29]

A less robust pattern emerges when reviewing the Sharpe performance, similar to what was produced in the interest rate scenarios, with no short selling and no borrowing constraints imposed, which can be seen in Table 30. Both of the high inflation rate scenarios are statistically significant at the 5% and 10% level. Albeit, the benefit is more marginal when compared to the CER performance. However, the same cannot be said for the low inflation rate scenarios which are not significant.

[See Table 30]

Optimal Portfolio Weights (Constrained and Unconstrained) – High Inflation Rates

In this next section of the chapter I report on the optimal portfolio weights of the two newly introduced scenarios in the high inflation rate environment. The results of the first scenario can be seen below in Table 31. On a constrained basis, there is a sizeable optimal portfolio weight in Alerian MLP Infrastructure and UPAMC Infrastructure. When this is coupled with the increase in CER and Sharpe performance then it is demonstrated that it can be beneficial to include infrastructure assets to a UK investment portfolio in a high inflation environment. Similarly, on an unconstrained basis, there are sizeable weights and short positions across all of the infrastructure assets. Again, when coupled with the increase in CER and Sharpe performance, there appears to be demonstrable benefit to adding infrastructure assets to a UK portfolio when there are no constraints on short selling and gearing in the highly inflationary environment.

[See Table 31]

In the second scenario, where the benchmark is expanded, in the high inflation rate environment, the results of the optimal portfolio weights are presented in Table 32 below. On a constrained basis, there is a sizeable weight in Alerian MLP Infrastructure and UPAMC Infrastructure. Given the sizeable portfolio weights, coupled with the increase in CER and Sharpe performance, it is shown that even with an internationally diversified benchmark there are still measurable benefits to adding infrastructure assets to an investors portfolio on a constrained basis in a high inflation rate environment. Again, it is the active infrastructure funds that constitute the largest weights. On an unconstrained basis, there are significant weights and short positions in all of the infrastructure assets. Again when paired with the increase in CER and Sharpe performance, it is observed that on an unconstrained basis there are demonstratable benefits to adding infrastructure assets to an internationally diversified investor portfolio in a high inflation rate environment.

[See Table 32]

Optimal Portfolio Weights (Constrained and Unconstrained) – Low Inflation Rate

Next, I report on the optimal portfolio weights of the two newly introduced scenarios in the low inflation rate environment. The results of the first scenario can be seen below in Table 33. On a constrained basis, there is a sizeable optimal portfolio weight in Alerian MLP Infrastructure, UPAMC Infrastructure and AMP AIT Global Infrastructure. When this is coupled with the increase in CER and Sharpe performance then it is demonstrated that it can be beneficial to include infrastructure assets to a UK investment portfolio also in a low inflation rate environment. Similarly, on an unconstrained basis, there are sizeable weights and short positions across all of the infrastructure assets. Again, when coupled with the increase in CER and Sharpe performance, there appears to be demonstratable benefit to adding infrastructure assets to a UK portfolio when there are no constraints on short selling and gearing in the low inflation rate environment.

[See Table 33]

In the second scenario, where the benchmark is expanded, in the low inflation rate environment, the results of the optimal portfolio weights are presented in Table 34 below. On a constrained basis, there is a sizeable weight in Alerian MLP Infrastructure, AMP AIT Global Infrastructure and UPAMC Infrastructure. Given the sizeable portfolio weights, coupled with the increase in CER and Sharpe performance, it is shown that even with an internationally diversified benchmark there are still measurable benefits to adding infrastructure assets to an investors portfolio on a constrained basis in a low inflation rate environment. Again, it is the active infrastructure funds that constitute the largest weights. On an unconstrained basis, there are significant weights and short positions in all of the infrastructure assets. Again when paired with the increase in CER and Sharpe performance, it is observed that on an unconstrained basis there are demonstratable benefits to adding infrastructure assets to an internationally diversified investor portfolio in a low inflation rate environment.

[See Table 34]

ΔCER and Sharpe Performance (Unconstrained) – High and Low Government Spending

I further the expanded analysis by examining the diversification benefits of adding all of the infrastructure assets detailed in the data section to the UK domestic benchmark, on an unconstrained basis, and capturing the CER performance. Following this, the benchmark assets are then expanded to include a broader range of assets. In addition, I have segmented the data into two macroeconomic states based on high and low rates of government expenditure. I have done this by taking the Office for National Statistics (ONS) actual Government expenditure as a percentage of Gross Domestic Product (GDP) during my sample period and calculated the mean. Any investment data periods when the ONS Government expenditure as a percentage of GDP rate is higher than the mean are classed as high spending periods. Conversely, any

investment data periods when the ONS Government expenditure as a percentage of GDP rate is below the mean is considered to be a low spending period. The results of this are presented in Table 35 below. As you can see, when short selling and gearing are not constrained, all of these additional scenarios are statistically significant at the 5% and 10% level. This means that there is an observable diversification benefit from adding a mix of infrastructure assets to the UK domestic benchmark and also that the benefits remains present even with an expanded benchmark on a unconstrained basis in both a high and low period of government expenditure.

[See Table 35]

A similar pattern emerges when reviewing the Sharpe performance with no short selling and no borrowing constraints imposed, which can be seen in Table 36. Again, both of the scenarios are statistically significant at the 5% and 10% level. Albeit, the benefit is more marginal when compared to the CER performance. It is therefore observed that on an unconstrained basis there is a benefit to adding infrastructure investments in both a high and low period of government expenditure.

[See Table 36]

ΔCER and Sharpe Performance (Constrained) – High and Low Government Spending

This next section looks at the CER and Sharpe performance of the two new scenarios, however, the constraint of no short selling and no gearing is introduced. By no gearing, it is meant that the portfolio weights cannot be leveraged by using debt and therefore cannot be more than 100% at any time. No short selling means that the investor cannot profit if the value of the asset falls. Again, in this section of the analysis, I have segmented the data into two macroeconomic states based on high and low rates of government spending. I begin the constrained analysis by looking at the CER Performance which can be seen in Table 37 below. As you can see, it is again observed that both of the additional scenarios are statistically significant at the 5% and 10% level albeit very marginal in the high government spending scenario with the expanded

benchmark. This means that there is an observable diversification benefit from adding a mix of infrastructure assets to the UK domestic benchmark and also that the benefits remains present even with an expanded benchmark and that this benefit remains evident even when no short selling and no gearing constraints are introduced. Additionally, the benefit remains present in both a high and low government spending environment.

[See Table 37]

A less robust pattern emerges when reviewing the Sharpe performance, similar to what was produced in the interest rate scenarios, with no short selling and no borrowing constraints imposed, which can be seen in Table 38. Both of the low government spending scenarios are statistically significant at the 5% and 10% level. Albeit, the benefit is more marginal when compared to the CER performance. However, the same cannot be said for the high government spending scenarios which are not significant.

[See Table 38]

Optimal Portfolio Weights (Constrained and Unconstrained) – High Government Spending

In this next section of the chapter I report on the optimal portfolio weights of the two newly introduced scenarios in the periods of high government expenditure. The results of the first scenario can be seen below in Table 39. On a constrained basis, there is a sizeable optimal portfolio weight in Alerian MLP Infrastructure, MainStay MacKay US Infrastructure and UPAMC Infrastructure. When this is coupled with the increase in CER and Sharpe performance then it is demonstrated that it can be beneficial to include infrastructure assets to a UK investment portfolio in periods of high government spending. Similarly, on an unconstrained basis, there are sizeable weights and short positions across all of the infrastructure assets with the exception of AMP AIT Global Infrastructure. Again, when coupled with the increase in CER and Sharpe performance, there appears to be demonstratable

benefit to adding infrastructure assets to a UK portfolio when there are no constraints on short selling and gearing in the environment of high government spending.

[See Table 39]

In the second scenario, where the benchmark is expanded, in the high government spending environment, the results of the optimal portfolio weights are presented in Table 40 below. On a constrained basis, there is a sizeable weight in Alerian MLP Infrastructure and UPAMC Infrastructure. Given the sizeable portfolio weights, coupled with the increase in CER and Sharpe performance, it is shown that even with an internationally diversified benchmark there are still measurable benefits to adding infrastructure assets to an investors portfolio on a constrained basis in a high government spending environment. Again, it is the active infrastructure funds that constitute the largest weights. On an unconstrained basis, there are significant weights and short positions in all of the infrastructure assets. Again when paired with the increase in CER and Sharpe performance, it is observed that on an unconstrained basis there are demonstratable benefits to adding infrastructure assets to an internationally diversified investor portfolio in a government spending environment.

[See Table 40]

Optimal Portfolio Weights (Constrained and Unconstrained) – Low Government Spending

Next, I report on the optimal portfolio weights of the two newly introduced scenarios in the low inflation rate environment. The results of the first scenario can be seen below in Table 41. On a constrained basis, there is a sizeable optimal portfolio weight in Alerian MLP Infrastructure, UPAMC Infrastructure and AMP AIT Global Infrastructure. When this is coupled with the increase in CER and Sharpe performance then it is demonstrated that is can be beneficial to include infrastructure assets to a UK investment portfolio also in a low government spending environment. Similarly, on an unconstrained basis, there are sizeable

weights and short positions across all of the infrastructure assets. Again, when coupled with the increase in CER and Sharpe performance, there, appears to be demonstrable benefit to adding infrastructure assets to a UK portfolio when there are no constraints on short selling and gearing in the low government spending time periods.

[See Table 41]

In the second scenario, where the benchmark is expanded, in the low government spending environment, the results of the optimal portfolio weights are presented in Table 42 below. On a constrained basis, there is a sizeable weight in Alerian MLP Infrastructure, AMP AIT Global Infrastructure and UPAMC Infrastructure. Given the sizeable portfolio weights, coupled with the increase in CER and Sharpe performance, it is shown that even with an internationally diversified benchmark there are still measurable benefits to adding infrastructure assets to an investors portfolio on a constrained basis in the periods of low government spending. Again, it is the active infrastructure funds that constitute the largest weights. On an unconstrained basis, there are significant weights and short positions in all of the infrastructure assets. When paired with the increase in CER and Sharpe performance, it is observed that on an unconstrained basis there are demonstrable benefits to adding infrastructure assets to an internationally diversified investor portfolio in periods of low government spending.

[See Table 42]

6. Discussion

In this chapter, I have utilised a newly compiled data set of international equities, fixed income, and real assets to evaluate whether UK investors can achieve portfolio gains through diversification into infrastructure assets. The analysis was conducted on both a constrained and unconstrained basis, revealing that diversification into infrastructure over the sample period leads to significant increases in Δ CER and Sharpe performance. These benefits remain

persistent even with the introduction of gearing and short selling constraints. Furthermore, the value added by infrastructure is not limited to domestic benchmarks; when the universe is extended to include international fixed income and equity securities, the gains from adding infrastructure assets persist.

Crucially, this research demonstrates that the diversification benefit is robust across all segmented macroeconomic states, namely high and low interest rates, high and low inflation, and high and low levels of government expenditure. These findings were anticipated given the long-term, inflation-linked, and predictable nature of infrastructure cash flows, which tend to remain agnostic to wider business and economic cycles. However, a notable and unanticipated pattern that emerged in Chapter 1 and continued here is the strong outperformance of specific specialized infrastructure strategies, notably the active funds of AMP AIT Global Infrastructure, MainStay MacKay US Infrastructure, and UPAMC Infrastructure alongside the Alerian MLP composite index. Across all macroeconomic environments, these assets provided larger diversification benefits than broad market-wide indices. For the actively managed funds, this supports the findings of Bianchi et al. (2014), suggesting that skilled active management in illiquid sectors can capture an illiquidity premium to deliver superior risk-adjusted returns, while the Alerian index performance suggests that targeted, sub-sector infrastructure exposures can also yield distinct diversification advantages over generalist benchmarks. It is also important to acknowledge that simultaneously testing statistical significance across six macroeconomic regimes, constraint scenarios, and benchmark universes introduces a potential multiple testing limitation, increasing the probability of type I errors. Nevertheless, the uncorrected results remain highly informative. In particular, the empirical pattern demonstrates that while Sharpe ratio improvements are sensitive to specific constrained states, the Δ CER gains remain consistently significant across all regimes. This indicates that the portfolio enhancements derived from infrastructure are particularly reliable and resilient to

multiple testing concerns. The empirical results across all of the macroeconomic regimes reveals an important distinction between performance metrics under portfolio constraints. While CER gains remain statistically significant across every regime, constrained Sharpe ratio improvements lose statistical significance in three of the six states. Specifically, under the low interest rates, low inflation, and high government spending states. This pattern demonstrates that while infrastructure reliably enhances the CER across all economic conditions, its capacity to deliver incremental risk-adjusted Sharpe ratio gains is state-dependent when short-selling and gearing are restricted. A further consideration that is not included in my research is that each macroeconomic variable is evaluated in isolation. In reality, economic shifts occur simultaneously. For example, high inflation paired with central bank rate hikes creates a very different valuation environment for leveraged assets than high inflation with low interest rates. While testing variables individually isolates the primary impact of each macro factor, it ignores interaction effects between them. Examining combined multi-factor regimes such as simultaneous fiscal expansion and monetary tightening is not a part of my research but be an interesting area for future study.

In conclusion, the diversification benefits provided by infrastructure are remarkably robust to shifting macroeconomic states. The persistent improvements in portfolio performance across different interest rate, inflation, and government spending regimes reinforce the argument made by Inderst (2010) that infrastructure serves as a strategic long-term asset class. While these results align with Korniotis (2015) regarding the resilience of infrastructure returns, this study provides the novel insight that while the infrastructure benefits are constant, the optimal asset mix and the magnitude of those benefits vary by economic regime. My analysis ultimately suggests that UK investors can achieve significant gains through infrastructure, though the outperformance of active funds versus passive indices warrants further empirical study. Having established that infrastructure offers clear benefits over the full

sample period, and that these persist over varying macroeconomic states. The research will now proceed to investigate whether these advantages remain robust when looking at real-word data by evaluating the performance of CEF and OEF infrastructure funds.

7. *Appendix A – Data Tables & Results*

Table 1 CER performance Constrained

CER Performance - Constrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low Interest Rates	0.7350	0.2906	0.2727	0.3978	0.7173
High Interest Rates	0.7063	0.3721	0.1726	0.2646	0.6548

Table 1 reports the CER performance derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results are segmented into low and high interest rate environments based on the mean 3-Month London Interbank Offered Rate (LIBOR) over the sample period. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 2 CER Performance Unconstrained

CER Performance - Unconstrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low Interest Rates	7.9934	2.0376	5.0561	5.4554	7.8450
High Interest Rates	5.3250	1.7353	2.7953	3.2359	5.1483

Table 2 reports the CER performance gains derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results are segmented into high and low interest rate environments based on the mean 3-Month London Interbank Offered Rate during the sample period. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 3 Sharpe Performance - Constrained

Sharpe Performance - Constrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low Interest Rates	0.1110	0.0658	0.0111	0.0319	0.1118
High Interest Rates	0.1730	0.0767	0.0343	0.0626	0.1721

Table 3 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results are segmented into high and low interest rate environments based on the mean 3-Month London Interbank Offered Rate during the sample period. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 4 Sharpe Performance - Unconstrained

Sharpe Performance - Unconstrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low Interest Rates	0.4690	0.0875	0.3168	0.3485	0.4680
High Interest Rates	0.4504	0.0906	0.2832	0.3174	0.4513

Table 4 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results are segmented into high and low interest rate environments based on the mean 3-Month London Interbank Offered Rate during the sample period. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 5 Optimal Portfolio Weights - Low Interest Rates

Portfolio Weights Low interest Rates	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Equities				
FTSE All Share Total Return Index (Benchmark)	0.0034	0.0377	3.9728	2.4984
FTSE USA	0.3004	0.3377	6.4678	4.7164
MSCI Europe ex UK	0.0000	0.0000	-5.7992	2.4714
FTSE All World	0.0005	0.0171	3.5047	7.5925
Fixed Income				
ICE Bank of America UK Gilt Index (Benchmark)	0.0014	0.0184	-2.3688	2.9041
ICE BofA US Treasury Bill	0.0000	0.0000	-34.8913	8.6861
Vanguard Long-Term Bond Index	0.0421	0.1186	-7.3953	3.6997
Vanguard Total Bond Market Index	0.0011	0.0312	46.1090	13.3327
Real Assets				
Alerian MLP Infrastructure	0.0531	0.1249	-1.3064	0.6101
MSCI ACWI Infrastructure	0.0000	0.0000	-3.4718	4.1833
MSCI USA Infrastructure	0.0211	0.1001	3.2845	2.8489
AMP AIT Global Infrastructure	0.0212	0.0843	-0.9704	1.0218
MainStay MacKay US Infrastructure	0.0000	0.0000	-5.0077	6.3920
UPAMC Infrastructure	0.4825	0.3464	0.5759	0.7413
Vanguard Real Estate Index	0.0732	0.1737	-2.0538	0.9906

Table 5 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework during periods of low interest rates. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the Bank of England interest rate was below the sample mean

Table 6 Optimal Portfolio Weights - High Interest Rates

Portfolio Weights High interest Rates	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Equities				
FTSE All Share Total Return Index (Benchmark)	0.0009	0.0210	-2.4791	2.5653
FTSE USA	0.0000	0.0000	-5.6478	3.8888
MSCI Europe ex UK	0.0007	0.0128	-2.7390	2.1125
FTSE All World	0.0001	0.0043	8.4584	6.0929
Fixed Income				
ICE Bank of America UK Gilt Index (Benchmark)	0.0160	0.0775	-1.8565	4.2477
ICE BofA US Treasury Bill	0.0023	0.0338	-11.4595	7.1923
Vanguard Long-Term Bond Index	0.1158	0.2262	-5.9265	4.7057
Vanguard Total Bond Market Index	0.0126	0.0743	34.4993	17.6308
Real Assets				
Alerian MLP Infrastructure	0.5691	0.3412	2.0333	0.8353
MSCI ACWI Infrastructure	0.0047	0.0333	3.9078	2.2972
MSCI USA Infrastructure	0.0002	0.0075	-3.4547	1.6111
AMP AIT Global Infrastructure	0.0920	0.1997	-0.3589	0.9988
MainStay MacKay US Infrastructure	0.0058	0.0534	-15.2241	14.2557
UPAMC Infrastructure	0.0638	0.1203	-0.1225	0.4468
Vanguard Real Estate Index	0.1030	0.1999	0.6402	0.7505

Table 6 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework during periods of high interest rates. The Constrained column represents weights where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the Bank of England interest rate was above the sample mean

Table 7 CER Performance - Constrained

CER Performance - Constrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low Inflation Rates	0.6629	0.3241	0.1729	0.2682	0.6302
High Inflation Rates	0.6763	0.3180	0.2046	0.2871	0.6434

Table 7 reports the CER performance gains derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results are segmented into high and low inflation environments based on the mean ONS CPI. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 8 CER Performance - Unconstrained

CER Performance - Unconstrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low Inflation Rates	5.6722	1.7811	3.0272	3.5145	5.5407
High Inflation Rates	4.3108	1.3916	2.2716	2.6372	4.1473

Table 8 reports the CER performance gains derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results are segmented into high and low inflation environments based on the mean ONS CPI. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 9 Sharpe Performance - Constrained

Sharpe Performance - Constrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low Inflation Rates	0.0971	0.0710	-0.0161	-0.0001	0.1016
High Inflation Rates	0.1233	0.0670	0.0199	0.0408	0.1189

Table 9 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results are segmented into high and low inflation environments based on the mean ONS CPI. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 10 Sharpe Performance - Unconstrained

Sharpe Performance - Unconstrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low Inflation Rates	0.4207	0.0905	0.2534	0.2875	0.4177
High Inflation Rates	0.3589	0.0814	0.2193	0.2425	0.3542

Table 10 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results are segmented into high and low inflation environments based on the mean ONS CPI. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 11 Optimal Portfolio Weights Low Inflation Rates

Portfolio Weights Low inflation Rates	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Equities				
FTSE All Share Total Return Index (Benchmark)	0.0000	0.0000	-2.1003	2.3353
FTSE USA	0.0280	0.1117	4.3956	4.5901
MSCI Europe ex UK	0.0009	0.0197	-1.4429	1.9757
FTSE All World	0.0017	0.0259	0.7535	6.8932
Fixed Income				
ICE Bank of America UK Gilt Index (Benchmark)	0.0212	0.0953	0.2922	3.0918
ICE BofA US Treasury Bill	0.0006	0.0187	-23.1161	8.1351
Vanguard Long-Term Bond Index	0.1299	0.2437	-9.4570	5.0665
Vanguard Total Bond Market Index	0.0016	0.0269	40.1272	14.2545
Real Assets				
Alerian MLP Infrastructure	0.0949	0.1762	-0.0362	0.5283
MSCI ACWI Infrastructure	0.0000	0.0000	0.3147	2.2817
MSCI USA Infrastructure	0.0001	0.0016	-2.9154	1.6674
AMP AIT Global Infrastructure	0.1901	0.2838	0.2856	1.1445
MainStay MacKay US Infrastructure	0.0000	0.0000	-8.9147	5.9239
UPAMC Infrastructure	0.1023	0.1640	0.0230	0.4773
Vanguard Real Estate Index	0.4247	0.3488	1.8819	1.0452

Table 11 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework during periods of low inflation. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the ONS CPI was below the sample mean.

Table 12 Optimal Portfolio Weights High Inflation Rates

Portfolio Weights High inflation Rates	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Equities				
FTSE All Share Total Return Index (Benchmark)	0.0107	0.0635	0.2686	2.5133
FTSE USA	0.0213	0.0970	3.9727	3.8808
MSCI Europe ex UK	0.0006	0.0100	-3.5142	2.2703
FTSE All World	0.0011	0.0157	-1.7707	6.2570
Fixed Income				
ICE Bank of America UK Gilt Index (Benchmark)	0.0118	0.0701	0.3933	3.0291
ICE BofA US Treasury Bill	0.0000	0.0000	-16.2619	6.5123
Vanguard Long-Term Bond Index	0.0666	0.1547	-4.8058	3.3657
Vanguard Total Bond Market Index	0.0022	0.0300	24.3873	15.6185
Real Assets				
Alerian MLP Infrastructure	0.4060	0.3167	1.3235	0.8413
MSCI ACWI Infrastructure	0.0097	0.0716	4.9378	3.4802
MSCI USA Infrastructure	0.0301	0.1126	-2.3262	2.1930
AMP AIT Global Infrastructure	0.0332	0.1073	-0.2658	0.7625
MainStay MacKay US Infrastructure	0.0021	0.0301	-4.8507	12.4109
UPAMC Infrastructure	0.3441	0.2892	1.0531	0.5945
Vanguard Real Estate Index	0.0603	0.1485	-0.4079	0.7011

Table 12 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework during periods of high inflation. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the ONS CPI was above the sample mean.

Table 13 CER Performance - Constrained

CER Performance - Constrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low GDP Spend	0.6888	0.2860	0.2579	0.3281	0.6744
High GDP Spend	0.6578	0.3374	0.1638	0.2513	0.6224

Table 13 reports the CER performance gains derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results are segmented into high and low government spending environments. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 14 CER Performance - Unconstrained

CER Performance - Unconstrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low GDP Spend	4.4906	1.4269	2.4294	2.8222	4.3172
High GDP Spend	7.2146	2.1203	4.0553	4.6797	7.0635

Table 14 reports the CER performance gains derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results are segmented into high and low government spending environments. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 15 Sharpe Performance - Constrained

Sharpe Performance - Constrained					
All Assets					
	Mean	Sdev	5%	10%	Med
Low GDP Spend	0.1474	0.0678	0.0363	0.0592	0.1467
High GDP Spend	0.0851	0.0691	-0.0226	-0.0072	0.0893

Table 15

reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results are segmented into high and low government spending environments. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 16 Sharpe Performance - Unconstrained

Sharpe Performance - Unconstrained

All Assets					
	Mean	Sdev	5%	10%	Med
Low GDP Spend	0.3916	0.0812	0.2469	0.2792	0.3882
High GDP Spend	0.4718	0.0959	0.2971	0.3353	0.4695

Table 16 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results are segmented into high and low government spending environments. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 17 Portfolio Weights Low GDP Spend

Portfolio Weights Low GDP Spend	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Equities				
FTSE All Share Total Return Index (Benchmark)	0.0043	0.0361	-1.1954	2.2502
FTSE USA	0.0020	0.0253	-3.0347	3.9946
MSCI Europe ex UK	0.0026	0.0278	-2.8701	1.9805
FTSE All World	0.0027	0.0248	7.2582	6.1474
Fixed Income				
ICE Bank of America UK Gilt Index (Benchmark)	0.0042	0.0392	0.9022	2.8152
ICE BofA US Treasury Bill	0.0000	0.0000	-12.6605	7.2869
Vanguard Long-Term Bond Index	0.0158	0.0808	-5.3246	4.7954
Vanguard Total Bond Market Index	0.0002	0.0060	37.9336	15.4140
Real Assets				
Alerian MLP Infrastructure	0.3636	0.3306	1.2245	0.7128
MSCI ACWI Infrastructure	0.0024	0.0242	1.7704	2.1162
MSCI USA Infrastructure	0.0005	0.0103	-2.7008	1.5559
AMP AIT Global Infrastructure	0.3266	0.3311	0.3682	0.9863
MainStay MacKay US Infrastructure	0.0000	0.0000	-21.2121	10.2831
UPAMC Infrastructure	0.1535	0.1838	0.1047	0.4108
Vanguard Real Estate Index	0.1209	0.2314	0.8039	0.8252

Table 17 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework during periods of low government spending. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the government spending was below the sample mean.

Table 18 Portfolio Weights High GDP Spend

Portfolio Weights High GDP Spend	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Equities				
FTSE All Share Total Return Index (Benchmark)	0.0024	0.0290	0.4463	2.7482
FTSE USA	0.1607	0.2605	8.3243	4.5725
MSCI Europe ex UK	0.0002	0.0059	-2.4260	2.4062
FTSE All World	0.0010	0.0305	-4.1600	7.3569
Fixed Income				
ICE Bank of America UK Gilt Index (Benchmark)	0.0278	0.1141	0.1014	3.4613
ICE BofA US Treasury Bill	0.0004	0.0139	-28.9562	8.4538
Vanguard Long-Term Bond Index	0.2371	0.2887	-8.0752	3.9755
Vanguard Total Bond Market Index	0.0242	0.1068	35.5174	13.4712
Real Assets				
Alerian MLP Infrastructure	0.1254	0.1979	-0.3121	0.6078
MSCI ACWI Infrastructure	0.0000	0.0001	-1.1074	4.3405
MSCI USA Infrastructure	0.0163	0.0844	-0.0083	2.5913
AMP AIT Global Infrastructure	0.0116	0.0593	-0.4388	0.9340
MainStay MacKay US Infrastructure	0.0233	0.1111	1.2124	6.5972
UPAMC Infrastructure	0.2446	0.2797	1.2626	0.8246
Vanguard Real Estate Index	0.1229	0.2136	-0.2794	0.7981

Table 18 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework during periods of high government spending. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where government spending rate was above the sample mean.

Table 19 CER Performance - Unconstrained

CER Performance - Unconstrained	Mean	Sdev	5%	10%	Med
High Interest Rates - Infrastructure Assets	2.5537	1.1010	0.9619	1.1862	2.4265
Low Interest Rates - Infrastructure Assets	1.9723	0.8719	0.7919	0.9713	1.8029
High Interest Rates - Expanded Benchmark	3.1869	1.2851	1.3730	1.6805	3.0115
Low Interest Rates - Expanded Benchmark	2.0045	0.9055	0.7641	0.9717	1.8783

Table 19 reports the CER performance gains derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results compare the performance of infrastructure assets against the expanded benchmark across high and low interest rate environments, partitioned by the mean 3-Month LIBOR. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 20 Sharpe Performance - Unconstrained

Sharpe Performance - Unconstrained					
	Mean	Sdev	5%	10%	Med
High Interest Rates - Infrastructure Assets	0.2825	0.0842	0.1340	0.1598	0.2817
Low Interest Rates - Infrastructure Assets	0.1648	0.0793	0.0724	0.0872	0.1590
High Interest Rates - Expanded Benchmark	0.2802	0.0878	0.1427	0.1741	0.2729
Low Interest Rates - Expanded Benchmark	0.1389	0.0753	0.0568	0.0696	0.1319

Table 20 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results compare the performance of infrastructure assets against the expanded benchmark across high and low interest rate environments, partitioned by the mean 3-Month LIBOR. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 21 CER Performance - Constrained

CER Performance - Constrained	Mean	Sdev	5%	10%	Med
High Interest Rates - Infrastructure Assets	0.6471	0.3784	0.0993	0.1784	0.6074
Low Interest Rates - Infrastructure Assets	0.6578	0.3374	0.1638	0.2513	0.6224
High Interest Rates - Expanded Benchmark	0.5517	0.3772	0.0431	0.0929	0.5125
Low Interest Rates - Expanded Benchmark	0.3934	0.2812	0.0156	0.0547	0.3527

Table 21 reports the CER performance gains derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results compare the performance of infrastructure assets against the expanded benchmark across high and low interest rate environments, partitioned by the mean 3-Month LIBOR. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 22 Sharpe Performance - Constrained

Sharpe Performance - Constrained	Mean	Sdev	5%	10%	Med
High Interest Rates - Infrastructure Assets	0.1622	0.0783	0.0185	0.0465	0.1612
Low Interest Rates - Infrastructure Assets	0.0773	0.0673	-0.0239	0.0000	0.0780
High Interest Rates - Expanded Benchmark	0.1213	0.0781	0.0047	0.0194	0.1130
Low Interest Rates - Expanded Benchmark	0.0265	0.0633	-0.0359	-0.0224	0.0171

Table 22 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results compare the performance of infrastructure assets against the expanded benchmark across high and low interest rate environments, partitioned by the mean 3-Month LIBOR. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 23 Portfolio Weights High Interest Rates - Infrastructure Assets

High Interest Rates - Infrastructure Assets	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0384	0.1392	-1.3040	2.9505
ICE Bank of America UK Gilt Index (Benchmark)	0.0024	0.0341	-1.6529	1.3820
Infrastructure				
Alerian MLP Infrastructure	0.6560	0.3275	1.9946	0.7524
MSCI ACWI Infrastructure	0.0102	0.0651	2.5353	1.6450
MSCI USA Infrastructure	0.0000	0.0009	-2.6933	1.3000
AMP AIT Global Infrastructure	0.1304	0.2331	0.4731	0.8197
MainStay MacKay US Infrastructure	0.0784	0.1951	0.8959	1.5383
UPAMC Infrastructure	0.0626	0.1300	-0.0289	0.3564

Table 23 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, specifically focusing on the Infrastructure Assets group during periods of high interest rates. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the 3-Month LIBOR was above the sample mean.

Table 24 Portfolio Weights High Interest Rates - Expanded Benchmark

High Interest Rates - Expanded Benchmark	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0410	0.1447	0.2429	3.1097
ICE Bank of America UK Gilt Index (Benchmark)	0.0004	0.0088	-1.6010	2.1392
FTSE All World (Benchmark)	0.0003	0.0084	-0.3536	2.4982
Vanguard Total Bond Market Index (Benchmark)	0.0604	0.1676	25.7498	12.8880
Infrastructure				
Alerian MLP Infrastructure	0.6523	0.3295	1.9143	0.8006
MSCI ACWI Infrastructure	0.0073	0.0524	2.6713	1.7709
MSCI USA Infrastructure	0.0000	0.0001	-3.3082	1.3468
AMP AIT Global Infrastructure	0.1237	0.2196	0.0522	0.8999
MainStay MacKay US Infrastructure	0.0305	0.1238	-23.7405	12.3762
UPAMC Infrastructure	0.0698	0.1313	-0.0870	0.3993

Table 24 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, specifically focusing on the Expanded Benchmark group during periods of high interest rates. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the 3-Month LIBOR was above the sample mean.

Table 25 Portfolio Weights Low Interest Rates - Infrastructure Assets

Low Interest Rates - Infrastructure Assets	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0149	0.0686	2.5072	1.8138
ICE Bank of America UK Gilt Index (Benchmark)	0.0286	0.1154	2.6637	1.4210
Infrastructure				
Alerian MLP Infrastructure	0.0811	0.1599	-0.1011	0.4903
MSCI ACWI Infrastructure	0.0000	0.0000	-5.9050	2.8375
MSCI USA Infrastructure	0.1104	0.2136	4.1638	1.9057
AMP AIT Global Infrastructure	0.0716	0.1743	0.1471	0.8294
MainStay MacKay US Infrastructure	0.0058	0.0459	0.0886	1.5102
UPAMC Infrastructure	0.6872	0.3018	1.2832	0.5795

Table 25 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, focusing on the Infrastructure Assets group during periods of low interest rates. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the 3-Month LIBOR was below the sample mean.

Table 26 Portfolio Weights Low Interest Rates - Expanded Benchmark

Low Interest Rates - Expanded Benchmark	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0155	0.0876	2.8678	2.0393
ICE Bank of America UK Gilt Index (Benchmark)	0.0061	0.0536	0.1567	2.0622
FTSE All World (Benchmark)	0.1110	0.2356	4.7114	2.3643
Vanguard Total Bond Market Index (Benchmark)	0.0106	0.0623	6.5586	5.8840
Infrastructure				
Alerian MLP Infrastructure	0.0870	0.1679	-0.0270	0.4905
MSCI ACWI Infrastructure	0.0000	0.0000	-6.8052	3.0457
MSCI USA Infrastructure	0.0928	0.1990	3.7131	2.0306
AMP AIT Global Infrastructure	0.0430	0.1330	-0.3389	0.8521
MainStay MacKay US Infrastructure	0.0001	0.0034	-6.5039	5.4588
UPAMC Infrastructure	0.6339	0.3295	0.6618	0.6423

Table 26 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, specifically focusing on the Expanded Benchmark group during periods of low interest rates. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the 3-month LIBOR was below the sample mean.

Table 27 CER Performance - Unconstrained

CER Performance - Unconstrained	Mean	Sdev	10%	Med
High Inflation Rates - Infrastructure Assets	1.7466	0.8331	0.7562	1.6141
Low Inflation Rates - Infrastructure Assets	1.5793	0.7956	0.6810	1.4422
High Inflation Rates - Expanded Benchmark	1.8559	0.8492	0.8610	1.7557
Low Inflation Rates - Expanded Benchmark	2.2119	0.9889	1.0416	2.0987

Table 27 reports the CER performance gains derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results compare the performance of infrastructure assets against the expanded benchmark across high and low inflation environments, partitioned by the mean ONS CPI. Statistics provided include the posterior mean, standard deviation, 10th percentile, and the median.

Table 28 Sharpe Performance - Unconstrained

Sharpe Performance - Unconstrained	Mean	Sdev	10%	Med
High Inflation Rates - Infrastructure Assets	0.1895	0.0784	0.0944	0.1864
Low Inflation Rates - Infrastructure Assets	0.1719	0.0777	0.0837	0.1651
High Inflation Rates - Expanded Benchmark	0.1732	0.0751	0.0899	0.1629
Low Inflation Rates - Expanded Benchmark	0.1788	0.0802	0.0937	0.1713

Table 28 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results compare the performance of infrastructure assets against the expanded benchmark across high and low inflation environments, partitioned by the mean ONS CPI. Statistics provided include the posterior mean, standard deviation, 10th percentile, and the median.

Table 29 CER Performance - Constrained

CER Performance - Constrained	Mean	Sdev	5%	10%	Med
High Inflation Rates - Infrastructure Assets	0.6364	0.3279	0.1617	0.2276	0.599
Low Inflation Rates - Infrastructure Assets	0.475	0.3328	0.0255	0.0797	0.4211
High Inflation Rates - Expanded Benchmark	0.5426	0.3199	0.0813	0.1533	0.4905
Low Inflation Rates - Expanded Benchmark	0.3729	0.2933	0.0076	0.0428	0.3143

Table 29 reports the CER performance gains derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results compare the performance of infrastructure assets against the expanded benchmark across high and low inflation environments, partitioned by the mean ONS CPI. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 30 Sharpe Performance - Constrained

Sharpe Performance - Constrained	Mean	Sdev	5%	10%	Med
High Inflation Rates - Infrastructure Assets	0.1160	0.0688	0.0112	0.0296	0.1129
Low Inflation Rates - Infrastructure Assets	0.0583	0.0673	-0.0399	-0.0236	0.0493
High Inflation Rates - Expanded Benchmark	0.0854	0.0705	0.0015	0.0124	0.0759
Low Inflation Rates - Expanded Benchmark	0.0410	0.0632	-0.0344	-0.0166	0.0309

Table 30 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results compare the performance of infrastructure assets against the expanded benchmark across high and low inflation environments, partitioned by the mean ONS CPI. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 31 High Inflation Rates - Infrastructure Assets

High Inflation Rates - Infrastructure Assets	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0192	0.0884	3.0248	2.1906
ICE Bank of America UK Gilt Index (Benchmark)	0.0169	0.0848	-0.7083	1.4902
Infrastructure				
Alerian MLP Infrastructure	0.4497	0.3230	1.7174	0.7677
MSCI ACWI Infrastructure	0.0144	0.0778	1.1884	2.4643
MSCI USA Infrastructure	0.0591	0.1648	-0.3936	1.6340
AMP AIT Global Infrastructure	0.0470	0.1426	-0.2919	0.6877
MainStay MacKay US Infrastructure	0.0272	0.1107	-0.7002	1.6060
UPAMC Infrastructure	0.3656	0.2904	0.6983	0.4851

Table 31 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, focusing on the Infrastructure Assets group during periods of high inflation. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the ONS CPI was above the sample mean.

Table 32 High Inflation Rates - Expanded Benchmark

High Inflation Rates - Expanded Benchmark	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0253	0.1026	2.2576	2.4066
ICE Bank of America UK Gilt Index (Benchmark)	0.0118	0.0702	-0.9125	2.2214
FTSE All World (Benchmark)	0.0126	0.0699	0.0592	2.3991
Vanguard Total Bond Market Index (Benchmark)	0.0276	0.1044	11.7773	10.0832
Infrastructure				
Alerian MLP Infrastructure	0.4580	0.3252	1.6104	0.8064
MSCI ACWI Infrastructure	0.0109	0.0624	1.4150	2.6060
MSCI USA Infrastructure	0.0417	0.1269	-0.7341	1.6604
AMP AIT Global Infrastructure	0.0441	0.1235	-0.2924	0.7262
MainStay MacKay US Infrastructure	0.0044	0.0514	-11.8007	9.5320
UPAMC Infrastructure	0.3637	0.2997	0.6812	0.5188

Table 32 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, specifically focusing on the Expanded Benchmark group during periods of high inflation. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the ONS CPI was above the sample mean.

Table 33 Low Inflation Rates - Infrastructure Assets

Low Inflation Rates - Infrastructure Assets	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.1387	0.2437	2.5534	2.0949
ICE Bank of America UK Gilt Index (Benchmark)	0.0072	0.0609	-0.2615	1.2264
Infrastructure				
Alerian MLP Infrastructure	0.1482	0.2246	0.1727	0.4689
MSCI ACWI Infrastructure	0.0020	0.0254	-0.8537	1.6323
MSCI USA Infrastructure	0.0035	0.0414	-0.4444	1.1877
AMP AIT Global Infrastructure	0.4742	0.3440	1.5949	0.9269
MainStay MacKay US Infrastructure	0.0748	0.1915	0.1417	1.4367
UPAMC Infrastructure	0.1463	0.1960	0.3722	0.3794

Table 33 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, focusing on the Infrastructure Assets group during periods of low inflation. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the ONS CPI was below the sample mean.

Table 34 Low Inflation Rates - Expanded Benchmark

Low Inflation Rates - Expanded Benchmark	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.1120	0.2295	2.8362	2.2891
ICE Bank of America UK Gilt Index (Benchmark)	0.0018	0.0249	-2.9549	1.9564
FTSE All World (Benchmark)	0.0270	0.1063	4.5635	2.2540
Vanguard Total Bond Market Index (Benchmark)	0.0967	0.2134	8.2587	5.8863
Infrastructure				
Alerian MLP Infrastructure	0.1568	0.2313	0.3831	0.5015
MSCI ACWI Infrastructure	0.0010	0.0214	-1.6925	1.7863
MSCI USA Infrastructure	0.0014	0.0213	-1.2993	1.2793
AMP AIT Global Infrastructure	0.4514	0.3455	1.1813	0.9490
MainStay MacKay US Infrastructure	0.0078	0.0575	-8.0882	5.4268
UPAMC Infrastructure	0.1415	0.1928	-0.0935	0.4350

Table 34 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, specifically focusing on the Expanded Benchmark group during periods of low inflation. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where the ONS CPI was below the sample mean.

Table 35 CER Performance - Unconstrained

CER Performance - Unconstrained	Mean	Sdev	10%	Med
High Gov Spending - Infrastructure Assets	2.0050	0.9711	0.8870	1.8709
Low Gov Spending - Infrastructure Assets	1.9878	0.8842	0.9605	1.8800
High Gov Spending - Expanded Benchmark	2.1398	1.0064	1.0097	1.9649
Low Gov Spending - Expanded Benchmark	2.7810	1.0610	1.4925	2.6732

Table 35 reports the CER performance gains derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results compare the performance of infrastructure assets against the expanded benchmark across high and low government spending environments, partitioned by the mean UK Government Total Expenditure. Statistics provided include the posterior mean, standard deviation, 10th percentile, and the median.

Table 36 Sharpe Performance - Unconstrained

Sharpe Performance - Unconstrained	Mean	Sdev	10%	Med
High Gov Spending - Infrastructure Assets	0.1961	0.0847	0.0990	0.1871
Low Gov Spending - Infrastructure Assets	0.2278	0.0761	0.1297	0.2216
High Gov Spending - Expanded Benchmark	0.1651	0.0856	0.0838	0.1561
Low Gov Spending - Expanded Benchmark	0.2522	0.0765	0.1563	0.2473

Table 36 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework on an unconstrained basis, permitting both short-selling and gearing. The results compare the performance of infrastructure assets against the expanded benchmark across high and low government spending environments, partitioned by the mean UK Government Total Expenditure. Statistics provided include the posterior mean, standard deviation, 10th percentile, and the median.

Table 37 CER Performance - Constrained

CER Performance - Constrained	Mean	Sdev	5%	10%	Med
High Gov Spending - Infrastructure Assets	0.5402	0.3531	0.0542	0.1269	0.482
Low Gov Spending - Infrastructure Assets	0.6584	0.2914	0.1936	0.2843	0.6397
High Gov Spending - Expanded Benchmark	0.3211	0.3045	0.0002	0.0136	0.2353
Low Gov Spending - Expanded Benchmark	0.5936	0.2749	0.1637	0.2558	0.5721

Table 37 reports the CER performance gains derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results compare the performance of infrastructure assets against the expanded benchmark across high and low government spending environments, partitioned by the mean UK Government Total Expenditure. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 38 Sharpe Performance - Constrained

Sharpe Performance - Constrained	Mean	Sdev	5%	10%	Med
High Gov Spending - Infrastructure Assets	0.0743	0.0651	-0.0288	-0.0044	0.0661
Low Gov Spending - Infrastructure Assets	0.1418	0.0713	0.0248	0.0479	0.1413
High Gov Spending - Expanded Benchmark	0.0276	0.0664	-0.0330	-0.0177	0.0194
Low Gov Spending - Expanded Benchmark	0.1241	0.0692	0.0166	0.0403	0.1210

Table 38 reports the risk-adjusted performance gains using the Sharpe ratio derived from the Bayesian mean–variance framework under constrained conditions, where short-selling and gearing are prohibited. The results compare the performance of infrastructure assets against the expanded benchmark across high and low government spending environments, partitioned by the mean UK Government Total Expenditure. Statistics provided include the posterior mean, standard deviation, 5th and 10th percentiles, and the median.

Table 39 Portfolio Weights High Gov Spending - Infrastructure Assets

High Gov Spending - Infrastructure Assets	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0848	0.1981	2.8006	2.0164
ICE Bank of America UK Gilt Index (Benchmark)	0.0158	0.0799	1.7405	1.5081
Infrastructure				
Alerian MLP Infrastructure	0.1592	0.2204	0.2966	0.4749
MSCI ACWI Infrastructure	0.0015	0.0293	-4.4762	2.8730
MSCI USA Infrastructure	0.0779	0.1910	1.8586	1.8119
AMP AIT Global Infrastructure	0.0372	0.1294	0.0724	0.7326
MainStay MacKay US Infrastructure	0.2254	0.2918	1.8666	1.6086
UPAMC Infrastructure	0.3958	0.3184	0.8655	0.5934

Table 39 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, focusing on the Infrastructure Assets group during periods of high government spending. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where UK Government Total Expenditure was above the sample mean.

Table 40 Portfolio Weights High Gov Spending - Expanded Benchmark

High Gov Spending - Expanded Benchmark	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0769	0.1956	3.4164	2.2928
ICE Bank of America UK Gilt Index (Benchmark)	0.0019	0.0246	-1.0101	2.2742
FTSE All World (Benchmark)	0.0531	0.1513	5.0095	2.7031
Vanguard Total Bond Market Index (Benchmark)	0.2038	0.2910	2.4008	6.1995
Infrastructure				
Alerian MLP Infrastructure	0.1652	0.2258	0.4303	0.4939
MSCI ACWI Infrastructure	0.0005	0.0129	-6.0060	3.0336
MSCI USA Infrastructure	0.0441	0.1428	1.7922	1.8715
AMP AIT Global Infrastructure	0.0244	0.0920	-0.4916	0.7934
MainStay MacKay US Infrastructure	0.0591	0.1891	-1.0749	5.6432
UPAMC Infrastructure	0.3696	0.3213	0.3375	0.6549

Table 40 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, specifically focusing on the Expanded Benchmark group during periods of high government spending. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where UK Government Total Expenditure was above the sample mean.

Table 41 Portfolio Weights Low Gov Spending - Infrastructure Assets

Low Gov Spending - Infrastructure Assets	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0117	0.0654	1.6488	2.1755
ICE Bank of America UK Gilt Index (Benchmark)	0.0092	0.0697	-0.5456	1.2254
Infrastructure				
Alerian MLP Infrastructure	0.4111	0.3442	1.3240	0.6866
MSCI ACWI Infrastructure	0.0043	0.0398	0.7133	1.5566
MSCI USA Infrastructure	0.0011	0.0172	-1.2490	1.1696
AMP AIT Global Infrastructure	0.3993	0.3481	1.5626	0.8755
MainStay MacKay US Infrastructure	0.0036	0.0399	-1.1803	1.4470
UPAMC Infrastructure	0.1583	0.1912	0.3440	0.3454

Table 41 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, focusing on the Infrastructure Assets group during periods of low government spending. The Constrained column represents allocations where short-selling and gearing are prohibited, whereas the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where UK Government Total Expenditure was below the sample mean.

Table 42 Portfolio Weights Low Gov Spending - Expanded Benchmark

Low Gov Spending - Expanded Benchmark	Assets Constrained		Assets Unconstrained	
	Mean	Sdev	Mean	Sdev
Benchmark				
FTSE All Share Total Return Index (Benchmark)	0.0127	0.0819	2.3858	2.2997
ICE Bank of America UK Gilt Index (Benchmark)	0.0052	0.0454	-1.4360	1.9062
FTSE All World (Benchmark)	0.0076	0.0597	1.1158	2.1593
Vanguard Total Bond Market Index (Benchmark)	0.0027	0.0225	24.8076	9.8718
Infrastructure				
Alerian MLP Infrastructure	0.4214	0.3395	1.3291	0.7048
MSCI ACWI Infrastructure	0.0047	0.0430	0.6607	1.6815
MSCI USA Infrastructure	0.0005	0.0083	-2.1188	1.2670
AMP AIT Global Infrastructure	0.3876	0.3353	1.1396	0.8969
MainStay MacKay US Infrastructure	0.0000	0.0000	-24.9873	9.4455
UPAMC Infrastructure	0.1569	0.1947	0.1080	0.3933

Table 42 reports the posterior mean and standard deviation of optimal portfolio weights derived from the Bayesian mean–variance framework, specifically focusing on the Expanded Benchmark group during periods of low government spending. The Constrained column represents allocations where short-selling and gearing are prohibited, while the Unconstrained column permits leveraging and short positions. All weights are calculated using monthly excess returns in British pounds for data periods where UK Government Total Expenditure was below the sample mean.

Chapter 3

1. An Empirical Analysis of UK Open-Ended and Closed-Ended Infrastructure Funds

The previous chapters have shown that investors can achieve benefits through diversification into infrastructure assets and that this remains persistent when expanding the benchmark to include international assets. I also find that this benefit remains persistent with the introduction of gearing and short selling constraints. In addition, in the previous Chapter 2, I have shown that these benefits remain present in various macroeconomic states such as high and low-interest rate environments, during high and low periods of inflation and in high and low periods of government spending. My observed diversification benefit from adding infrastructure assets into investors portfolio was anticipated due to the long-term, inflation-linked, stable and predictable nature of the cash flows, which tend to be agnostic to the wider business and economic cycles (Gatti, 2008). In this chapter, I aim to examine if this benefit remains persistent when expanding the analysis to UK OEF and CEF relative to different benchmarks. Again, I test this under the same various macroeconomic states from Chapter 2. The earlier analysis in Chapters 1 and 2 utilises a more theoretical approach, whereas this chapter draws on real-world fund performance data to provide practical insights into the tangible benefits and applications of infrastructure investment.

2. Open-end and Closed-end funds

The rise in infrastructure investment and motivations for investors accessing the asset class has already been outlined in Chapters 1 & 2. This chapter aims to develop upon this further by not only testing the inherent benefits of infrastructure investments, such as inflation protection and low correlation with traditional asset classes, but also to gain a deeper understanding of the differences between OEFs and CEFs. The structural differences between OEFs and CEFs result in markedly different exposures to infrastructure assets. CEFs, with their very stable capital

base, are able to invest directly in long-term infrastructure projects. In contrast, OEFs, due to their need to maintain liquidity for investor redemptions, primarily hold liquid, publicly traded securities linked to the infrastructure sector. To give a simplistic example of the difference between the two, OEFs will tend to hold large liquid listed equity assets like telecoms equities or National Grid Plc for example, whereas, CEFs will hold much more specific illiquid investments such as specific roads or windfarms. This distinction is critical for investors, as the choice of fund structure significantly influences both the nature of infrastructure exposure and the potential return profile.

Parwada and Siaw (2014) find that institutional investors use US CEFs to gain exposure to segments of the market the institutions typically cannot access directly. Infrastructure assets are accessible to retail investors through both CEFs and OEFs. Kammoun and Tandja (2020) analyse the performance of U.S. infrastructure-focused equity mutual funds and report that these funds deliver significantly superior average performance when evaluated using the Best Clientele (BC) measure developed by Chretien and Kammoun (2017). Most funds in their sample exhibit positive performance, with around 10% achieving statistically significant outperformance. Moreover, infrastructure funds, on average, generate higher Best Clientele alpha than the broader universe of U.S. equity mutual funds.

Further complementing this, Carlo et al. (2023) show that larger public pension funds, as well as those with greater allocations to other alternative assets, are more inclined to invest in infrastructure. Their findings highlight infrastructure as one of the top-performing asset classes in terms of net returns, with evidence of performance persistence over a one-year horizon. In this chapter, given the growth and importance of Infrastructure assets and their perceived advantages, I examine the performance benefits of U.K. Infrastructure CEF and OEF relative to traditional asset classes motivated by the growing prominence and perceived advantages of infrastructure investments. The analysis spans between July 2007 to September 2021, which is

then further segmented into the distinct high and low macroeconomic states, as per the methodology discussed in Chapter 2. The states being; high and low inflation, high and low interest rates and high and low periods of government spending. The focus on both fund types is driven by two main reasons: first, to capture the full breadth of the Morningstar infrastructure fund universe; and second, to assess whether structural differences between CEFs and OEFs lead to variations in performance. As previously outlined, the stable capital base of CEFs enables direct investment in long-term infrastructure projects, while OEFs, constrained by liquidity requirements, hold listed securities. These structural distinctions have important implications for the nature of infrastructure exposure and the resulting investment outcomes.

In this chapter, I evaluate the performance of UK infrastructure OEFs and CEFs relative to traditional asset classes using a time-series regression analysis of monthly excess returns. To measure risk-adjusted performance, I employ Jensen's alpha, a metric derived from the Capital Asset Pricing Model (CAPM) to capture the portion of a fund's return not explained by systematic risk Jensen (1968). A positive and statistically significant alpha indicates that a fund has outperformed its expected return, suggesting the presence of manager skill or access to unique investment opportunities. Two benchmark universes that are considered are:

- (1) U.K. Gilts and the FTSE U.K. All-Share Index, and
- (2) U.K. Gilts and the FTSE U.K. All-Share Index and FTSE U.S. equities.

Given that this chapter is focusing more on real world data, I chose to expand the domestic UK benchmark using U.S. equities as they tend to dominate global benchmarks with weightings typically in excess of 50%, therefore, its inclusion I believe is therefore more reflective of actual investors decision making.

There are four main findings. First, summary statistics show that CEF and OEF portfolios exhibit low volatility and low correlations with benchmark assets, reinforcing the diversification potential that was shown in Chapter 1 and 2. Second, the regression results

indicate that several CEFs deliver statistically significant positive alphas, particularly under certain macroeconomic regimes, while OEFs generally exhibit smaller and less significant alphas. Third, benchmark exposures differ across fund types. What I have found is that CEFs tend to display stronger sensitivity to U.K. equities, whereas OEFs show broader exposure to both U.K. and U.S. markets. Finally, performance dispersion across individual funds can be very wide, especially among CEFs, underscoring the importance of fund selection.

The findings in this chapter are consistent with the findings in Chapter 1 and Chapter 2 and are expected due to the inherent characteristics of infrastructure investments which tend to have stable, inflation-linked cash flows and are often agnostic to economic and business cycles. This study provides further evidence that the structural differences between CEFs and OEFs can further shape investor outcomes. As mentioned, CEFs, with their stable capital base, can invest in illiquid, long-term projects, potentially capturing illiquidity premium, whereas OEFs need to prioritise liquidity and hold listed securities, resulting in more diversified but less direct infrastructure exposure. My analysis has backed up this expected finding that the fund structure can have a significant impact on investor outcomes.

3. *Research Method*

This chapter evaluates the performance of U.K. infrastructure OEF and CEFs relative to more traditional asset classes using a time-series regression analysis of monthly excess returns. The objective is to assess whether these funds provide incremental diversification benefits and whether or not these performance advantages or abnormal returns remain persistent under different macroeconomic conditions.

Empirical Framework

I estimate the following regression for each fund and for equal-weighted CEF and OEF portfolios.

Model 1: Domestic Benchmark This model assesses fund performance relative to the primary U.K. asset classes, specifically U.K. government bonds and the domestic equity market.

$$r_{\{i,t\}} = \alpha_i + \beta_{\{i,\{Gilt\}\}} r_t^{\{\{Gilt\}\}} + \beta_{\{i,\{UK\}\}} r_t^{\{\{UK\}\}} + \varepsilon_{\{i,t\}}$$

Model 2: Expanded Benchmark This model expands upon the domestic universe by adding U.S. equity exposure. This reflects the global nature of many infrastructure mandates and is chosen due to the dominance of U.S. equities in international benchmarks.

$$r_{\{i,t\}} = \alpha_i + \beta_{\{i,\{Gilt\}\}} r_t^{\{\{Gilt\}\}} + \beta_{\{i,\{UK\}\}} r_t^{\{\{UK\}\}} + \beta_{\{i,\{US\}\}} r_t^{\{\{US\}\}} + \varepsilon_{\{i,t\}}$$

Where:

- $r_{\{i,t\}}$ = excess return of fund i at time t
- $r_t^{\{\{Gilt\}\}}$ = excess return on U.K. Gilts
- $r_t^{\{\{UK\}\}}$ = excess return on FTSE U.K. All-Share Index
- $r_t^{\{\{US\}\}}$ = excess return on FTSE U.S. Index
- α_i = Jensen's alpha
- β = factor loadings
- $\varepsilon_{\{i,t\}}$ = error term
- $\alpha_i = 0$ Null hypothesis

I report estimates of α_i , factor loadings (β), t-statistics, and adjusted R^2 . Regressions are implemented in Excel using ordinary least squares. Standard errors are those produced by OLS and do not adjust for heteroskedasticity or autocorrelation. This is a known limitation of the analysis, as monthly return data may exhibit these properties. Jensen's alpha (α_i) is a widely

used measure of risk-adjusted performance derived from the Capital Asset Pricing Model (CAPM) and multifactor models. It represents the intercept of a fund's excess return regression on one or more benchmark factors and captures the portion of a fund's return that is not explained by its exposure to systematic risk. A positive and statistically significant alpha indicates that a fund has outperformed its expected return given its risk profile, suggesting the presence of manager skill or access to unique investment opportunities. Conversely, a negative alpha implies underperformance relative to the benchmark-adjusted expectation. In this chapter, Jensen's alpha is used to assess whether infrastructure funds deliver abnormal returns beyond what would be predicted by their exposure to traditional asset classes, thereby providing insight into their potential value as diversifying investments.

Two benchmark sets are used:

1. **Domestic:** U.K. Gilts and FTSE U.K. All-Share Index.
2. **Expanded:** U.K. Gilts, FTSE U.K. All-Share Index, and FTSE U.S. equities.

The interpretation of results focuses on three aspects. First, I consider the sign and statistical significance of estimated alphas, as positive alpha indicates outperformance relative to the chosen benchmarks. Second, I examine the explanatory power of the models and the magnitude of factor impacts, as low sensitivity to benchmark assets suggests potential diversification benefits. Finally, I assess whether these patterns remain stable across the different macroeconomic regimes.

To compare the distributional properties of alpha and beta exposures between OEFs and CEFs, I conducted F-tests for equality of variances and t-tests for equality of means for each parameter. The F-test is used to assess whether the variance of each parameter differs significantly between the two fund types, while the t-test (assuming unequal variances) evaluates whether the mean values differ. These tests are performed to compare alpha, beta to UK Gilts, beta to UK All-Share, and beta to US Equities. The results of these tests inform

whether differences in performance and risk exposures between OEFs and CEFs are statistically significant, and guide the interpretation of subsequent regression results.

4. Data

Sample of Funds

My dataset comprises both U.K.-based OEFs and CEFs focused on infrastructure investments, covering the period from July 2007 to September 2021. For CEFs, I have included all funds categorised under Morningstar's Infrastructure Direct classification, selecting the primary share class and incorporating funds that have since closed. Monthly stock return data for these CEFs is primarily sourced from the LSPD maintained by the London Business School, with Morningstar used as a supplementary source when necessary. Data is excluded when less than six months of fund data is available.

For OEFs, I focus on U.K. funds listed under the Investment Association's Infrastructure category, again selecting the primary share class and including discontinued funds. Monthly Net Asset Value (NAV) returns for these funds are obtained from Morningstar Direct. My final sample includes 20 OEFs and 27 CEFs with at least partial monthly return data during the study period. To address incubation bias as identified by Evans (2010), I exclude any OEF returns recorded before the official inception date of each fund. The one-month U.K. Treasury Bill rate, sourced from LSPD and LSEG Datastream, serves as the risk-free benchmark.

The inclusion of both fund types allows me to assess how structural differences influence performance in the infrastructure fund sector. CEFs, unlike OEFs, are not subject to investor redemptions and can therefore hold less liquid assets without the pressure to sell during market downturns. Prior research supports this distinction, such as Elton et al. (2013) found superior performance in CEF bond funds compared to their OEF counterparts within the same fund asset class, while Giannetti and Kahraman (2018) reported that U.S. equity CEFs outperformed OEFs based on NAV returns.

To mitigate survivorship and look-ahead biases (Brown et al. (1992); Carhart et al. (2002), I construct equal-weighted portfolios for both fund types. Monthly portfolio returns are calculated as the average of all available fund returns for each month. This approach allows us to include funds with limited return histories. The use of equal-weighted portfolios is consistent with established practices in mutual fund performance research Ferson and Mo (2016) .

All returns are denominated in GBP and sourced from Morningstar Direct and London Share Price Database (LSPD). I construct equal-weighted portfolios of CEFs and OEFs each month. These portfolios provide an aggregate view of each fund type's performance and help capture their diversification properties. In addition to the full-sample analysis, I examine whether results vary across different macroeconomic environments. Following the approach in Chapter 2, the sample is segmented into high and low states for interest rates, inflation, and government spending using the mean splits of monthly indicators. For each regime, the regressions are re-estimated to assess whether performance and factor exposures change under different economic conditions. To balance fund inclusion against estimation reliability across macroeconomic sub-periods, a baseline observation threshold of three quarters ($N \geq 9$ monthly returns) was applied for the macroeconomic regime evaluation. This threshold accommodates the varying historical durations of different economic regimes without unnecessarily restricting cross-sectional coverage. Nonetheless, findings from shorter sub-sample horizons should be interpreted with appropriate caution due to reduced statistical power.

Benchmark Assets

In this chapter I use two benchmark asset sets including domestic UK equity, domestic UK bond and international equity indexes. The first benchmark universe includes a U.K. equity market index (U.K. Market), and domestic bond index (U.K. Gilts). The market index is formed using data from Morningstar. The domestic bond index is ICE Bank of America Sterling U.K. Gilts, also from Morningstar Direct. All of the data is in U.K. sterling. The

second benchmark universe includes the domestic assets and adds international equity exposure via the addition of the FTSE USA index (US) which I have taken from Morningstar Direct. The table below reports summary statistics of the fund portfolios and benchmark assets between July 2007 to September 2021. Tables 1 & 2 present the mean, standard deviation, minimum, and maximum monthly excess.

[See Tables 1-2]

4. Results

In this section, I will present the results of the multi-factor regression analysis conducted on the selected funds as detailed above. I will aim to comment on what I believe to be the relevant findings from each set of results separately.

Closed End Funds – UK Benchmark

In this section, I have analysed monthly excess returns for 27 CEFs against a passive domestic strategy comprising UK Gilts and the FTSE UK All-Share Index. As demonstrated in the results, six funds delivered significant positive alphas at the 5% level ($t > 1.96$), with values ranging from 0.55% to 0.81% per month. While no funds exhibited significant negative alphas at this threshold, it is important to observe performance at the 10% significance level ($t > 1.65$) to capture marginally significant trends. At this broader level of significance, several funds demonstrate a more pronounced, albeit borderline, departure from the passive benchmark. The importance of fund selection is further underscored by the wide dispersion in results; for instance, Infrastructure India (–1.09%) and Ecofin US Renewables (–1.40%) posted negative alphas, though these remained statistically insignificant. Equity exposure served as the primary driver of returns, with approximately half of the funds showing a strong positive sensitivity to the UK All-Share Index. Conversely, Gilt exposure was less consistent, with three funds showing significant positive sensitivity and three showing significant negative sensitivity.

Notably, the Adjusted R^2 values ranged from -0.42 to 0.44 . The presence of negative Adjusted R^2 values, such as the -0.42 observed here, indicating that additional factors are needed to fully explain the performance.

[See Table 3]

Open End Funds – UK Benchmarks

In this analysis, I examined the monthly excess returns for 20 OEFs against the domestic passive benchmarks of UK Gilts and the FTSE UK All-Share Index. Only one fund, VT Gravis Clean Energy Income, delivered a statistically significant positive alpha at the 5% level ($t > 1.96$), producing an alpha of approximately 0.93% per month. However, applying the 10% significance level ($t > 1.65$) provides a more nuanced view of performance. Several funds, including FP Foresight Global Real Infrastructure and FP Foresight UK Infrastructure, recorded positive alphas between 0.44% and 0.89%. While these did not meet the 5% threshold, they demonstrate marginal significance at the 10% level, suggesting potential outperformance relative to a passive strategy that warrants further observation. No fund in the sample exhibited a statistically significant negative alpha. While vehicles such as First Sentier Responsible Listed Infrastructure and Schroder Digital Infrastructure posted negative intercepts, these were economically small and statistically insignificant, rendering them largely meaningless in the context of benchmarking. Equity exposure was the dominant driver of returns across the OEF sector. Nearly all funds showed a positive sensitivity to this factor, with betas typically ranging between 0.34 and 0.86. This suggests that domestic equity market movements explain a substantial portion of performance variation for these funds. In contrast, UK Gilt exposure was mixed; significance was less consistent, and in several cases, the exposure was economically negligible or statistically insignificant. Adjusted R^2 values ranged from 0.15 to 0.72, indicating that while the two-factor model captures a large share of return variation for many funds, again, additional factors may be needed.

[See Table 4]

Comparison of Closed-End and Open-End Funds – UK Benchmark

The T and F statistical tests noted in the method section reveal notable differences in benchmark factor sensitivities between CEFs and OEFs, while alpha differences are less pronounced. CEFs exhibit a slightly higher mean monthly alpha (0.24%) compared to OEFs (0.18%), but this difference is not statistically significant ($t = 0.445$, $p = 0.659$). However, the variability in alpha is significantly greater for CEFs ($F = 2.84$, $p = 0.011$), where the F test reveals a significant difference in alpha variability,

For the benchmark comparison, OEFs maintain substantially higher sensitivity to UK Gilts, with a mean beta of 0.48 versus 0.11 for CEFs, a difference that is highly significant ($t = -3.96$, $p < 0.001$). Variance tests confirm greater dispersion among CEFs ($F = 2.57$, $p = 0.019$). Similarly, equity exposure is significantly higher for OEFs (mean beta = 0.59) compared to CEFs (0.29), supported by the t-test ($t = -2.99$, $p = 0.0045$). Again, CEFs display greater variability ($F = 2.38$, $p = 0.028$), reflecting a broader range of equity strategies.

OEFs exhibit more uniform and higher exposure to both UK Gilts and equities, whereas CEFs show greater variability across benchmark factors.

[See Table 5]

Open End Funds – Expanded Benchmark

In this section I have analysed monthly excess returns for 20 OEFs using the expanded benchmark which now includes US Equities. From this point onward, all of the analysis will use the expanded set of benchmark assets. As shown in the summary table, none of the funds delivered a statistically significant positive alpha at the 5% level, although a few, such as VT Gravis Clean Energy Income (0.50%) and FP Foresight Global Real Infrastructure (0.40%), posted economically positive alphas. Several funds, including Schroder Digital Infrastructure

and Macquarie Sustainable Global Listed Infrastructure, exhibited negative alphas, but these were not statistically significant.

Equity exposure was the dominant driver of returns. Most funds displayed strong sensitivity to UK and US Equities, with betas typically between 0.18 and 0.69. This suggests that domestic and US equity markets may explain a substantial portion of performance variation. In contrast, UK Gilt exposure was generally weaker and less consistent, with many funds showing small or insignificant coefficients, and in some cases even negative exposure. Adjusted R^2 values ranged from 0.18 to 0.79, indicating that the three-factor model explains a substantial share of return variation for most funds, though additional factors may still be needed.

[See Table 6]

Closed end Funds – Expanded benchmark

In this section I have analysed monthly excess returns for 27 infrastructure funds using the expanded benchmark. As shown in the summary table, below, there are five funds, being 3i Infrastructure, Bluefield Solar Income, Renewables Infrastructure Group, BBGI Global Infrastructure, and International Public Partnerships, that have delivered statistically significant positive alphas at the 5% level, with alphas of 0.55%–0.87% per month. One fund, Aquila Energy Efficiency Trust, showed a significant negative alpha of –0.08%. Several others posted negative intercepts that were economically meaningful but statistically insignificant, for example Infrastructure India (–1.50%) and Ecofin US Renewables (–1.28%). Again highlighting the importance of manager selection.

UK equities was the dominant driver of returns, with UK Gilt exposure being more mixed: US Equities captured meaningful variation for only a small subset of the funds. Adjusted R^2 values

ranged from -0.86 to 0.62 . Again, this suggests the model explains a substantial share of variation for a handful of funds, but additional factors may be needed.

[See Table 7]

Comparison of CEFs and OEFs with Expanded Benchmark Factors

The T and F statistical tests reveal notable differences in benchmark factor sensitivities between CEFs and OEFs, while alpha differences remain less pronounced. CEFs exhibit a slightly positive mean monthly alpha (0.10%) compared to a small negative alpha for OEFs (-0.13%), but this difference is not statistically significant ($t = 1.53$, $p = 0.135$). However, the variability in alpha is significantly greater for CEFs ($F = 5.25$, $p < 0.001$), indicating a broader dispersion of risk-adjusted performance among CEFs.

For factor exposures, OEFs maintain substantially higher sensitivity to UK Gilts, with a mean beta of 0.40 versus 0.05 for CEFs, a difference that is highly significant ($t = -4.36$, $p < 0.001$). Variance tests confirm greater dispersion among CEFs ($F = 2.17$, $p = 0.043$). Similarly, equity exposure to the FTSE All Share is significantly higher for OEFs (mean beta = 0.33) compared to CEFs (0.15), supported by the t-test ($t = -2.03$, $p = 0.049$). Again, CEFs display greater variability ($F = 2.47$, $p = 0.023$), reflecting a wider range of domestic equity strategies.

The inclusion of US equities as an additional benchmark factor reveals a similar pattern. OEFs exhibit a mean beta of 0.33 versus 0.17 for CEFs, a difference that is statistically significant ($t = -2.14$, $p = 0.039$). Variance tests show a pronounced difference ($F = 7.11$, $p < 0.001$), with CEFs demonstrating far greater dispersion in US equity exposure. This suggests that while OEFs maintain more uniform and higher exposure across all benchmark factors, CEFs exhibit considerable heterogeneity, particularly in global equity allocations. Overall, these findings underscore that OEFs are more consistently aligned with benchmark factors, whereas CEFs display greater variability in both alpha and factor sensitivities.

[See Table 8]

Closed end Funds – Government Spending High

In this case I analysed monthly excess returns for 26 CEFs, however, this time the data is segmented into high government spending, consistent with Chapter 2. As shown in the summary table, only one fund, BBGI Global Infrastructure, delivered a statistically significant positive alpha at the 5% level, with an alpha of approximately 0.64%. No fund exhibited a significant negative alpha, although several, such as Infrastructure India (–2.32%) and Ecofin US Renewables (–1.28%), had negative alphas that were economically meaningful but statistically insignificant.

UK equities was the most consistent driver of returns, with the likes of 3i Infrastructure and International Public Partnerships showing significant positive sensitivity. UK Gilt exposure was again mixed: US Equities is impactful for only a few funds, notably Aquila European Renewables and SDCL Energy Efficiency Income. Adjusted R^2 values ranged from –0.86 to 0.62, suggesting that while the three-factor model explains a reasonable share of variation for some funds, additional factors are needed.

[See Table 9]

Open end fund – Government spending high

In this section, I analyse the monthly excess returns for 20 OEFs segmented into periods of high government spending, consistent with Chapter 2. As shown in the summary table, none of the funds delivered a statistically significant positive alpha at the 5% level. However, several funds, such as VT Gravis Clean Energy Income ($\alpha = 0.50\%$, $t = 1.35$) and FP Foresight UK Infrastructure ($\alpha = 0.23\%$, $t = 0.99$), posted economically positive but statistically insignificant alphas. Conversely, two funds—Schroder Digital Infrastructure ($\alpha = -0.53\%$, $t = -2.03$) and Russell Global Listed Infrastructure ($\alpha = -0.41\%$, $t = -1.99$)—recorded statistically significant negative alphas at the 5% level, indicating underperformance relative to the benchmark.

Equity exposures were broadly influential across the sample. UK equity betas were positive and statistically significant for 17 of the 20 funds, with t-statistics frequently exceeding 2.0. US equity exposure was also a key driver, with 16 funds exhibiting statistically significant positive betas to the FTSE US Index. UK Gilt exposure was more mixed: 10 funds had statistically significant positive betas, while a few displayed weak or negative sensitivity. Adjusted R^2 values ranged from 0.18 to 0.79, suggesting that the three-factor model explains a substantial share of return variation for most OEFs during high government spending periods.

[See Table 10]

Comparison of CEFs and OEFs under High Government Spending Scenario

The T and F statistical tests reveal differences in benchmark factor sensitivities between CEFs and OEFs, while alpha differences remain statistically insignificant. CEFs exhibit a mean monthly alpha of -0.05% compared to -0.13% for OEFs, but this difference is not significant ($t = 0.48$, $p = 0.631$). However, the variability in alpha is substantially greater for CEFs ($F = 6.66$, $p < 0.001$), indicating a wider dispersion in risk-adjusted performance among closed-end structures.

For factor exposures, OEFs maintain markedly higher sensitivity to UK Gilts, with a mean beta of 0.41 versus 0.06 for CEFs, a difference that is significant ($t = -4.33$, $p < 0.001$). Variance tests suggest greater dispersion among CEFs ($F = 2.05$, $p \approx 0.056$), though this is marginally significant. Similarly, equity exposure to the FTSE All Share is significantly higher for OEFs (mean beta = 0.33) compared to CEFs (0.09), supported by the t-test ($t = -2.64$, $p = 0.011$). Again, CEFs display greater variability ($F = 2.39$, $p = 0.027$), reflecting a broader range of domestic equity strategies.

The inclusion of US equities as an additional benchmark factor reveals a different dynamic. OEFs exhibit a mean beta of 0.33 versus 0.24 for CEFs, but this difference is not statistically significant ($t = -1.22$, $p = 0.231$). However, variance tests show a pronounced difference ($F = 7.54$, $p < 0.001$), with CEFs demonstrating far greater dispersion in US equity exposure. This suggests that while OEFs maintain more uniform and higher exposure to UK benchmarks, CEFs exhibit considerable heterogeneity, particularly in global allocations.

Overall, these findings underscore that under conditions of high government spending, OEFs remain more consistently aligned with benchmark factors, whereas CEFs display greater variability in both alpha and factor sensitivities. This reinforces the importance of fund

structure and selection when constructing diversified portfolios in government spending driven environments.

[See Table 11]

Closed End Funds – Gov Spending low

I analysed monthly excess returns for 20 CEFs however, this time the data is segmented into low government spending. As shown in the summary table, four funds being 3i Infrastructure, Bluefield Solar Income, GCP Infrastructure, and Renewables Infrastructure Group, delivered statistically significant positive alphas at the 5% level, with alphas of 0.70%–1.44%. Aquila Energy Efficiency Trust exhibited a significant negative alpha of about –0.10% per month.

UK Equities was the dominant driver of returns. UK Gilt exposure was more mixed and less prevalent. US equity exposure mattered for only a few funds. Adjusted R^2 values ranged from –0.67 (US Solar Fund) to 0.79 (Aquila European Renewables), indicating that while the three-factor model captures a substantial share of variation for several strategies, additional factors may be required.

[See Table 12]

Open end fund – Government spending Low

In this section I analysed monthly excess returns for five funds; however, this time the data is segmented into low government spending, in the same way that it was done in Chapter 2. As shown in the summary table, only one fund, which is Nuveen Global Clean Infrastructure Impact, has a statistically significant positive alpha at the 5% level, with an alpha of 4.09% per month . No fund exhibited a significant negative alpha.

Again, UK equity was the main driver. UK equity impacts were positive and significant for Russell Global Listed Infrastructure, Schroder Digital Infrastructure, and WS Macquarie Global Infrastructure. US equity was significant for WS Macquarie only. UK Gilts showed one significant effect, a large negative impact for Nuveen while the other funds' gilt betas were not significant. Adjusted R^2 values ranged from 0.39 to 0.96, indicating the three-factor model explains most of the variation for some of the OEFs but may require additional factors for a complete explanation.

[See Table 13]

Comparison of CEFs and OEFs under Low Government Spending Scenario

The T and F statistical tests reveal that differences in alpha and benchmark factor sensitivities between CEFs and OEFs are generally not statistically significant, although variability patterns remain noteworthy. CEFs exhibit a mean monthly alpha of 0.41% compared to 1.52% for OEFs, but this difference is not significant ($t = -1.29$, $p = 0.267$). Variance tests, however, indicate a pronounced difference in alpha variability ($F = 0.065$, $p < 0.001$), with OEFs showing much higher dispersion, suggesting less consistency in risk-adjusted performance under low government spending conditions.

For factor exposures, both fund types display negative sensitivity to UK Gilts, with CEFs averaging -0.08 and OEFs -0.79 . While the difference is economically large, it is not statistically significant ($t = 1.62$, $p = 0.165$). Variance tests ($F = 0.53$, $p \approx 0.153$) also fail to indicate a significant difference in dispersion. Equity exposure to the FTSE All Share is higher for OEFs (mean beta = 0.51) compared to CEFs (0.30), but again, the difference is not significant ($t = -0.91$, $p = 0.384$). Variance tests suggest some variability ($F = 2.08$, $p \approx 0.251$), though not at conventional significance levels.

US equity exposure shows a similar pattern. OEFs exhibit a mean beta of 0.17 versus 0.05 for CEFs, but this difference is not statistically significant ($t = -0.77$, $p = 0.470$). Variance differences are also insignificant ($F = 0.93$, $p \approx 0.394$). Overall, these results suggest that under low government spending conditions, neither fund structure demonstrates strong or consistent alignment with benchmark factors, and differences in factor sensitivities are muted.

In summary, while OEFs tend to exhibit higher average exposure to equity benchmarks and CEFs show slightly positive alpha, none of these differences are statistically significant. The most notable finding is the substantial variance in alpha for OEFs, indicating greater inconsistency in performance. These results highlight that macroeconomic conditions such

lower government spending may reduce the explanatory power of traditional benchmark factors, reinforcing the need for broader models and careful fund selection.

[See Table 14]

Closed End Fund – Inflation High

In this section I have analysed monthly excess returns for 20 CEFs; however, this time the data is segmented into periods of high inflation, consistent with the method of Chapter 2. I have analysed monthly excess returns for infrastructure and renewable energy funds using the same three-factor model applied earlier: UK Gilts, UK Equities, and US Equities. As shown in the summary table, no fund delivered a statistically significant alpha at the 5% level, although several alphas were economically meaningful but not statistically significant. Factor exposures were more relevant than alpha. UK Gilts were significant for 7 funds, with all exposures positive except for one minor negative case. UK Equities were significant for 9 funds, again predominantly positive, suggesting strong sensitivity to domestic equity markets. US Equities showed mixed results, with 6 funds exhibiting positive and 3 negative exposures, indicating varying degrees of global diversification. Adjusted R^2 values ranged from -0.86 to 0.62, highlighting that while the three-factor model explains a modest share of return variation for some strategies, additional factors may be required to capture the full dynamics of performance.

[See Table 15]

Open End Fund – Inflation High

In this section, I have analysed monthly excess returns for 20 OEFs segmented into periods of high inflation, applying the same three-factor model used previously: UK Gilts, UK Equities, and US Equities. As shown in the summary table, none of the funds delivered a statistically significant alpha at the 5% level, although a few exhibited economically meaningful alphas, such as ARC TIME UK Infrastructure and Lazard Global Listed Infrastructure, both positive but not significant. Factor exposures were more influential than alpha in explaining performance. UK Gilts were significant for 8 funds, with all exposures positive, indicating sensitivity to domestic fixed income markets. UK Equities showed strong relevance, with 12 funds displaying significant positive betas, suggesting a pronounced link to UK equity performance. US Equities were the most consistently significant factor, with 14 funds exhibiting positive exposures, highlighting global diversification benefits. Adjusted R^2 values ranged from 0.10 to 0.72, suggesting that while the three-factor model explains a moderate share of return variation for most strategies, additional factors may be necessary to fully capture performance dynamics.

[See Table 16]

Comparison of CEFs and OEFs during High Inflation Periods

The T and F statistical tests reveal that differences in alpha between CEFs and OEFs are economically small and statistically insignificant. CEFs exhibit a mean monthly alpha of 0.05% compared to -0.07% for OEFs, with the t-test confirming no significant difference ($t = 0.64$, $p = 0.523$). However, the variability in alpha is substantially greater for CEFs ($F = 7.16$, $p < 0.001$), indicating wider dispersion in risk-adjusted performance among closed-end structures during inflationary periods.

For factor exposures, OEFs maintain higher sensitivity to UK Gilts, with a mean beta of 0.29 versus 0.14 for CEFs. While this difference is economically meaningful, it is only marginally significant ($t = -1.83$, $p = 0.076$). Variance tests were not reported for this factor, but the observed spread suggests more consistent gilt exposure among OEFs. Equity exposure to the FTSE All Share is broadly similar across fund types, with CEFs averaging 0.21 and OEFs 0.28; the difference is not statistically significant ($t = -0.51$, $p = 0.613$). Variance tests ($F = 1.49$, $p \approx 0.188$) confirm no strong evidence of dispersion differences for this factor.

The inclusion of US equities reveals a bigger contrast. OEFs exhibit a mean beta of 0.33 compared to 0.05 for CEFs, a difference that is highly significant ($t = -3.58$, $p = 0.001$). Variance tests show a pronounced difference ($F = 7.17$, $p < 0.001$), with CEFs demonstrating far greater dispersion in US equity exposure. This suggests that while OEFs maintain more uniform and higher exposure to global equities during inflationary periods, CEFs exhibit considerable heterogeneity in international allocations.

Overall, these findings indicate that under high inflation conditions, OEFs remain more consistently aligned with benchmark factors, particularly global equities, whereas CEFs display greater variability in both alpha and factor sensitivities. This reinforces the importance of fund structure and selection when navigating high inflation market environments.

[See Table 17]

Closed End Funds – Inflation Low

In this section I have analysed monthly excess returns for 19 CEFs, however, this time the data is segmented into periods of low inflation, similarly to Chapter 2. As shown in the summary table, only one fund, VT Gravis Clean Energy Income, delivered a statistically significant positive alpha at the 5% level, while Schroder Digital Infrastructure showed the only significant negative alpha.

Gilt impact was widespread and positive: 11 funds had a significant sensitivity. UK equity exposure was also strong with nine funds exhibiting positive and significant relevance. US equity exposure was impactful for nine funds. Adjusted R^2 values ranged from 0.21 to 0.85, indicating the three-factor model explains a large share of return variation for many CEFs in this economic state.

[See Table 18]

Open End Fund – Inflation Low

In this section, I have analysed monthly excess returns for 19 OEFs during periods of low inflation, using the same three-factor model: UK Gilts, UK Equities, and US Equities. As shown in the summary table, no fund achieved a statistically significant alpha at the 5% level, although FP Foresight Global Real Infrastructure and VT Gravis Clean Energy Income displayed economically meaningful positive alphas. Factor exposures were again more influential than alpha. UK Gilts were significant for 11 funds, with most exposures positive, indicating sensitivity to domestic bond markets. UK Equities were significant for 13 funds, predominantly positive, suggesting strong alignment with UK equity performance. US Equities remained the most consistently significant factor, with 15 funds exhibiting positive exposures, reinforcing the role of global diversification. Adjusted R^2 values ranged from 0.20 to 0.85, indicating that the three-factor model explains a substantial share of return variation for most

strategies, though additional factors may still be required to capture residual performance dynamics.

[See Table 19]

Comparison of CEFs and OEFs during Low Inflation Periods

The T and F statistical tests reveal significant differences in alpha and benchmark factor sensitivities between CEFs and OEFs under low inflation conditions. CEFs exhibit a mean monthly alpha of 0.32% compared to -0.26% for OEFs, and this difference is statistically significant ($t = 2.91$, $p = 0.006$). Variance tests indicate no meaningful difference in alpha dispersion ($F = 1.09$, $p \approx 0.428$), suggesting similar variability in risk-adjusted performance across both fund structures.

For factor exposures, OEFs maintain substantially higher sensitivity to UK Gilts, with a mean beta of 0.53 versus -0.12 for CEFs, a difference that is highly significant ($t = -4.81$, $p < 0.001$). Variance tests ($F = 2.08$, $p \approx 0.062$) suggest marginal evidence of greater dispersion among CEFs. Equity exposure to the FTSE All Share is also significantly higher for OEFs (mean beta = 0.32) compared to CEFs (0.07), supported by the t-test ($t = -3.36$, $p = 0.002$). Variance differences are not statistically significant ($F = 1.49$, $p \approx 0.199$), indicating similar consistency in domestic equity exposure.

US equity exposure shows a different pattern. OEFs exhibit a mean beta of 0.36 versus 0.31 for CEFs, and this difference is not statistically significant ($t = -0.41$, $p = 0.683$). However, variance tests reveal a pronounced difference ($F = 10.20$, $p < 0.001$), with CEFs demonstrating far greater dispersion in US equity exposure. This suggests that while OEFs maintain more uniform exposure to global equities, CEFs exhibit considerable heterogeneity in international allocations during low inflation periods.

Overall, these findings indicate that under low inflation conditions, OEFs remain more consistently aligned with benchmark factors, particularly UK Gilts and domestic equities,

whereas CEFs display greater variability in global exposures. The significant alpha advantage for CEFs in this environment highlights the potential for active strategies to outperform when inflationary pressures are subdued.

[See Table 20]

Closed End Fund – Interest Rates High

In this section I have analysed monthly excess returns for 5 CEFs, however, this time the data is segmented into periods of high interest rates, in much the same way that it was done in Chapter 2. As shown in the summary table, no CEFs deliver a significant positive alpha at the 5% level, while Aquila Energy Efficiency Trust recorded a significant negative alpha of – 0.46%. Several alphas were positive but statistically insignificant, including 3i Infrastructure 1.31%, HICL 1.89%, and Infrastructure India 24.11%, however, the latter is affected by a very small data history of this fund trading within the study period in high interest rates.

UK equities was the dominant driver of returns with 3i Infrastructure, HICL, and International Public Partnerships all showed positive sensitivity to UK equities. UK Gilt exposure was mixed as Aquila Energy Efficiency Trust had a small but significant positive impact, while Infrastructure India exhibited a large significant negative impact. US equity exposure was largely muted in this case. Adjusted R^2 values ranged from 0.17 to 0.49, indicating the three-factor model explains a modest share of variation for these funds and that additional drivers may be required.

[See Table 21]

Open End Fund – Interest Rates High

Unusually, for this segment of data, there is only one OEF with data when the data is segmented into periods of low interest rates. Therefore, I analysed monthly excess returns for Macquarie Global Infrastructure. As shown in the summary table, the fund did not deliver a statistically significant alpha at the 5% level. UK equities exposure was the dominant driver, with

a positive and statistically significant impact. UK Gilt and US equity exposures were positive but not statistically significant. The Adjusted R^2 of 0.75 indicates the three-factor model explains a large share of the fund's return variation.

There are not sufficient data points such that I can run the comparison between CEF and OEF in the high-interest rate segment. It is notable that the UK infrastructure fund sector has minimal return history in high interest rate environments.

[See Table 22]

Closed End Funds – Interest Rates Low

In this section I analysed monthly excess returns for 27 CEFs however, this time the data is segmented into periods of low interest rates, consistent with how it was conducted in Chapter 2. As shown in the summary table below, five funds being 3i Infrastructure, Bluefield Solar Income, Renewables Infrastructure Group, BBGI Global Infrastructure, and International Public Partnerships have delivered statistically significant positive alphas at the 5% level, with alphas ranging from 0.60%–0.87%. Indicating that CEFs may perform well during low-interest rate environments, however, manager selection is still required. Aquila Energy Efficiency Trust has shown a small significant negative alpha of –0.04%, while other negative alphas were economically larger but statistically insignificant.

UK equities was the dominant driver of returns. Seven funds exhibited positive and significant sensitivity to UK equities. UK Gilt exposure was more mixed and less prevalent. US equity exposure mattered for only a small subset of funds. Adjusted R^2 values ranged from –0.86 (VH Global Sustainable Energy Opportunities) to 0.62 (Digital 9 Infrastructure), indicating that while the three-factor model explains a substantial share of variation for some CEFs but additional drivers are needed.

[See Table 23]

Open end Fund - Interest Rates Low

In this section I have analysed monthly excess returns for 20 OEFs, however, this time the data is segmented into periods of low interest rates, in the same way that it was done in Chapter 2. As shown in the summary table, no fund delivered a statistically significant positive alpha at the 5% level, however, three funds recorded significant negative alphas being Macquarie Global Listed Infrastructure, Nuveen Global Clean Infrastructure Impact, and Schroder Digital Infrastructure.

UK Gilt sensitivity was widely positive and significant for 13 funds. UK equities were significant for 12 funds, again predominantly positive. US Equities were broadly important as well with 13 funds being positive and significant. Adjusted R^2 values ranged from 0.18 to 0.79, indicating the three-factor model captures a large share of return variation for many of the OEFs in this macroeconomic state.

[See Table 24]

Comparison of CEFs and OEFs during Low-Interest Rate Periods

The T and F statistical tests show that alpha differences between CEFs and OEFs are economically small and statistically insignificant. CEFs exhibit a mean monthly alpha of 0.10% compared to -0.13% for OEFs, with the t-test confirming no significant difference ($t = 1.50$, $p = 0.143$). However, the variability in alpha is substantially greater for CEFs ($F = 5.61$, $p < 0.001$), indicating wider dispersion in risk-adjusted performance among closed-end structures during periods of low interest rates.

For factor exposures, OEFs maintain markedly higher sensitivity to UK Gilts, with a mean beta of 0.39 versus 0.07 for CEFs, a difference that is highly significant ($t = -4.31$, $p < 0.001$). Variance tests ($F = 1.84$, $p \approx 0.086$) suggest marginal evidence of greater dispersion among CEFs. Equity exposure to the FTSE All Share is also significantly higher for OEFs (mean beta

= 0.33) compared to CEFs (0.14), supported by the t-test ($t = -2.10$, $p = 0.041$). Variance differences are statistically significant ($F = 2.58$, $p \approx 0.019$), indicating more variability in domestic equity exposure among CEFs.

US equity exposure shows a similar pattern. OEFs exhibit a mean beta of 0.33 versus 0.19 for CEFs, and this difference is marginally significant ($t = -1.92$, $p = 0.062$). Variance tests reveal a pronounced difference ($F = 7.25$, $p < 0.001$), with CEFs demonstrating far greater dispersion in US equity exposure. This suggests that while OEFs maintain more uniform and higher exposure to global equities during low-interest rate periods, CEFs exhibit considerable heterogeneity in international allocations.

Overall, these findings indicate that under low-interest rate conditions, OEFs remain more consistently aligned with benchmark factors, particularly UK Gilts and domestic equities, whereas CEFs display greater variability in both alpha and factor sensitivities. This reinforces the importance of fund structure and selection when navigating environments characterised by low-interest rate environments.

[See Table 25]

5. Conclusion

This chapter has set out to determine whether the diversification benefits of infrastructure investments, initially established in Chapters 1 and 2, remain robust when applied to U.K. OEFs and CEFs, and whether these benefits persist across different macroeconomic environments. The analysis provides further evidence that infrastructure funds can enhance portfolio efficiency, but the extent of these benefits is highly dependent on fund structure, market conditions, and manager selection.

Several key findings have emerged in this chapter. First, both OEF and CEF portfolios exhibit low correlations with traditional equity and bond benchmarks, cementing their role as effective diversifiers. This characteristic holds across most macroeconomic states, reinforcing the point

that infrastructure exposure can provide stability during periods of market stress. This supports the broader characterisation of infrastructure as a strategic diversifier as proposed by Inderst (2010), who argued that the unique risk profile of the asset class provides a natural hedge against traditional market volatility.

Second, while full-sample tests show no statistically significant difference in average risk-adjusted returns between CEFs and OEFs, a number of individual CEFs performed very well and delivered statistically significant positive alphas, particularly in low-interest-rate and low-government-spending environments. In contrast, OEFs, while offering liquidity and broader diversification through listed securities, exhibit fewer instances of statistically significant outperformance and generally deliver more modest alpha. These findings align with the observations of Giannetti and Kahraman (2018), who noted that the closed-end structure can lead to superior risk-adjusted performance due to its ability to manage illiquid assets without the immediate pressure of investor redemptions. The fund structure, not just manager selection, can have a large impact on the return profile.

Third, the analysis highlights that macroeconomic conditions influence infrastructure performance outcomes. For example, CEFs appear to benefit disproportionately during low-interest-rate regimes, while OEFs show relatively stable but less pronounced performance across different states. Inflation and government spending periods also affect factor sensitivities, with equity market exposure remaining the dominant driver of returns for both fund types. This finding adds a practical layer to the work of Wilde, Whittaker, and Blanc-Brude (2017), who examined listed infrastructure through a mean-variance spanning lens. Whereas they often found that listed infrastructure fails to provide a distinct asset class benefit over traditional equities, my results suggest that the closed-ended vehicle is better suited to capturing a unique infrastructure premium that remains distinct from broader market factors. These results underscore the fact that infrastructure is not a homogeneous asset class

and its risk-return profile is shaped by fund design, the manager, and prevailing economic conditions.

Finally, performance dispersion across individual funds is wide, particularly among CEFs. This variability reflects differences in sectoral focus, geographic focus, and management quality, emphasising the importance of careful fund selection. This heterogeneity reinforces the arguments of Blanc-Brude et al. (2017), who suggest that the method of implementation is as critical as the asset allocation decision itself. While the majority of the results support the inclusion of infrastructure funds, especially the CEFs, in the portfolio of an investor seeking diversification and inflation protection, it is still important to emphasise the high level of heterogeneity and the potential for idiosyncratic risk.

In conclusion, this chapter reinforces that infrastructure funds offer meaningful portfolio benefits, but these benefits are neither uniform nor guaranteed. Structural differences between OEFs and CEFs, combined with macroeconomic dynamics and manager selection, play a critical role in shaping outcomes. Future research could extend this analysis by incorporating additional benchmarks, examining the impact of leverage, and exploring the dynamics of discounts and premiums which are particularly impactful for CEFs. Furthermore, exploring how regulatory changes and evolving investor inflows influence performance remains an interesting area for further study. For example, if increasing infrastructure popularity causes more money to flow into CEFs, however, there is only a limited set of physical infrastructure assets to invest into, does this dampen future return potential.

6. *Appendix A – Data Tables & Results*

Table 1 CEF Summary Statistics

Closed End Funds	Mean	Std Dev	Minimum	Maximum
3i Infrastructure Ord	0.8750	4.0675	-19.6915	13.3963
Aquila Energy Efficiency Trust Ord	-1.2954	5.2790	-12.4572	15.9660
Aquila European Renewables Ord	-0.5255	4.7268	-8.9600	16.3520
Bluefield Solar Income Fund	0.5068	3.0140	-8.0876	7.7142
Cordiant Digital Infrastructure Ord	-0.3505	6.4551	-16.5439	16.5594
Digital 9 Infrastructure Ord	-2.8000	12.2202	-35.0390	26.1662
Downing Renewables & Infrastructure Ord	-0.2887	3.8834	-10.4157	6.2453
Ecofin US Renewables Infrastructure Ord	-1.0882	5.5432	-17.3572	9.3642
Foresight Solar Ord	0.7013	5.6089	-10.0004	44.5561
GCP Infrastructure Investment Ord	0.3907	3.3669	-11.1247	10.2594
Gore Street Energy Storage Fund Ord	-0.0023	6.1219	-21.8341	26.4594
Greencoat Renewables	0.1296	3.8224	-10.6341	12.5594
Greencoat UK Wind	0.6188	3.2240	-8.7739	9.8593
Gresham House Energy Storage Ord	0.3469	10.9993	-47.2341	35.9660
HICL Infrastructure PLC Ord	0.4369	3.3847	-10.7171	16.2594
Infrastructure India Ord	-1.2402	29.5917	-88.3389	186.9371
NextEnergy Solar Ord	0.3497	3.9994	-13.6576	12.4645
Octopus Renewables Infrastructure Ord	-0.4059	4.2649	-14.8338	8.9367
Renewables Infrastructure Grp	0.3969	3.0945	-12.5439	10.0594
SDCL Energy Efficiency Income Ord	-0.0735	6.0863	-16.4572	18.9660
Sequoia Economic Infrastructure Inc Ord	0.2188	3.3125	-17.1576	7.3963
Triple Point Energy Transition Ord	-0.5210	6.2685	-14.4392	18.8572
US Solar Fund Ord	-0.8189	3.9486	-12.2557	8.7948
VH Glob Sustainable Energy Opp Ord	-0.4729	4.0475	-7.9441	12.3726
BBGI Global Infrastructure Ord	0.5079	2.9419	-8.9324	12.6694
Foresight Environmental Infra Ord	0.3541	3.4672	-13.2917	11.0577
International Public Partnerships Ord	0.4397	3.5888	-10.1101	19.2752

Table 1 provides a summary of the monthly return characteristics CEFs within the infrastructure sector. The statistics include the arithmetic mean return, standard deviation, and the minimum and maximum returns observed over the sample period. These figures highlight the significant variation in risk-return profiles across different sub-sectors, ranging from diversified global infrastructure (e.g., BBGI, HICL) to specialized digital and renewable energy storage assets, which exhibit notably higher levels of idiosyncratic volatility.

Table 2 OEF Summary Statistics

Open End Funds	Mean	Std Dev	Minimum	Maximum
ARC TIME UK Infrastructure Inc II C Acc	0.0431	2.8981	-10.4139	8.9794
Cohen & Steers Glb Lstd Infra I Acc USD	0.6564	3.4482	-9.2476	13.8874
First Sentier RespnB Lst Infra B GBP Acc	0.1478	3.4900	-7.5639	9.7126
First State Glbl Lstd Infrs A Acc EUR	0.6813	4.0333	-13.7471	14.7374
FP Foresight Global RI Infrs A GBP Acc	0.1719	4.5475	-14.0876	9.6748
FP Foresight UK Infrs Inc A GBP Acc	0.0704	2.7822	-9.7939	7.3494
GS Global Infrs Eq E Acc EUR	0.1610	3.4892	-9.5776	10.0226
L&G Global Infrastructure Index I Acc	0.4842	3.4634	-8.2976	11.4226
Lazard Global Lstd Infrs Eq BP Acc USD	0.3183	3.9038	-15.2176	9.4520
Legg Mason IF CB Glb Infrs Inc A Acc	0.7620	3.7284	-12.5976	7.6540
M&G Global Listed Infrs GBP A Acc	0.5203	3.9761	-16.5176	12.1548
Macquarie Sst Glbl Lstd Infra A EUR	0.4136	3.2440	-15.1576	11.5174
Nuveen Global Clean Infrs Imp C USD Acc	0.4657	3.4315	-15.8976	12.6074
PATRIZIA Low Carbon Cor InfREUR	0.0425	2.9891	-8.3439	7.1089
Premier Miton Global Infrs Inc B Acc	0.2717	3.4204	-13.4376	8.0148
Russell Inv Global List Infrs C EUR	0.4970	3.4363	-18.4076	12.3574
Schroder Digital Infrs A Acc GBP	0.2388	4.2550	-27.3176	12.0574
VT Gravis Clean Energy Income C GBP Acc	0.4382	3.9569	-12.5876	8.6748
VT Gravis UK Infrs Inc C EUR Hdg Acc	0.0795	2.8366	-8.9839	8.6274
VT RM Alternative Income Retail USD Acc	-0.0433	2.3315	-5.8602	4.8461
Wellington Enduring Assets USD DL Ac	0.1610	3.1121	-9.2776	6.0389
WS Macquarie Global Infrs Secs A Acc	0.4593	3.6942	-15.4576	10.0348

Table 2 presents the monthly return characteristics of the OEFs within the infrastructure assets in this study. These statistics, comprising the arithmetic mean, standard deviation, and the range of returns (minimum and maximum), reflect the performance of listed infrastructure securities, which typically offer different liquidity and valuation profiles compared to their closed-end counterparts.

Table 3. Closed End - Two Benchmarks

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Adjusted R ²
3i Infrastructure Ord	0.811%	2.730	0.013	0.088	0.389	5.512	0.144
Aquila Energy Efficiency Trust Ord	-0.081%	-7.179	-0.004	-0.700	0.008	3.159	0.050
Aquila European Renewables Ord	-0.058%	-0.097	0.512	1.865	0.287	2.336	0.174
Bluefield Solar Income Fund	0.723%	2.651	-0.320	-2.432	0.157	2.061	0.081
Cordiant Digital Infrastructure Ord	0.594%	0.375	0.492	0.777	0.481	0.747	-0.082
Digital 9 Infrastructure Ord	-0.599%	-0.218	1.491	1.345	1.747	1.337	0.378
Downing Renewables & Infrastructure Ord	1.051%	0.863	-0.076	-0.208	-0.401	-0.805	-0.182
Ecofin US Renewables Infrastructure Ord	-1.401%	-1.717	-0.491	-2.005	0.159	0.475	0.203
Foresight Solar Ord	0.242%	0.658	-0.094	-0.518	0.030	0.300	-0.013
GCP Infrastructure Investment Ord	0.324%	1.517	0.174	1.648	0.189	3.212	0.070
Gore Street Energy Storage Fund Ord	0.746%	1.272	-0.204	-0.700	-0.027	-0.201	-0.040
Greencoat Renewables	0.537%	1.188	0.248	1.070	-0.056	-0.513	-0.007
Greencoat UK Wind	0.549%	2.058	0.211	1.639	0.148	2.001	0.043
Gresham House Energy Storage Ord	0.647%	1.182	0.324	1.273	0.460	3.862	0.284
HICL Infrastructure PLC Ord	0.424%	1.848	0.259	2.250	0.246	4.505	0.114
Infrastructure India Ord	-1.094%	-0.522	-0.448	-0.439	1.349	2.695	0.035
NextEnergy Solar Ord	0.355%	1.122	-0.034	-0.230	0.303	3.480	0.104
Octopus Renewables Infrastructure Ord	0.326%	0.376	0.157	0.401	0.033	0.205	-0.100
Renewables Infrastructure Grp	0.692%	2.608	-0.170	-1.324	0.077	1.042	0.010
SDCL Energy Efficiency Income Ord	0.376%	0.745	0.160	0.684	0.567	5.184	0.438
Sequoia Economic Infrastructure Inc Ord	0.174%	0.617	0.395	2.878	0.474	6.327	0.366
Triple Point Energy Transition Ord	0.152%	0.103	-0.020	-0.041	0.101	0.320	-0.234
US Solar Fund Ord	-0.287%	-0.607	0.560	2.548	0.364	3.667	0.343
VH Global Sustainable Energy Opp Ord	-0.318%	-0.324	0.147	0.375	0.077	0.194	-0.419
BBGI Global Infrastructure Ord	0.723%	3.260	0.022	0.196	0.121	1.928	0.015
Foresight Environmental Infra Ord	0.407%	1.622	0.035	0.301	0.260	3.742	0.119
International Public Partnerships Ord	0.566%	2.267	-0.253	-2.024	0.328	5.527	0.169

Table 3 presents the results of a two-factor regression analysis for the CEF sample, using UK Gilts and UK Equities (FTSE All-Share) as the benchmarks. The table reports Jensen's Alpha, indicating the risk-adjusted excess return, alongside Beta coefficients that measure the sensitivity of each fund to interest rate movements (Gilts) and broader market volatility (Equities). The inclusion of t-statistics allows for the assessment of statistical significance, while the Adjusted R² values highlight the proportion of return variance explained by these two factors.

Table 4 Open End 2 Benchmarks

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Adjusted R ²
ARCTIME UK Infrastructure Inc II C Acc	0.401%	1.644	-0.007	-0.061	0.319	5.627	0.437
Cohen & Steers Glb Lstd Infra I Acc USD	0.334%	1.098	0.779	5.388	0.541	6.691	0.486
FP Foresight Global RI Infrs A GBP Acc	0.888%	1.560	0.945	3.608	0.614	5.239	0.554
FP Foresight UK Infrs Inc A GBP Acc	0.436%	1.903	0.127	1.093	0.368	6.852	0.506
First Sentier Respnb Lst Infra B GBP Acc	-0.465%	-0.455	0.153	0.374	1.191	2.869	0.555
GS Global Infrs Eq E Acc EUR	-0.017%	-0.058	0.743	4.752	0.608	8.035	0.580
L&G Global Infrastructure Index I Acc	0.456%	1.213	0.613	3.275	0.574	6.591	0.532
Lazard Global Lstd Infrs Eq BP Acc USD	0.127%	0.390	0.369	2.265	0.761	10.075	0.718
M&G Global Listed Infrs GBP A Acc	0.457%	1.326	0.659	3.719	0.854	10.519	0.709
Macquarie Sst Glbl Lstd Infra A EUR	-0.078%	-0.404	0.536	5.614	0.667	12.748	0.567
Nuveen Global Clean Infrs Imp C USD Acc	-0.006%	-0.028	0.637	6.072	0.695	11.888	0.570
PATRIZIA Low Carbon Cor InfREUR	0.119%	0.260	0.502	2.315	0.438	4.789	0.491
Premier Miton Global Infrs Inc B Acc	0.156%	0.511	0.705	4.408	0.663	8.796	0.617
Russell Inv Global List Infrs C EUR	-0.066%	-0.335	0.487	4.971	0.739	13.781	0.595
Schroder Digital Infrs A Acc GBP	-0.191%	-0.725	0.626	4.791	0.860	11.797	0.542
VT Gravis Clean Energy Income C GBP Acc	0.933%	2.409	0.380	1.929	0.523	5.793	0.418
VT Gravis UK Infrs Inc C EUR Hdg Acc	0.105%	0.424	0.389	3.312	0.346	5.317	0.349
VT RM Alternative Income Retail USD Acc	-0.058%	-0.172	0.240	1.437	-0.174	-2.255	0.154
WS Macquarie Global Infrs Secs A Acc	0.037%	0.215	0.363	4.247	0.751	18.499	0.672
Wellington Enduring Assets USD DL Ac	0.111%	0.234	0.345	1.611	0.537	5.981	0.660

Table 4 presents the results of a two-factor regression analysis for the OEF sample, using UK Gilts and UK Equities (FTSE All-Share) as the benchmarks. The table reports Jensen's Alpha, indicating the risk-adjusted excess return, alongside Beta coefficients that measure the sensitivity of each fund to interest rate movements (Gilts) and broader market volatility (Equities). The inclusion of t-statistics allows for the assessment of statistical significance, while the Adjusted R² values highlight the proportion of return variance explained by these two factors.

Table 5. Comparison of Closed-End and Open-End Funds – UK Benchmark

Alpha

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	Variable 2
Mean	0.002438	0.001841
Variance	3.3E-05	1.16E-05
Observations	27	20
Hypothesized Mean Difference	0	
df	43	
t Stat	0.445081	
P(T<=t) one-tail	0.329247	
t Critical one-tail	1.681071	
P(T<=t) two-tail	0.658494	
t Critical two-tail	2.016692	

Alpha

F-Test Two-Sample for Variances

	Variable 1	Variable 2
Mean	0.002438	0.001841
Variance	3.3E-05	1.16E-05
Observations	27	20
df	26	19
F	2.836778	
P(F<=f) one-tail	0.011161	
F Critical one-tail	2.097821	

Beta UK Gilts

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	Variable 2
Mean	0.114254	0.479483
Variance	0.150889	0.058653
Observations	27	20
Hypothesized Mean Difference	0	
df	44	
t Stat	-3.95654	
P(T<=t) one-tail	0.000137	
t Critical one-tail	1.68023	
P(T<=t) two-tail	0.000273	
t Critical two-tail	2.015368	

Beta UK Gilts

F-Test Two-Sample for Variances

	Variable 1	Variable 2
Mean	0.114254	0.479483
Variance	0.150889	0.058653
Observations	27	20
df	26	19
F	2.572587	
P(F<=f) one-tail	0.018741	
F Critical one-tail	2.097821	

Beta UK Equities

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	Variable 2
Mean	0.291624	0.593751
Variance	0.175844	0.073848
Observations	27	20
Hypothesized Mean Difference	0	
df	44	
t Stat	-2.99075	
P(T<=t) one-tail	0.002273	
t Critical one-tail	1.68023	
P(T<=t) two-tail	0.004546	
t Critical two-tail	2.015368	

Beta UK Equities

F-Test Two-Sample for Variances

	Variable 1	Variable 2
Mean	0.291624	0.593751
Variance	0.175844	0.073848
Observations	27	20
df	26	19
F	2.38117	
P(F<=f) one-tail	0.027632	
F Critical one-tail	2.097821	

Table 5 presents a comparative statistical analysis of the performance metrics between the CEF and OEF samples. The upper portion of the table utilizes a Two-Sample t-Test (assuming unequal variances) to determine if significant differences exist between the mean Alpha, Gilt Beta, and Equity Beta of the two groups. The lower portion employs an F-Test to compare the variances of these same parameters. These tests are to establish whether the observed differences in risk-adjusted returns and market sensitivities between closed-end and open-end structures are statistically significant or merely a result of sample volatility.

Table 6 Open End Funds – Expanded Benchmark

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
ARCTIME UK Infrastructure Inc II C Acc	0.244%	0.924	-0.045	-0.369	0.206	2.155	0.135	1.442	0.453
Cohen & Steers Glb Lstd Infra I Acc USD	-0.160%	-0.556	0.669	5.189	0.154	1.405	0.504	4.652	0.605
First Sentier Respnb Lst Infra B GBP Acc	-0.683%	-0.658	0.000	0.000	0.871	1.678	0.317	1.019	0.560
FP Foresight Global RI Infrs A GBP Acc	0.397%	0.656	0.739	2.694	0.272	1.250	0.436	1.834	0.594
FP Foresight UK Infrs Inc A GBP Acc	0.234%	0.994	0.083	0.741	0.215	2.553	0.192	2.304	0.552
GS Global Infrs Eq E Acc EUR	-0.378%	-1.333	0.653	4.640	0.287	2.720	0.420	3.931	0.669
L&G Global Infrastructure Index I Acc	-0.072%	-0.200	0.486	2.896	0.197	1.508	0.454	3.546	0.642
Lazard Global Lstd Infrs Eq BP Acc USD	0.032%	0.088	0.347	2.073	0.691	5.323	0.086	0.669	0.714
M&G Global Listed Infrs GBP A Acc	-0.019%	-0.061	0.569	3.744	0.489	4.433	0.473	4.243	0.790
Macquarie Sst Glbl Lstd Infra A EUR	-0.373%	-2.042	0.481	5.511	0.380	5.344	0.390	5.412	0.643
Nuveen Global Clean Infrs Imp C USD Acc	-0.395%	-1.981	0.538	5.707	0.343	4.352	0.471	5.897	0.664
PATRIZIA Low Carbon Cor InfREUR	-0.108%	-0.213	0.405	1.717	0.280	1.587	0.204	1.041	0.493
Premier Miton Global Infrs Inc B Acc	-0.218%	-0.770	0.621	4.380	0.339	3.269	0.426	4.053	0.706
Russell Inv Global List Infrs C EUR	-0.353%	-1.866	0.433	4.788	0.460	6.239	0.379	5.082	0.659
Schroder Digital Infrs A Acc GBP	-0.558%	-2.147	0.539	4.351	0.526	5.134	0.452	4.346	0.600
VT Gravis Clean Energy Income C GBP Acc	0.501%	1.352	0.295	1.655	0.181	1.392	0.441	3.367	0.531
VT Gravis UK Infrs Inc C EUR Hdg Acc	-0.133%	-0.528	0.329	2.873	0.154	1.624	0.253	2.689	0.406
VT RM Alternative Income Retail USD Acc	-0.263%	-0.725	0.192	1.142	-0.327	-2.515	0.186	1.449	0.179
Wellington Enduring Assets USD DL Ac	-0.086%	-0.156	0.284	1.220	0.426	2.416	0.142	0.733	0.650
WS Macquarie Global Infrs Secs A Acc	-0.169%	-1.031	0.289	3.581	0.498	8.070	0.324	5.170	0.715

Table 6 expands the performance analysis of the OEF sample by utilizing a three-factor regression model. In addition to the UK Gilts and UK Equities (FTSE All-Share) factors used previously, a third factor, US Equities is introduced. The table reports Jensen's Alpha, Beta coefficients for all three benchmarks, their respective t-statistics, and the Adjusted R².

Table 7 Closed End Funds – Expanded Benchmark

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
3i Infrastructure Ord	0.812%	2.646	0.014	0.090	0.391	3.382	-0.003	-0.023	0.138
Aquila Energy Efficiency Trust Ord	-0.082%	-7.076	-0.004	-0.779	0.007	1.516	0.002	0.522	0.046
Aquila European Renewables Ord	-0.887%	-1.595	0.163	0.649	-0.291	-1.456	0.736	3.373	0.424
Bluefield Solar Income Fund	0.874%	3.047	-0.275	-2.055	0.292	2.565	-0.179	-1.584	0.096
Cordiant Digital Infrastructure Ord	0.437%	0.241	0.383	0.505	0.252	0.277	0.228	0.418	-0.363
Digital 9 Infrastructure Ord	-1.409%	-0.644	0.921	0.997	0.713	0.604	1.132	1.720	0.624
Downing Renewables & Infrastructure Ord	0.677%	0.637	-0.334	-0.970	-1.097	-1.901	0.648	1.789	0.135
Ecofin US Renewables Infrastructure Ord	-1.284%	-1.472	-0.410	-1.451	0.377	0.796	-0.203	-0.684	0.125
Foresight Solar Ord	0.372%	0.953	-0.061	-0.332	0.147	0.950	-0.156	-0.997	-0.013
GCP Infrastructure Investment Ord	0.325%	1.429	0.174	1.630	0.190	2.132	-0.001	-0.008	0.062
Gore Street Energy Storage Fund Ord	0.303%	0.489	-0.306	-1.056	-0.352	-1.567	0.395	1.785	0.018
Greencoat Renewables	0.401%	0.826	0.216	0.917	-0.164	-0.933	0.139	0.786	-0.016
Greencoat UK Wind	0.456%	1.603	0.188	1.435	0.070	0.625	0.106	0.942	0.042
Gresham House Energy Storage Ord	0.499%	0.858	0.271	1.026	0.317	1.456	0.170	0.790	0.276
HICL Infrastructure PLC Ord	0.395%	1.666	0.248	2.121	0.210	2.352	0.046	0.504	0.110
Infrastructure India Ord	-1.496%	-0.687	-0.576	-0.554	0.912	1.129	0.568	0.691	0.032
NextEnergy Solar Ord	0.338%	0.987	-0.038	-0.252	0.290	2.172	0.018	0.132	0.094
Octopus Renewables Infrastructure Ord	0.933%	0.934	0.349	0.832	0.377	1.137	-0.437	-1.185	-0.076
Renewables Infrastructure Grp	0.800%	2.846	-0.137	-1.049	0.173	1.552	-0.127	-1.148	0.013
SDCL Energy Efficiency Income Ord	-0.236%	-0.460	-0.058	-0.253	0.119	0.615	0.558	2.688	0.535
Sequoia Economic Infrastructure Inc Ord	0.196%	0.651	0.401	2.839	0.494	4.206	-0.026	-0.220	0.358
Triple Point Energy Transition Ord	-0.517%	-0.376	-0.297	-0.637	-0.410	-1.003	0.803	1.730	0.012
US Solar Fund Ord	-0.407%	-0.769	0.513	2.146	0.275	1.413	0.111	0.536	0.324
VH Glob Sustainable Energy Opp Ord	-0.264%	-0.230	0.185	0.385	0.155	0.271	-0.077	-0.225	-0.860
BBGI Global Infrastructure Ord	0.598%	2.548	-0.013	-0.118	0.014	0.150	0.146	1.564	0.027
Foresight Environmental Infra Ord	0.352%	1.305	0.020	0.167	0.215	2.042	0.060	0.572	0.112
International Public Partnerships Ord	0.551%	2.133	-0.259	-2.031	0.309	3.177	0.025	0.248	0.165

Table 7 expands the performance analysis of the CEF sample by utilizing a three-factor regression model. In addition to the UK Gilts and UK Equities (FTSE All-Share) factors used previously, a third factor, US Equities is introduced. The table reports Jensen's Alpha, Beta coefficients for all three benchmarks, their respective t-statistics, and the Adjusted R².

Table 8 Comparison of CEFs and OEFs with Expanded Benchmark Factors

Alpha			UK Gilts			UK Equities			US Equities		
t-Test: Two-Sample Assuming Unequal Variance			t-Test: Two-Sample Assuming Unequal Variance			t-Test: Two-Sample Assuming Unequal Variance			t-Test: Two-Sample Assuming Unequal Variance		
	Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2
Mean	0.001014	-0.00128	Mean	0.047361	0.395277	Mean	0.147548	0.332199	Mean	0.17332	0.334252
Variance	4.84E-05	9.21E-06	Variance	0.10595	0.048827	Variance	0.14484	0.058598	Variance	0.128065	0.018022
Observations	27	20	Observations	27	20	Observations	27	20	Observations	27	20
Hypothesis	0		Hypothesis	0		Hypothesis	0		Hypothesis	0	
df	38		df	45		df	44		df	35	
t Stat	1.52855		t Stat	-4.36074		t Stat	-2.0275		t Stat	-2.1421	
P(T<=t) on two-tail	0.067329		P(T<=t) on two-tail	3.73E-05		P(T<=t) on two-tail	0.024348		P(T<=t) on two-tail	0.019611	
t Critical two-tail	1.685954		t Critical two-tail	1.679427		t Critical two-tail	1.68023		t Critical two-tail	1.689572	
P(T<=t) two-tail	0.134658		P(T<=t) two-tail	7.46E-05		P(T<=t) two-tail	0.048695		P(T<=t) two-tail	0.039221	
t Critical two-tail	2.024394		t Critical two-tail	2.014103		t Critical two-tail	2.015368		t Critical two-tail	2.030108	
Alpha			Beta UK Gilts			Beta UK Equities			Beta US Equities		
F-Test Two-Sample for Variances			F-Test Two-Sample for Variances			F-Test Two-Sample for Variances			F-Test Two-Sample for Variances		
	Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2
Mean	0.001014	-0.00128	Mean	0.047361	0.395277	Mean	0.147548	0.332199	Mean	0.17332	0.334252
Variance	4.84E-05	9.21E-06	Variance	0.10595	0.048827	Variance	0.14484	0.058598	Variance	0.128065	0.018022
Observations	27	20	Observations	27	20	Observations	27	20	Observations	27	20
df	26	19	df	26	19	df	26	19	df	26	19
F	5.251972		F	2.169934		F	2.471761		F	7.105836	
P(F<=f) on two-tail	0.00023		P(F<=f) on two-tail	0.042913		P(F<=f) on two-tail	0.022964		P(F<=f) on two-tail	2.5E-05	
F Critical two-tail	2.097821		F Critical two-tail	2.097821		F Critical two-tail	2.097821		F Critical two-tail	2.097821	

Table 8 provides a statistical comparison of the regression results from the three-factor asset pricing model for the CEF and OEF samples. The analysis utilizes Two-Sample t-Tests (assuming unequal variances) to evaluate whether the mean differences in Alpha and the Betas for UK Gilts, UK Equities, and US Equities are statistically significant between the two fund structures. Additionally, F-Tests are conducted to compare the variances of these estimators.

Table 9 Closed end Funds – Government Spending High

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
3i Infrastructure Ord	0.755%	1.868	-0.028	-0.141	0.428	2.900	-0.042	-0.269	0.145
Aquila European Renewables Ord	-0.754%	-1.182	-0.007	-0.027	-0.189	-0.892	0.644	2.732	0.417
Bluefield Solar Income Fund	0.270%	0.595	-0.215	-0.998	0.124	0.717	0.004	0.022	0.000
Cordiant Digital Infrastructure Ord	0.437%	0.241	0.383	0.505	0.252	0.277	0.228	0.418	-0.363
Digital 9 Infrastructure Ord	-1.409%	-0.644	0.921	0.997	0.713	0.604	1.132	1.720	0.624
Downing Renewables & Infrastructure Ord	0.677%	0.637	-0.334	-0.970	-1.097	-1.901	0.648	1.789	0.135
Ecofin US Renewables Infrastructure Ord	-1.284%	-1.472	-0.410	-1.451	0.377	0.796	-0.203	-0.684	0.125
Foresight Solar Ord	0.566%	1.100	-0.423	-1.692	0.194	0.965	-0.226	-1.041	0.031
GCP Infrastructure Investment Ord	0.055%	0.190	0.295	2.144	0.075	0.684	0.156	1.306	0.105
Gore Street Energy Storage Fund Ord	0.591%	0.722	-0.071	-0.207	-0.462	-1.702	0.417	1.379	0.012
Greencoat Renewables	-0.143%	-0.152	0.101	0.257	-0.320	-1.027	0.381	1.098	-0.062
Greencoat UK Wind	0.179%	0.419	0.259	1.316	0.059	0.367	0.032	0.184	-0.007
Gresham House Energy Storage Ord	0.677%	0.681	0.325	0.778	0.242	0.735	0.329	0.896	0.287
HIQL Infrastructure PLC Ord	0.422%	1.659	0.244	1.926	0.164	1.765	0.063	0.645	0.126
Infrastructure India Ord	-2.317%	-1.226	0.301	0.328	0.766	1.132	0.608	0.851	0.065
NextEnergy Solar Ord	-0.262%	-0.431	-0.088	-0.341	0.100	0.445	0.238	0.972	0.079
Octopus Renewables Infrastructure Ord	0.933%	0.934	0.349	0.832	0.377	1.137	-0.437	-1.185	-0.076
Renewables Infrastructure Grp	0.417%	1.018	-0.198	-1.017	0.092	0.586	-0.133	-0.789	-0.012
SDCL Energy Efficiency Income Ord	-0.385%	-0.516	-0.200	-0.637	0.040	0.163	0.729	2.640	0.602
Sequoia Economic Infrastructure Inc Ord	-0.333%	-0.499	0.251	0.767	0.224	0.907	0.368	1.372	0.374
Triple Point Energy Transition Ord	-0.517%	-0.376	-0.297	-0.637	-0.410	-1.003	0.803	1.730	0.012
US Solar Fund Ord	-0.532%	-0.750	0.532	1.786	0.211	0.897	0.224	0.853	0.378
VH Glob Sustainable Energy Opp Ord	-0.264%	-0.230	0.185	0.385	0.155	0.271	-0.077	-0.225	-0.860
BBGI Global Infrastructure Ord	0.639%	2.435	-0.051	-0.394	0.024	0.243	0.068	0.622	-0.015
Foresight Environmental Infra Ord	-0.201%	-0.502	0.123	0.704	-0.029	-0.200	0.276	1.713	0.130
International Public Partnerships Ord	0.590%	1.910	-0.305	-1.987	0.319	2.833	-0.030	-0.253	0.177

Table 9 presents the results of the three-factor regression analysis for the CEF sample specifically during periods of high government spending. By regressing CEF returns against UK Gilts, UK Equities, and US Equities during these regimes, the table identifies how increased public expenditure influences the Alpha and Beta sensitivities of infrastructure funds. Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Table 10 Open end Funds – Government Spending High

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
ARCTIME UK Infrastructure Inc II C Acc	0.244%	0.924	-0.045	-0.369	0.206	2.155	0.135	1.442	0.453
Cohen & Steers Glb Lstd Infra I Acc USD	-0.160%	-0.556	0.669	5.189	0.154	1.405	0.504	4.652	0.605
First Sentier Respnb Lst Infra B GBP Acc	-0.683%	-0.658	0.000	0.000	0.871	1.678	0.317	1.019	0.560
FP Foresight Global RI Infrs A GBP Acc	0.397%	0.656	0.739	2.694	0.272	1.250	0.436	1.834	0.594
FP Foresight UK Infrs Inc A GBP Acc	0.234%	0.994	0.083	0.741	0.215	2.553	0.192	2.304	0.552
GS Global Infrs Eq E Acc EUR	-0.378%	-1.333	0.653	4.640	0.287	2.720	0.420	3.931	0.669
L&G Global Infrastructure Index I Acc	-0.072%	-0.200	0.486	2.896	0.197	1.508	0.454	3.546	0.642
Lazard Global Lstd Infrs Eq BP Acc USD	0.032%	0.088	0.347	2.073	0.691	5.323	0.086	0.669	0.714
M&G Global Listed Infrs GBP A Acc	-0.019%	-0.061	0.569	3.744	0.489	4.433	0.473	4.243	0.790
Macquarie Sst Glbl Lstd Infra A EUR	-0.301%	-1.594	0.543	6.076	0.445	6.005	0.346	4.616	0.683
Nuveen Global Clean Infrs Imp C USD Acc	-0.318%	-1.557	0.586	6.046	0.350	4.351	0.447	5.512	0.658
PATRIZIA Low Carbon Cor InfREUR	-0.108%	-0.213	0.405	1.717	0.280	1.587	0.204	1.041	0.493
Premier Miton Global Infrs Inc B Acc	-0.218%	-0.770	0.621	4.380	0.339	3.269	0.426	4.053	0.706
Russell Inv Global List Infrs C EUR	-0.413%	-1.995	0.490	4.987	0.461	5.656	0.390	4.747	0.664
Schroder Digital Infrs A Acc GBP	-0.534%	-2.031	0.590	4.725	0.498	4.809	0.453	4.341	0.608
VT Gravis Clean Energy Income C GBP Acc	0.501%	1.352	0.295	1.655	0.181	1.392	0.441	3.367	0.531
VT Gravis UK Infrs Inc C EUR Hdg Acc	-0.133%	-0.528	0.329	2.873	0.154	1.624	0.253	2.689	0.406
VT RM Alternative Income Retail USD Acc	-0.263%	-0.725	0.192	1.142	-0.327	-2.515	0.186	1.449	0.179
Wellington Enduring Assets USD DL Ac	-0.086%	-0.156	0.284	1.220	0.426	2.416	0.142	0.733	0.650
WS Macquarie Global Infrs Secs A Acc	-0.248%	-1.294	0.442	4.864	0.502	6.670	0.351	4.615	0.695

Table 10 presents the results of the three-factor regression analysis for the OEF sample specifically during periods of high government spending. By regressing OEF returns against UK Gilts, UK Equities, and US Equities during periods of high government spending, the table shows how increased public expenditure influences the Alpha and Beta sensitivities of infrastructure funds. Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Table 11 Comparison of CEFs and OEFs under High Government Spending Scenario

Alpha	UK Gilts			UK Equities			US Equities				
t-Test: Two-Sample Assuming Unequal Variances	t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances				
	Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2			
Mean	-0.00046	-0.00126	Mean	0.063121	0.413832	Mean	0.093399	0.334548	Mean	0.238382	0.332797
Variance	5.98E-05	8.99E-06	Variance	0.104478	0.050907	Variance	0.140493	0.058685	Variance	0.132978	0.017633
Observations	26	20	Observations	26	20	Observations	26	20	Observations	26	20
Hypothesized Std. Dev.	0		Hypothesized Std. Dev.	0		Hypothesized Std. Dev.	0		Hypothesized Std. Dev.	0	
df	34		df	44		df	43		df	33	
t Stat	0.484393		t Stat	-4.32887		t Stat	-2.64094		t Stat	-1.21929	
P(T<=t) on the left	0.315607		P(T<=t) on the left	4.26E-05		P(T<=t) on the left	0.005739		P(T<=t) on the left	0.11569	
t Critical two-tail	1.690924		t Critical two-tail	1.68023		t Critical two-tail	1.681071		t Critical two-tail	1.69236	
P(T<=t) two-tail	0.631213		P(T<=t) two-tail	8.52E-05		P(T<=t) two-tail	0.011478		P(T<=t) two-tail	0.23138	
t Critical two-tail	2.032245		t Critical two-tail	2.015368		t Critical two-tail	2.016692		t Critical two-tail	2.034515	
Alpha	Beta UK Gilts			Beta UK Equities			Beta US Equities				
F-Test Two-Sample for Variances	F-Test Two-Sample for Variances			F-Test Two-Sample for Variances			F-Test Two-Sample for Variances				
	Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2
Mean	-0.00046	-0.00126	Mean	0.063121	0.413832	Mean	0.093399	0.334548	Mean	0.238382	0.332797
Variance	5.98E-05	8.99E-06	Variance	0.104478	0.050907	Variance	0.140493	0.058685	Variance	0.132978	0.017633
Observations	26	20	Observations	26	20	Observations	26	20	Observations	26	20
df	25	19	df	25	19	df	25	19	df	25	19
F	6.655759		F	2.052345		F	2.394027		F	7.541571	
P(F<=f) on the left	4.32E-05		P(F<=f) on the left	0.055973		P(F<=f) on the left	0.027489		P(F<=f) on the left	1.67E-05	
F Critical	2.105686		F Critical	2.105686		F Critical	2.105686		F Critical	2.105686	

Table 11 provides a comparative statistical analysis of the three-factor regression results for CEF and OEF samples during periods of high government spending. Using Two-Sample t-Tests (assuming unequal variances), the table evaluates the significance of differences in mean Alpha and Beta sensitivities (UK Gilts, UK Equities, and US Equities) between the two fund structures. Additionally, F-Tests compare the variances of these estimates. This comparison is vital for determining whether the fiscal environment of high government expenditure significantly alters the relative performance or risk-exposure profiles of CEFs compared to OEFs. Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Table 12 Closed End Funds – Gov Spending low

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
3i Infrastructure Ord	0.935%	2.142	0.118	0.560	0.261	1.347	0.098	0.588	0.052
Aquila Energy Efficiency Trust Ord	-0.099%	-4.551	-0.008	-0.724	0.006	0.594	0.005	0.613	-0.008
Aquila European Renewables Ord	-0.700%	-0.833	0.573	1.078	-1.121	-2.130	1.108	2.547	0.793
Bluefield Solar Income Fund	1.437%	4.171	-0.414	-2.634	0.482	3.123	-0.343	-2.665	0.251
Foresight Solar Ord	0.129%	0.223	0.492	1.869	-0.084	-0.324	-0.018	-0.084	0.014
GCP Infrastructure Investment Ord	0.704%	1.974	-0.043	-0.265	0.426	2.669	-0.229	-1.717	0.083
Gore Street Energy Storage Fund Ord	0.158%	0.166	-0.601	-1.143	0.280	0.604	0.149	0.439	0.075
Greencoat Renewables	0.675%	1.152	0.210	0.648	-0.161	-0.635	0.019	0.091	-0.069
Greencoat UK Wind	0.728%	1.939	0.082	0.480	0.178	1.058	0.177	1.266	0.097
Gresham House Energy Storage Ord	0.088%	0.240	0.148	0.814	0.516	2.266	-0.168	-1.192	0.286
HIIC Infrastructure PLC Ord	0.253%	0.477	0.242	0.948	0.443	1.885	0.011	0.053	0.074
Infrastructure India Ord	-0.133%	-0.022	-2.662	-0.974	2.220	0.828	0.284	0.127	-0.016
NextEnergy Solar Ord	0.711%	1.751	-0.070	-0.380	0.417	2.292	-0.110	-0.728	0.066
Renewables Infrastructure Grp	1.081%	2.803	-0.116	-0.658	0.328	1.898	-0.099	-0.684	0.031
SDCL Energy Efficiency Income Ord	0.282%	0.455	0.105	0.344	0.030	0.077	0.227	0.759	-0.053
Sequoia Economic Infrastructure Inc Ord	0.485%	1.768	0.407	3.254	0.563	4.582	-0.236	-2.298	0.380
US Solar Fund Ord	-0.007%	-0.007	0.239	0.407	0.222	0.352	-0.159	-0.360	-0.669
BBGI Global Infrastructure Ord	0.510%	1.158	0.028	0.137	0.068	0.345	0.241	1.464	0.042
Foresight Environmental Infra Ord	0.662%	1.905	-0.176	-1.113	0.540	3.472	-0.112	-0.860	0.221
International Public Partnerships Ord	0.354%	0.734	-0.148	-0.640	0.386	1.805	0.166	0.908	0.134

Table 12 presents the results of the three-factor regression analysis for the CEF sample during periods of low government spending. By regressing CEF returns against UK Gilts, UK Equities, and US Equities in this specific fiscal regime, the table highlights how a low government spending periods influences risk-adjusted excess returns (Alpha) and market sensitivities (Betas). Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Table 13 Open End Funds – Gov Spending low

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R²
Macquarie Sst Gbl Lstd Infra A EUR	-0.244%	-0.345	0.036	0.094	0.139	0.589	0.446	1.612	0.391
Nuveen Global Clean Infrs Imp CUSD Acc	4.092%	2.392	-2.025	-2.848	0.174	0.826	0.407	1.466	0.960
Russell Inv Global List Infrs CEUR	0.745%	1.600	-0.392	-1.533	0.558	3.604	0.041	0.224	0.744
Schroder Digital Infrs A Acc GBP	2.938%	1.444	-1.505	-1.474	1.152	2.346	-0.320	-0.518	0.639
WS Macquarie Global Infrs Secs A Acc	0.062%	0.196	-0.072	-0.447	0.506	4.794	0.286	2.626	0.763

Table 13 presents the results of the three-factor regression analysis for the OEF sample during periods of low government spending. By regressing OEF returns against UK Gilts, UK Equities, and US Equities in this specific fiscal regime, the table highlights low government expenditure influences risk-adjusted excess returns (Alpha) and market sensitivities (Betas). Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Table 14 Comparison of CEFs and OEFs under Low Government Spending Scenario

Alpha t-Test: Two-Sample Assuming Unequal Variances	UK Gilts t-Test: Two-Sample Assuming Unequal Variances	UK Equities t-Test: Two-Sample Assuming Unequal Variances	US Equities t-Test: Two-Sample Assuming Unequal Variances																																																																																																																																				
<table><tr><th></th><th>Variable 1</th><th>Variable 2</th></tr><tr><td>Mean</td><td>0.004126</td><td>0.015186</td></tr><tr><td>Variance</td><td>2.35E-05</td><td>0.000362</td></tr><tr><td>Observations</td><td>20</td><td>5</td></tr><tr><td>Hypothesized</td><td>0</td><td></td></tr><tr><td>df</td><td>4</td><td></td></tr><tr><td>t Stat</td><td>-1.29002</td><td></td></tr><tr><td>P(T<=t) on</td><td>0.133285</td><td></td></tr><tr><td>t Critical one-tail</td><td>2.131847</td><td></td></tr><tr><td>P(T<=t) two-tail</td><td>0.26657</td><td></td></tr><tr><td>t Critical two-tail</td><td>2.776445</td><td></td></tr></table>		Variable 1	Variable 2	Mean	0.004126	0.015186	Variance	2.35E-05	0.000362	Observations	20	5	Hypothesized	0		df	4		t Stat	-1.29002		P(T<=t) on	0.133285		t Critical one-tail	2.131847		P(T<=t) two-tail	0.26657		t Critical two-tail	2.776445		<table><tr><th></th><th>Variable 1</th><th>Variable 2</th></tr><tr><td>Mean</td><td>-0.07975</td><td>-0.7912</td></tr><tr><td>Variance</td><td>0.448085</td><td>0.848192</td></tr><tr><td>Observations</td><td>20</td><td>5</td></tr><tr><td>Hypothesized</td><td>0</td><td></td></tr><tr><td>df</td><td>5</td><td></td></tr><tr><td>t Stat</td><td>1.623471</td><td></td></tr><tr><td>P(T<=t) on</td><td>0.082708</td><td></td></tr><tr><td>t Critical one-tail</td><td>2.015048</td><td></td></tr><tr><td>P(T<=t) two-tail</td><td>0.165416</td><td></td></tr><tr><td>t Critical two-tail</td><td>2.570582</td><td></td></tr></table>		Variable 1	Variable 2	Mean	-0.07975	-0.7912	Variance	0.448085	0.848192	Observations	20	5	Hypothesized	0		df	5		t Stat	1.623471		P(T<=t) on	0.082708		t Critical one-tail	2.015048		P(T<=t) two-tail	0.165416		t Critical two-tail	2.570582		<table><tr><th></th><th>Variable 1</th><th>Variable 2</th></tr><tr><td>Mean</td><td>0.300013</td><td>0.505671</td></tr><tr><td>Variance</td><td>0.345528</td><td>0.166276</td></tr><tr><td>Observations</td><td>20</td><td>5</td></tr><tr><td>Hypothesized</td><td>0</td><td></td></tr><tr><td>df</td><td>9</td><td></td></tr><tr><td>t Stat</td><td>-0.91488</td><td></td></tr><tr><td>P(T<=t) on</td><td>0.192055</td><td></td></tr><tr><td>t Critical one-tail</td><td>1.833113</td><td></td></tr><tr><td>P(T<=t) two-tail</td><td>0.38411</td><td></td></tr><tr><td>t Critical two-tail</td><td>2.262157</td><td></td></tr></table>		Variable 1	Variable 2	Mean	0.300013	0.505671	Variance	0.345528	0.166276	Observations	20	5	Hypothesized	0		df	9		t Stat	-0.91488		P(T<=t) on	0.192055		t Critical one-tail	1.833113		P(T<=t) two-tail	0.38411		t Critical two-tail	2.262157		<table><tr><th></th><th>Variable 1</th><th>Variable 2</th></tr><tr><td>Mean</td><td>0.050576</td><td>0.17193</td></tr><tr><td>Variance</td><td>0.093192</td><td>0.100633</td></tr><tr><td>Observations</td><td>20</td><td>5</td></tr><tr><td>Hypothesized</td><td>0</td><td></td></tr><tr><td>df</td><td>6</td><td></td></tr><tr><td>t Stat</td><td>-0.77082</td><td></td></tr><tr><td>P(T<=t) on</td><td>0.235035</td><td></td></tr><tr><td>t Critical one-tail</td><td>1.94318</td><td></td></tr><tr><td>P(T<=t) two-tail</td><td>0.470071</td><td></td></tr><tr><td>t Critical two-tail</td><td>2.446912</td><td></td></tr></table>		Variable 1	Variable 2	Mean	0.050576	0.17193	Variance	0.093192	0.100633	Observations	20	5	Hypothesized	0		df	6		t Stat	-0.77082		P(T<=t) on	0.235035		t Critical one-tail	1.94318		P(T<=t) two-tail	0.470071		t Critical two-tail	2.446912	
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Table 14 provides a comparative statistical analysis of the three-factor regression results for CEF and OEF samples during periods of low government spending. Using Two-Sample t-Tests (assuming unequal variances), the table evaluates the significance of differences in mean Alpha and Beta sensitivities (UK Gilts, UK Equities, and US Equities) between the two fund structures. Additionally, F-Tests compare the variances of these estimates. This analysis is used for determining if there are structural differences between CEFs and OEFs. Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Table 15 Closed End Fund – Inflation High

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
3i Infrastructure Ord	0.788%	1.944	-0.066	-0.309	0.440	2.871	-0.131	-0.858	0.090
Aquila Energy Efficiency Trust Ord	-0.103%	-6.130	-0.009	-0.996	0.012	1.919	0.000	-0.013	0.069
Aquila European Renewables Ord	-0.478%	-0.354	0.219	0.501	-0.075	-0.103	0.104	0.227	-0.451
Bluefield Solar Income Fund	0.787%	1.942	-0.094	-0.427	0.303	1.575	-0.402	-2.652	0.106
Cordiant Digital Infrastructure Ord	0.437%	0.241	0.383	0.505	0.252	0.277	0.228	0.418	-0.363
Digital 9 Infrastructure Ord	-1.409%	-0.644	0.921	0.997	0.713	0.604	1.132	1.720	0.624
Downing Renewables & Infrastructure Ord	0.677%	0.637	-0.334	-0.970	-1.097	-1.901	0.648	1.789	0.135
Ecofin US Renewables Infrastructure Ord	-1.284%	-1.472	-0.410	-1.451	0.377	0.796	-0.203	-0.684	0.125
Foresight Solar Ord	0.892%	1.471	-0.127	-0.393	0.170	0.647	-0.266	-1.080	-0.026
GCP Infrastructure Investment Ord	0.433%	1.610	0.388	2.758	0.024	0.208	0.069	0.634	0.066
Gore Street Energy Storage Fund Ord	0.303%	0.332	0.346	0.824	0.028	0.061	0.259	0.897	-0.058
Greencoat Renewables	0.185%	0.349	0.565	2.158	-0.128	-0.554	0.238	1.320	0.132
Greencoat UK Wind	0.670%	1.600	0.519	2.316	0.038	0.201	-0.091	-0.572	0.062
Gresham House Energy Storage Ord	0.957%	1.602	0.173	0.797	0.756	1.780	-0.230	-1.026	0.105
HIQL Infrastructure PLC Ord	0.287%	0.969	0.338	2.151	0.257	2.296	0.006	0.053	0.120
Infrastructure India Ord	-3.190%	-2.060	-0.156	-0.199	1.266	2.205	-0.238	-0.418	0.060
NextEnergy Solar Ord	0.683%	2.005	0.448	2.566	0.168	1.091	-0.205	-1.645	0.157
Octopus Renewables Infrastructure Ord	-1.132%	-0.546	-0.079	-0.118	0.982	0.871	-0.262	-0.371	-0.363
Renewables Infrastructure Grp	0.513%	1.228	0.067	0.298	0.222	1.120	-0.185	-1.183	-0.036
SDCL Energy Efficiency Income Ord	0.145%	0.218	-0.216	-0.999	0.380	1.051	0.170	0.750	0.213
Sequoia Economic Infrastructure Inc Ord	0.440%	1.225	0.563	3.061	0.482	2.963	-0.174	-1.328	0.338
Triple Point Energy Transition Ord	-0.385%	-0.228	-0.445	-0.810	-1.138	-1.238	1.086	1.884	0.065
US Solar Fund Ord	0.260%	0.204	0.830	2.010	0.088	0.128	-0.080	-0.185	0.175
VH Glob Sustainable Energy Opp Ord	-0.264%	-0.231	0.185	0.385	0.155	0.271	-0.077	-0.225	-0.860
BBGI Global Infrastructure Ord	0.594%	1.896	-0.051	-0.303	0.194	1.446	0.034	0.279	0.030
Foresight Environmental Infra Ord	0.240%	0.496	0.230	0.930	0.308	1.408	-0.049	-0.276	0.017
International Public Partnerships Ord	0.433%	1.269	-0.305	-1.687	0.439	3.405	-0.095	-0.744	0.173

Table 15 presents the results of the three-factor regression analysis for the CEF sample specifically during periods of high inflation (defined as data periods where the ONS CPI was above the sample mean). By regressing CEF returns against UK Gilts, UK Equities, and US Equities, the table identifies how inflationary pressures influence risk-adjusted excess returns (Alpha) and market sensitivities (Betas). The inclusion of t-statistics and the Adjusted R² allows for an assessment of the statistical significance of these factors. Includes funds with a minimum baseline threshold of three quarters (N≥9 monthly returns) within the specified regime.

Table 16 Open End Fund – Inflation High

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
ARCTIME UK Infrastructure Inc II C Acc	0.421%	1.264	0.153	1.011	0.024	0.138	0.179	1.667	0.208
Cohen & Steers Glb Lstd Infra I Acc USD	0.105%	0.340	0.543	3.440	0.247	1.770	0.511	4.542	0.672
First Sentier Respnb Lst Infra B GBP Acc	-0.683%	-0.658	0.000	0.000	0.871	1.678	0.317	1.019	0.560
FP Foresight Global RI Infrs A GBP Acc	0.093%	0.089	0.442	1.299	-0.894	-1.568	0.616	1.724	0.383
FP Foresight UK Infrs Inc A GBP Acc	0.281%	0.865	0.167	1.060	0.099	0.693	0.194	1.848	0.254
GS Global Infrs Eq E Acc EUR	-0.265%	-0.821	0.418	2.535	0.322	2.208	0.442	3.760	0.618
L&G Global Infrastructure Index I Acc	0.433%	1.001	0.201	1.022	0.029	0.132	0.512	3.682	0.620
Lazard Global Lstd Infrs Eq BP Acc USD	0.467%	0.846	0.510	2.009	0.733	2.644	0.075	0.430	0.490
M&G Global Listed Infrs GBP A Acc	0.119%	0.395	0.260	1.732	0.353	2.818	0.324	3.271	0.668
Macquarie Sst Glbl Lstd Infra A EUR	-0.287%	-1.254	0.327	2.667	0.350	3.687	0.342	3.747	0.541
Nuveen Global Clean Infrs Imp C USD Acc	-0.362%	-1.651	0.373	3.219	0.372	3.948	0.433	4.899	0.678
PATRIZIA Low Carbon Cor InfREUR	-0.699%	-0.645	0.236	0.671	0.838	1.423	0.197	0.533	0.389
Premier Miton Global Infrs Inc B Acc	-0.307%	-0.821	0.438	2.248	0.362	2.216	0.400	3.004	0.552
Russell Inv Global List Infrs CEUR	-0.208%	-0.953	0.272	2.332	0.464	5.132	0.288	3.308	0.604
Schroder Digital Infrs A Acc GBP	-0.334%	-1.114	0.231	1.435	0.457	3.561	0.344	2.834	0.482
VT Gravis Clean Energy Income C GBP Acc	-0.231%	-0.492	0.290	1.260	-0.078	-0.403	0.423	2.769	0.286
VT Gravis UK Infrs Inc CEUR Hdg Acc	-0.036%	-0.110	0.419	2.483	0.301	2.020	0.125	1.039	0.343
VT RM Alternative Income Retail USD Acc	0.177%	0.464	0.025	0.146	-0.363	-1.933	0.215	1.815	0.098
Wellington Enduring Assets USD DL Ac	0.071%	0.079	0.301	1.036	0.501	1.031	0.368	1.208	0.538
WS Macquarie Global Infrs Secs A Acc	-0.121%	-0.644	0.119	1.195	0.514	7.227	0.266	3.762	0.721

Table 16 presents the results of the three-factor regression analysis for the OEF sample specifically during periods of high inflation (defined as data periods where the ONS CPI was above the sample mean). By regressing OEF returns against UK Gilts, UK Equities, and US Equities, the table identifies how inflationary pressures influence risk-adjusted excess returns (Alpha) and market sensitivities (Betas). The inclusion of t-statistics and the Adjusted R² allows for an assessment of the statistical significance of these factors. Includes funds with a minimum baseline threshold of three quarters (N≥9 monthly returns) within the specified regime.

Table 17 Comparison of CEFs and OEFs during High Inflation Periods

Alpha			UK Gilts			UK Equities			US Equities		
t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances		
	Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2
Mean	0.000548	-0.00068	Mean	0.143778	0.286265	Mean	0.207965	0.275053	Mean	0.047586	0.328552
Variance	8.28E-05	1.16E-05	Variance	0.13332	0.022709	Variance	0.24613	0.165438	Variance	0.140293	0.019579
Observations	27	20	Observations	27	20	Observations	27	20	Observations	27	20
Hypothesized Std. Dev.	0		Hypothesized Std. Dev.	0		Hypothesized Std. Dev.	0		Hypothesized Std. Dev.	0	
df	35		df	37		df	44		df	35	
t Stat	0.644794		t Stat	-1.82837		t Stat	-0.50877		t Stat	-3.5755	
P(T<=t) one-tail	0.261632		P(T<=t) one-tail	0.037783		P(T<=t) one-tail	0.306728		P(T<=t) one-tail	0.000522	
t Critical two-tail	1.689572		t Critical two-tail	1.687094		t Critical two-tail	1.68023		t Critical two-tail	1.689572	
P(T<=t) two-tail	0.523265		P(T<=t) two-tail	0.075565		P(T<=t) two-tail	0.613457		P(T<=t) two-tail	0.001045	
t Critical two-tail	2.030108		t Critical two-tail	2.026192		t Critical two-tail	2.015368		t Critical two-tail	2.030108	
Alpha			Beta UK Gilts			Beta UK Equities			Beta US Equities		
F-Test Two-Sample for Variances			F-Test Two-Sample for Variances			F-Test Two-Sample for Variances			F-Test Two-Sample for Variances		
	Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2
Mean	0.000548	-0.00068	Mean			Mean	0.207965	0.275053	Mean	0.047586	0.328552
Variance	8.28E-05	1.16E-05	Variance			Variance	0.24613	0.165438	Variance	0.140293	0.019579
Observations	27	20	Observations			Observations	27	20	Observations	27	20
df	26	19	df			df	26	19	df	26	19
F	7.157294		F			F	1.48775		F	7.165556	
P(F<=f) one-tail	2.36E-05		P(F<=f) one-tail			P(F<=f) one-tail	0.187824		P(F<=f) one-tail	2.34E-05	
F Critical one-tail	2.097821		F Critical one-tail			F Critical one-tail	2.097821		F Critical one-tail	2.097821	

Table 17 provides a comparative statistical analysis of the three-factor regression results for CEF and OEF samples during periods of high inflation. Using Two-Sample t-Tests (assuming unequal variances), the table evaluates the significance of differences in mean Alpha and Beta sensitivities (UK Gilts, UK Equities, and US Equities) between the two fund structures. Additionally, F-Tests are conducted to compare the variances of these estimators. Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Table 18 Closed End Funds – Inflation Low

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
3i Infrastructure Ord	0.560%	1.259	0.054	0.286	0.264	1.607	0.312	1.760	0.312
Aquila Energy Efficiency Trust Ord	-0.039%	-15.197	-0.001	-1.277	0.000	-0.230	0.001	0.792	-0.009
Aquila European Renewables Ord	-1.089%	-1.769	0.189	0.604	-0.469	-2.336	1.031	4.500	0.650
Bluefield Solar Income Fund	0.895%	2.199	-0.424	-2.452	0.183	1.216	0.018	0.110	0.137
Foresight Solar Ord	-0.351%	-0.727	-0.002	-0.010	0.048	0.270	0.023	0.120	-0.046
GCP Infrastructure Investment Ord	0.334%	0.861	-0.008	-0.050	0.304	2.118	-0.031	-0.202	0.123
Gore Street Energy Storage Fund Ord	0.799%	0.919	-0.988	-2.387	-0.579	-1.936	0.580	1.735	0.152
Greencoat Renewables	1.121%	1.231	-0.258	-0.595	-0.143	-0.457	0.012	0.035	-0.098
Greencoat UK Wind	0.340%	0.870	-0.027	-0.164	-0.054	-0.373	0.333	2.130	0.104
Gresham House Energy Storage Ord	-0.286%	-0.332	0.388	0.947	0.100	0.337	0.484	1.462	0.324
HICL Infrastructure PLC Ord	0.589%	1.404	0.082	0.458	0.108	0.699	0.137	0.818	0.052
Infrastructure India Ord	0.550%	0.098	-1.736	-0.725	0.203	0.098	2.209	0.982	0.011
NextEnergy Solar Ord	0.143%	0.277	-0.298	-1.412	0.161	0.839	0.262	1.268	0.173
Octopus Renewables Infrastructure Ord	1.602%	1.062	0.596	0.873	0.549	1.322	-0.672	-1.379	-0.073
Renewables Infrastructure Grp	1.072%	2.683	-0.286	-1.686	0.132	0.893	-0.086	-0.540	0.030
SDCL Energy Efficiency Income Ord	-0.699%	-1.002	0.158	0.476	0.017	0.071	0.729	2.723	0.576
Sequoia Economic Infrastructure Inc Ord	-0.028%	-0.058	0.272	1.287	0.379	2.111	0.156	0.810	0.370
US Solar Fund Ord	-0.286%	-0.409	0.285	0.816	0.205	0.896	0.201	0.793	0.309
BBGI Global Infrastructure Ord	0.435%	1.183	-0.019	-0.122	-0.138	-1.016	0.283	1.927	0.027
Foresight Environmental Infra Ord	0.435%	1.297	-0.124	-0.884	0.125	1.004	0.162	1.210	0.164
International Public Partnerships Ord	0.583%	1.562	-0.271	-1.712	0.042	0.307	0.280	1.881	0.176

Table 18 presents the results of the three-factor regression analysis for the CEF sample during periods of low inflation. By regressing CEF returns against UK Gilts, UK Equities, and US Equities in this specific macroeconomic regime (where ONS CPI was below the sample mean), the table highlights how a low-inflation environment influences risk-adjusted excess returns (Alpha) and market sensitivities (Betas). The inclusion of t-statistics and the Adjusted R² allows for a rigorous assessment of fund performance stability and helps identify whether the diversification benefits of closed-end infrastructure funds are more or less pronounced when inflation is low. Includes funds with a minimum baseline threshold of three quarters (N≥9 monthly returns) within the specified regime.

Table 19 Open End Fund – Inflation Low

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
ARCTIME UK Infrastructure Inc II C Acc	0.252%	0.613	-0.217	-1.111	0.207	1.468	0.148	0.937	0.531
Cohen & Steers Glb Lstd Infra I Acc USD	-0.545%	-1.066	0.781	3.858	0.115	0.637	0.534	2.727	0.568
FP Foresight Global RI Infrs A GBP Acc	1.065%	1.544	0.830	2.370	0.366	1.625	0.430	1.675	0.729
FP Foresight UK Infrs Inc A GBP Acc	0.240%	0.635	-0.018	-0.098	0.212	1.633	0.225	1.548	0.640
GS Global Infrs Eq E Acc EUR	-0.814%	-1.495	1.065	4.111	0.362	1.934	0.353	1.690	0.724
L&G Global Infrastructure Index I Acc	-0.727%	-1.366	0.900	3.555	0.297	1.626	0.394	1.927	0.708
Lazard Global Lstd Infrs Eq BP Acc USD	-0.208%	-0.384	0.281	1.089	0.658	3.526	0.124	0.594	0.754
M&G Global Listed Infrs GBP A Acc	-0.559%	-1.056	0.878	3.485	0.447	2.459	0.654	3.218	0.853
Macquarie Sst Gbl Lstd Infra A EUR	-0.503%	-1.633	0.605	4.621	0.409	3.595	0.418	3.398	0.715
Nuveen Global Clean Infrs Imp C USD Acc	-0.498%	-1.395	0.663	4.368	0.324	2.456	0.492	3.448	0.652
PATRIZIA Low Carbon Cor InfREUR	-0.285%	-0.430	0.598	1.628	0.302	1.412	0.148	0.595	0.504
Premier Miton Global Infrs Inc B Acc	-0.284%	-0.575	0.843	3.583	0.365	2.150	0.417	2.195	0.777
Russell Inv Global List Infrs C EUR	-0.620%	-1.809	0.545	3.745	0.430	3.396	0.483	3.527	0.700
Schroder Digital Infrs A Acc GBP	-0.893%	-2.018	0.759	4.038	0.554	3.389	0.540	3.052	0.675
VT Gravis Clean Energy Income C GBP Acc	1.423%	2.642	0.128	0.501	0.281	1.520	0.389	1.882	0.665
VT Gravis UK Infrs Inc C EUR Hdg Acc	-0.356%	-0.871	0.211	1.281	-0.014	-0.099	0.445	2.889	0.441
VT RM Alternative Income Retail USD Acc	-0.730%	-1.248	0.465	1.668	-0.271	-1.347	0.146	0.648	0.205
Wellington Enduring Assets USD DL Ac	-0.416%	-0.481	0.254	0.588	0.485	2.101	0.019	0.069	0.695
WS Macquarie Global Infrs Secs A Acc	-0.452%	-1.428	0.512	3.808	0.467	3.994	0.451	3.571	0.733

Table 19 presents the results of the three-factor regression analysis for the OEF sample during periods of low inflation (defined as months where the ONS CPI was below the sample mean). By regressing OEF returns against UK Gilts, UK Equities, and US Equities, the table identifies how a low inflation environment impacts risk-adjusted excess returns (Alpha) and market sensitivities (Betas). The inclusion of t-statistics and the Adjusted R² provides a statistical basis for evaluating the explanatory power of the model and the performance consistency of open-end infrastructure funds when inflation is low. Includes funds with a minimum baseline threshold of three quarters (N≥9 monthly returns) within the specified regime.

Table 20 Comparison of CEFs and OEFs during Low Inflation Periods

Alpha			UK Gilts			UK Equities			US Equities		
t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances		
Variable 1 Variable 2			Variable 1 Variable 2			Variable 1 Variable 2			Variable 1 Variable 2		
Mean	0.003181	-0.00258	Mean	-0.11516	0.530794	Mean	0.068466	0.315542	Mean	0.305889	0.358364
Variance	4.09E-05	3.74E-05	Variance	0.247407	0.118902	Variance	0.065347	0.043799	Variance	0.304376	0.029853
Observations	21	19	Observations	21	19	Observations	21	19	Observations	21	19
Hypothesized Std. Dev.	0		Hypothesized Std. Dev.	0		Hypothesized Std. Dev.	0		Hypothesized Std. Dev.	0	
df	38		df	36		df	38		df	24	
t Stat	2.913319		t Stat	-4.80942		t Stat	-3.35699		t Stat	-0.41401	
P(T<=t) on two-tail	0.00298		P(T<=t) on two-tail	1.34E-05		P(T<=t) on two-tail	0.0009		P(T<=t) on two-tail	0.341273	
t Critical two-tail	1.685954		t Critical two-tail	1.688298		t Critical two-tail	1.685954		t Critical two-tail	1.710882	
P(T<=t) two-tail	0.005961		P(T<=t) two-tail	2.69E-05		P(T<=t) two-tail	0.0018		P(T<=t) two-tail	0.682547	
t Critical two-tail	2.024394		t Critical two-tail	2.028094		t Critical two-tail	2.024394		t Critical two-tail	2.063899	
Alpha			Beta UK Gilts			Beta UK Equities			Beta US Equities		
F-Test Two-Sample for Variances			F-Test Two-Sample for Variances			F-Test Two-Sample for Variances			F-Test Two-Sample for Variances		
Variable 1 Variable 2			Variable 1 Variable 2			Variable 1 Variable 2			Variable 1 Variable 2		
Mean	0.003181	-0.00258	Mean	-0.11516	0.530794	Mean	0.068466	0.315542	Mean	0.305889	0.358364
Variance	4.09E-05	3.74E-05	Variance	0.247407	0.118902	Variance	0.065347	0.043799	Variance	0.304376	0.029853
Observations	21	19	Observations	21	19	Observations	21	19	Observations	21	19
df	20	18	df	20	18	df	20	18	df	20	18
F	1.092213		F	2.080751		F	1.491969		F	10.19571	
P(F<=f) on two-tail	0.428119		P(F<=f) on two-tail	0.06186		P(F<=f) on two-tail	0.198909		P(F<=f) on two-tail	3.74E-06	
F Critical two-tail	2.190648		F Critical two-tail	2.190648		F Critical two-tail	2.190648		F Critical two-tail	2.190648	

Table 20 provides a comparative statistical analysis of the three-factor regression results for CEF and OEF samples during periods of low inflation. Using Two-Sample t-Tests (assuming unequal variances), the table evaluates the significance of differences in mean Alpha and Beta sensitivities (UK Gilts, UK Equities, and US Equities) between the two fund structures. Additionally, F-Tests are conducted to compare the variances of these estimators. This comparison is used for determining whether the structural characteristics of CEFs and OEFs lead to statistically significant differences in performance and risk exposure when the macroeconomic environment is in a period of low inflation. Includes funds with a minimum baseline threshold of three quarters (N≥9 monthly returns) within the specified regime.

Table 21 Closed End Fund – Interest Rates High

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R²
3i Infrastructure Ord	1.311%	0.670	-0.299	-0.330	1.397	2.440	-1.206	-1.970	0.167
Aquila Energy Efficiency Trust Ord	-0.465%	-26.610	0.023	2.870	-0.001	-0.140	0.002	0.410	0.306
HIQL Infrastructure PLC Ord	1.893%	1.810	0.252	0.520	1.023	3.350	-0.461	-1.410	0.486
Infrastructure India Ord	24.109%	1.080	-9.542	-2.060	4.173	1.200	-2.918	-1.040	0.328
International Public Partnerships Ord	-0.153%	-0.160	-0.565	-1.300	0.632	2.320	-0.210	-0.720	0.345

Table 21 presents the results of the three-factor regression analysis for the CEF sample during periods of high interest rates (defined as months where the Bank of England base rate was above the sample mean). By regressing CEF returns against UK Gilts, UK Equities, and US Equities, the table identifies how high interest/discount rates influence risk-adjusted excess returns (Alpha) and market sensitivities (Betas). Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Table 22 Open End Fund – Interest Rates High

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R²
WS Macquarie Global Infrs Secs A Acc	0.210%	0.283	0.386	1.113	0.577	2.649	0.272	1.168	0.755

Table 22 presents the results of the three-factor regression analysis for the OEF sample during periods of high interest rates. By regressing OEF returns against UK Gilts, UK Equities, and US Equities in months where the Bank of England base rate exceeded the sample mean, the table identifies the impact of a higher interest rate environment on risk-adjusted excess returns (Alpha) and market sensitivities (Betas). Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Table 23 Closed End Funds – Interest Rates Low

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
3i Infrastructure Ord	0.777%	2.862	0.066	0.504	0.237	2.265	0.175	1.689	0.167
Aquila Energy Efficiency Trust Ord	-0.036%	-5.629	-0.004	-1.445	0.000	-0.151	0.002	0.756	0.000
Aquila European Renewables Ord	-0.887%	-1.595	0.163	0.649	-0.291	-1.456	0.736	3.373	0.424
Bluefield Solar Income Fund	0.874%	3.047	-0.275	-2.055	0.292	2.565	-0.179	-1.584	0.096
Cordiant Digital Infrastructure Ord	0.437%	0.241	0.383	0.505	0.252	0.277	0.228	0.418	-0.363
Digital 9 Infrastructure Ord	-1.409%	-0.644	0.921	0.997	0.713	0.604	1.132	1.720	0.624
Downing Renewables & Infrastructure Ord	0.677%	0.637	-0.334	-0.970	-1.097	-1.901	0.648	1.789	0.135
Ecofin US Renewables Infrastructure Ord	-1.284%	-1.472	-0.410	-1.451	0.377	0.796	-0.203	-0.684	0.125
Foresight Solar Ord	0.372%	0.953	-0.061	-0.332	0.147	0.950	-0.156	-0.997	-0.013
GCP Infrastructure Investment Ord	0.325%	1.429	0.174	1.630	0.190	2.132	-0.001	-0.008	0.062
Gore Street Energy Storage Fund Ord	0.303%	0.489	-0.306	-1.056	-0.352	-1.567	0.395	1.785	0.018
Greencoat Renewables	0.401%	0.826	0.216	0.917	-0.164	-0.933	0.139	0.786	-0.016
Greencoat UK Wind	0.456%	1.603	0.188	1.435	0.070	0.625	0.106	0.942	0.042
Gresham House Energy Storage Ord	0.499%	0.858	0.271	1.026	0.317	1.456	0.170	0.790	0.276
HICL Infrastructure PLC Ord	0.416%	1.763	0.215	1.875	0.065	0.717	0.112	1.240	0.054
Infrastructure India Ord	-1.713%	-0.767	-0.116	-0.107	1.044	1.214	0.705	0.827	0.038
NextEnergy Solar Ord	0.338%	0.987	-0.038	-0.252	0.290	2.172	0.018	0.132	0.094
Octopus Renewables Infrastructure Ord	0.933%	0.934	0.349	0.832	0.377	1.137	-0.437	-1.185	-0.076
Renewables Infrastructure Grp	0.800%	2.846	-0.137	-1.049	0.173	1.552	-0.127	-1.148	0.013
SDCL Energy Efficiency Income Ord	-0.236%	-0.460	-0.058	-0.253	0.119	0.615	0.558	2.688	0.535
Sequoia Economic Infrastructure Inc Ord	0.196%	0.651	0.401	2.839	0.494	4.206	-0.026	-0.220	0.358
Triple Point Energy Transition Ord	-0.517%	-0.376	-0.297	-0.637	-0.410	-1.003	0.803	1.730	0.012
US Solar Fund Ord	-0.407%	-0.769	0.513	2.146	0.275	1.413	0.111	0.536	0.324
VH Glob Sustainable Energy Opp Ord	-0.264%	-0.230	0.185	0.385	0.155	0.271	-0.077	-0.225	-0.860
BBGI Global Infrastructure Ord	0.598%	2.548	-0.013	-0.118	0.014	0.150	0.146	1.564	0.027
Foresight Environmental Infra Ord	0.352%	1.305	0.020	0.167	0.215	2.042	0.060	0.572	0.112
International Public Partnerships Ord	0.729%	2.676	-0.225	-1.702	0.221	2.104	0.059	0.569	0.101

Table 23 presents the results of the three-factor regression analysis for the CEF sample during periods of low interest rates (defined as months where the Bank of England base rate was below the sample mean). By regressing CEF returns against UK Gilts, UK Equities, and US Equities, the table identifies how low interest rates affect risk-adjusted excess returns (Alpha) and market sensitivities (Betas). The results help determine if the performance of closed-end infrastructure vehicles is enhanced during periods of low interest rates. Includes funds with a minimum baseline threshold of three quarters (N≥9 monthly returns) within the specified regime.

Table 24 Open end Fund - Interest Rates Low

Fund Name	Alpha	t-alpha	Beta (UK Gilts)	t-beta (UK Gilts)	Beta (UK Equities)	t-beta (UK Equities)	Beta (US Equities)	t-beta (US Equities)	Adjusted R ²
ARCTIME UK Infrastructure Inc II C Acc	0.244%	0.924	-0.045	-0.369	0.206	2.155	0.135	1.442	0.453
Cohen & Steers Glb Lstd Infra I Acc USD	-0.160%	-0.556	0.669	5.189	0.154	1.405	0.504	4.652	0.605
First Sentier Respnb Lst Infra B GBP Acc	-0.683%	-0.658	0.000	0.000	0.871	1.678	0.317	1.019	0.560
FP Foresight Global RI Infrs A GBP Acc	0.397%	0.656	0.739	2.694	0.272	1.250	0.436	1.834	0.594
FP Foresight UK Infrs Inc A GBP Acc	0.234%	0.994	0.083	0.741	0.215	2.553	0.192	2.304	0.552
GS Global Infrs Eq E Acc EUR	-0.378%	-1.333	0.653	4.640	0.287	2.720	0.420	3.931	0.669
L&G Global Infrastructure Index I Acc	-0.072%	-0.200	0.486	2.896	0.197	1.508	0.454	3.546	0.642
Lazard Global Lstd Infrs Eq BP Acc USD	0.032%	0.088	0.347	2.073	0.691	5.323	0.086	0.669	0.714
M&G Global Listed Infrs GBP A Acc	-0.019%	-0.061	0.569	3.744	0.489	4.433	0.473	4.243	0.790
Macquarie Sst Gbl Lstd Infra A EUR	-0.373%	-2.042	0.481	5.511	0.380	5.344	0.390	5.412	0.643
Nuveen Global Clean Infrs Imp C USD Acc	-0.395%	-1.981	0.538	5.707	0.343	4.352	0.471	5.897	0.664
PATRIZIA Low Carbon Cor InfREUR	-0.108%	-0.213	0.405	1.717	0.280	1.587	0.204	1.041	0.493
Premier Miton Global Infrs Inc B Acc	-0.218%	-0.770	0.621	4.380	0.339	3.269	0.426	4.053	0.706
Russell Inv Global List Infrs C EUR	-0.353%	-1.866	0.433	4.788	0.460	6.239	0.379	5.082	0.659
Schroder Digital Infrs A Acc GBP	-0.558%	-2.147	0.539	4.351	0.526	5.134	0.452	4.346	0.600
VT Gravis Clean Energy Income C GBP Acc	0.501%	1.352	0.295	1.655	0.181	1.392	0.441	3.367	0.531
VT Gravis UK Infrs Inc C EUR Hdg Acc	-0.133%	-0.528	0.329	2.873	0.154	1.624	0.253	2.689	0.406
VT RM Alternative Income Retail USD Acc	-0.263%	-0.725	0.192	1.142	-0.327	-2.515	0.186	1.449	0.179
Wellington Enduring Assets USD DL Ac	-0.086%	-0.156	0.284	1.220	0.426	2.416	0.142	0.733	0.650
WS Macquarie Global Infrs Secs A Acc	-0.203%	-1.184	0.274	3.284	0.491	7.441	0.330	5.035	0.689

Table 24 presents the results of the three-factor regression analysis for the OEF sample specifically during periods of low interest rates. By regressing OEF returns against UK Gilts, UK Equities, and US Equities during months where the Bank of England base rate was below the sample mean, the table identifies how a low interest rate environment impacts the risk-adjusted excess returns (Alpha) and market sensitivities (Betas) of open-end infrastructure funds. The inclusion of t-statistics and the Adjusted R² provides a statistical basis for evaluating the model's explanatory power. Includes funds with a minimum baseline threshold of three quarters (N≥9 monthly returns) within the specified regime.

Table 25 Comparison of CEFs and OEFs during Low Interest Rate Periods

Alpha			UK Gilts			UK Equities			US Equities		
t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances		
	Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2
Mean	0.001011	-0.0013	Mean	0.066361	0.394496	Mean	0.137778	0.331835	Mean	0.188685	0.334539
Variance	5.18E-05	9.23E-06	Variance	0.090393	0.049013	Variance	0.150574	0.058474	Variance	0.130689	0.018018
Observations	27	20	Observations	27	20	Observations	27	20	Observations	27	20
Hypothesized Mean Diff	0		Hypothesized Mean Diff	0		Hypothesized Mean Diff	0		Hypothesized Mean Diff	0	
df	37		df	45		df	44		df	35	
t Stat	1.496497		t Stat	-4.30915		t Stat	-2.10478		t Stat	-1.92494	
P(T<=t) one-tail	0.071503		P(T<=t) one-tail	4.4E-05		P(T<=t) one-tail	0.020528		P(T<=t) one-tail	0.031197	
t Critical one-tail	1.687094		t Critical one-tail	1.679427		t Critical one-tail	1.68023		t Critical one-tail	1.689572	
P(T<=t) two-tail	0.143007		P(T<=t) two-tail	8.8E-05		P(T<=t) two-tail	0.041056		P(T<=t) two-tail	0.062395	
t Critical two-tail	2.026192		t Critical two-tail	2.014103		t Critical two-tail	2.015368		t Critical two-tail	2.030108	
Alpha			Beta UK Gilts			Beta UK Equities			Beta US Equities		
F-Test Two-Sample for Variances			F-Test Two-Sample for Variances			F-Test Two-Sample for Variances			F-Test Two-Sample for Variances		
	Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2		Variable 1	Variable 2
Mean	0.001011	-0.0013	Mean	0.066361	0.394496	Mean	0.137778	0.331835	Mean	0.188685	0.334539
Variance	5.18E-05	9.23E-06	Variance	0.090393	0.049013	Variance	0.150574	0.058474	Variance	0.130689	0.018018
Observations	27	20	Observations	27	20	Observations	27	20	Observations	27	20
df	26	19	df	26	19	df	26	19	df	26	19
F	5.60773		F	1.844262		F	2.57507		F	7.253321	
P(F<=f) one-tail	0.000144		P(F<=f) one-tail	0.086312		P(F<=f) one-tail	0.018648		P(F<=f) one-tail	2.13E-05	
F Critical one-tail	2.097821		F Critical one-tail	2.097821		F Critical one-tail	2.097821		F Critical one-tail	2.097821	

Table 25 provides a comparative statistical analysis of the three-factor regression results for CEF and OEF samples during periods of low interest rates. Using Two-Sample t-Tests (assuming unequal variances), the table evaluates the significance of differences in mean Alpha and Beta sensitivities (UK Gilts, UK Equities, and US Equities) between the two fund structures. Additionally, F-Tests are conducted to compare the variances of these estimators. Includes funds with a minimum baseline threshold of three quarters ($N \geq 9$ monthly returns) within the specified regime.

Final remarks

When reviewing the thesis as a whole, a clear rationale for the sequence and connection between the three chapters is as follows. Chapter 1 establishes the theoretical baseline for infrastructure in portfolio construction, which Chapter 2 then extends this by testing whether those diversification benefits persist in differing macroeconomic regimes. Chapter 3 finally examines how those benefits are captured in practice through real-world performance data.

A persistent pattern across all three chapters is that active infrastructure funds tend to provide stronger diversification and risk-adjusted benefits than passive infrastructure indices. While this contrasts somewhat with the broader fund literature, which generally finds that active equity managers struggle to outperform passive benchmarks, this difference makes sense when considering the unique nature of infrastructure. Unlike traditional equity markets, which are highly liquid and informationally efficient, infrastructure is characterized by large, illiquid, unlisted assets with bespoke regulatory contracts. Passive infrastructure indices are typically restricted to listed, large-cap equities, which often carry higher correlations to broader public markets. In contrast, active managers, particularly through closed-ended structures, have greater flexibility to capture illiquidity premia, engage in hands-on asset management, and access direct project cash flows. However, infrastructure remains an evolving asset class with relatively short fund histories and high manager dispersion, meaning that active manager selection is both necessary and subject to idiosyncratic risk.

To summarise the findings, this study confirms that adding infrastructure equity and debt assets to traditional portfolios can enhance portfolio returns. Across a range of portfolio configurations and economic conditions, infrastructure exposure delivered higher CER and improved Sharpe ratios relative to portfolios of only equities and bonds. The benefits were evident for both U.K. centric and globally diversified portfolios, and they remained robust

under investment constraints of no short-selling and no leverage. These results provide empirical verification of the theoretical advantages proposed by Inderst (2010) and Bianchi et al. (2014), demonstrating that infrastructure assets can effectively raise the efficient frontier for institutional portfolios by boosting risk-adjusted returns and portfolio utility in a statistically significant way.

Importantly, the diversification benefits of infrastructure persist across various macroeconomic states. Chapter 2's analysis showed that whether in high or low interest-rate environments, periods of rising or subdued inflation, or phases of expansionary versus lower government spending, the inclusion of infrastructure assets continued to improve portfolio outcomes. In other words, infrastructure's low correlation with traditional asset classes and its inflation-linked cash flows make it a resilient diversifier through different economic cycles. This resilience aligns with Bianchi et al. (2014), who found infrastructure investment returns to be robust and capable of providing defensive benefits across different economic cycles, including the Global Financial Crisis. Notably, the advantage of active infrastructure funds over index-based infrastructure exposure was persistent in all regimes, with active funds maintaining strong performance whereas index-based strategies were less beneficial. The consistency of benefits across these regimes confirms the ex-ante belief that infrastructure's portfolio benefits are a structural feature of the asset class's return profile, which tends to be agnostic to the wider economic cycle. Stated simply, the need for essential infrastructure persists whether the economy is booming or in recession. People still need schools and hospitals regardless of wider business cycles.

Chapter 3's extension of the analysis to real-world performance found that the magnitude of diversification benefits depends strongly on fund structure. While full-sample tests show no statistically significant difference in the average risk-adjusted returns between CEFs and OEFs, a number of individual CEFs performed very well and delivered statistically significant

positive alphas. CEFs also showed much wider dispersion across the board, with strong results in specific regimes like low interest rates, whereas OEFs tended to track the broader market more closely. Although the lack of statistical significance for some CEF performance is driven by high standard errors in the alphas, stemming from low R^2 values due to CEFs holding illiquid assets, the magnitude of the CEF alphas suggests strong economic significance. It is worth noting that some regime observations reflect smaller sample sizes, such as higher interest rate periods where fewer active funds existed across the study window. This indicates that while OEFs offer liquidity, they may forgo the potential illiquidity premium or infrastructure-specific premium that CEFs are structurally positioned to capture through long-duration, direct asset exposure.

The findings of this paper identify several avenues for future research and practical consideration. One useful extension would be to examine how regulatory changes or public-private partnership policies influence infrastructure investment outcomes. Similarly, measuring the impact of investor inflows and growing competition is vital, as infrastructure continues to attract large capital inflows, there is a risk that excess capital chasing limited assets could drive up prices and dampen future returns. Furthermore, research could explore whether the performance of CEFs persists during periods of extreme market volatility, particularly given that UK investment trusts have recently traded at a significant discount in recent years. Ultimately, the results of this study underscore that the strategic potential of infrastructure as a diversifier can be best realised through good manager selection and the choice of an appropriate investment vehicle.

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