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Essays on Listed Real Estate: Inflation Hedging, Tenant Industry Sector, and ESG

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Summary

This dissertation explores three key aspects of listed real estate (LRE): its ability to hedge against inflation (**Essay 1 and 2**), the impact of the systematic risk associated with tenants' industry sectors on LRE returns (**Essay 3**), and the effect of ESG (Environmental, Social and Governance) ratings on LRE valuation (**Essay 4**). The findings reveal several key insights.

Essay 1 analyses whether listed real estate can be used to hedge against inflation. Overall, the study confirms the desired inflation-hedging properties of LRE. Key findings include that LRE effectively hedges against expected inflation in the long-term, mainly due to value appreciation from long-term leases, while in the short-term, the hedging ability can become negative during turbulent periods, making its effectiveness time-dependent. **Essay 2** highlights the response of LRE to inflation shocks is highly dependent on the economic environment. Key findings include that LRE provides an effective hedge against inflation in the long run, both in crisis and non-crisis periods. In the short-term, listed real estate only hedges against inflation in stable periods. **Essay 3** expands the empirical evidence on the connection between the performance of public real estate companies (PRECs) and the industry sectors of their tenants. It is observed that the industry sectors of the tenants are reflected in the equity returns of real estate companies. **Essay 4** examines the impact of ESG ratings on the market valuation and intrinsic value of public real estate companies. Utilizing instrumental variable analysis to address endogeneity, the findings indicate a positive correlation between ESG metrics and market valuation, particularly through the environmental and social components.

Overall, this dissertation provides deep insights into the inflation-hedging capabilities of LRE, the importance of tenant sector risk for PRECs, and the influence of ESG ratings on the valuations of public real estate companies.

Zusammenfassung

Die zugrundeliegende Dissertation untersucht drei Schlüsselaspekte von börsennotierten Immobilienunternehmen (LRE): ihre Fähigkeit, sich gegen Inflation abzusichern (**Aufsatz 1 und 2**), den Einfluss des systematischen Risikos der Branchen, in denen die Mieter tätig sind, auf die LRE-Renditen (**Aufsatz 3**) sowie die Auswirkungen von ESG-Ratings auf die LRE-Bewertung (**Aufsatz 4**). Die Ergebnisse liefern mehrere wichtige Erkenntnisse.

Aufsatz 1 analysiert, ob LRE zur Absicherung gegen Inflation genutzt werden können. Insgesamt bestätigt die Studie die gewünschten inflationsabsichernden Eigenschaften von LRE. Zu den wichtigsten Ergebnissen gehört, dass LRE in der Lage ist, langfristig effektiv gegen erwartete Inflation abzusichern, hauptsächlich aufgrund der Wertsteigerung durch langfristige Mietverträge. Kurzfristig kann die Absicherungsfähigkeit jedoch während turbulenter Perioden negativ werden, wodurch ihre Wirksamkeit zeitabhängig ist. **Aufsatz 2** hebt hervor, dass die Reaktion von LRE auf Inflationsschocks stark vom wirtschaftlichen Umfeld abhängt. Zu den wichtigsten Ergebnissen gehört, dass LRE sowohl in Krisen- als auch in Nichtkrisenzeiten langfristig einen effektiven Schutz gegen Inflation bietet. Kurzfristig sichern LRE nur in stabilen Perioden gegen Inflation ab. **Aufsatz 3** untersucht den Zusammenhang zwischen der Performance von PRECs und den Branchen ihrer Mieter und zeigt, dass Mietersektoren sich in den Aktienrenditen widerspiegeln. **Aufsatz 4** untersucht den Einfluss von ESG-Ratings auf die Marktbewertung von PRECs. Die Ergebnisse zeigen eine positive Korrelation zwischen ESG-Kennzahlen und der Marktbewertung, besonders durch Umwelt- und Sozialkomponenten.

Insgesamt bietet diese Dissertation tiefe Einblicke in die Inflationsabsicherungspotenziale von LRE, die Bedeutung des Mietersektorrisikos für PRECs und den Einfluss von ESG-Ratings auf die Bewertungen öffentlicher Immobilienunternehmen.

Content Overview

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List of Abbreviations

A

ARIMA	Autoregressive integrated moving average
ASX	Australian Securities Exchange
AU	Australia

C

CEO	Chief Executive Officer
COVID-19	Coronavirus disease 2019
CPI	Consumer Price Index
CRediT	Contributor Roles Taxonomy

E

EI	Expected Inflation
EPRA	European Public Real Estate Association
ESG	Environmental, Social, and Governance
Et al.	Et alii / et aliae / et alia
EU	European Union

G

GDP	Gross Domestic Product
GFC	Global Financial Crisis
GSCI	Goldman Sachs Commodity Index

F

FTSE	Financial Times Stock Exchange

J

JPN	Japan

K

KPSS	Kwiatkowski-Phillips-Schmidt-Shin

L

LPM	lower Partial Moments
LRE	Listed Real Estate

M

Max.	Maximum
Min.	Minimum
MS-VAR	Markov-Switching Vector Autoregressive
MS-VECM	Markov-Switching Vector Error Correction Model

N

NAREIT	National Association of Real Estate Investment Trusts

O

Obs.	Observations

P

PPI	Production Price Index
PRECS	Public Real Estate Companies
PRI	Principles for Responsible Investment

Q

QE	Quantitative Easing

R

REITs	Real Estate Investment Trusts
RPI	Retail Price Index

S

SNL	Predecessor of S&P Capital IQ Pro
SP	Starting point
S&P	Standard & Poor’s
Std.	Standard deviation

U

UI	Unexpected Inflation
U.K.	United Kingdom
U.S.	United States

V

VECM	Vector Error Correction Model

W

WPI	Wholesale Price Index

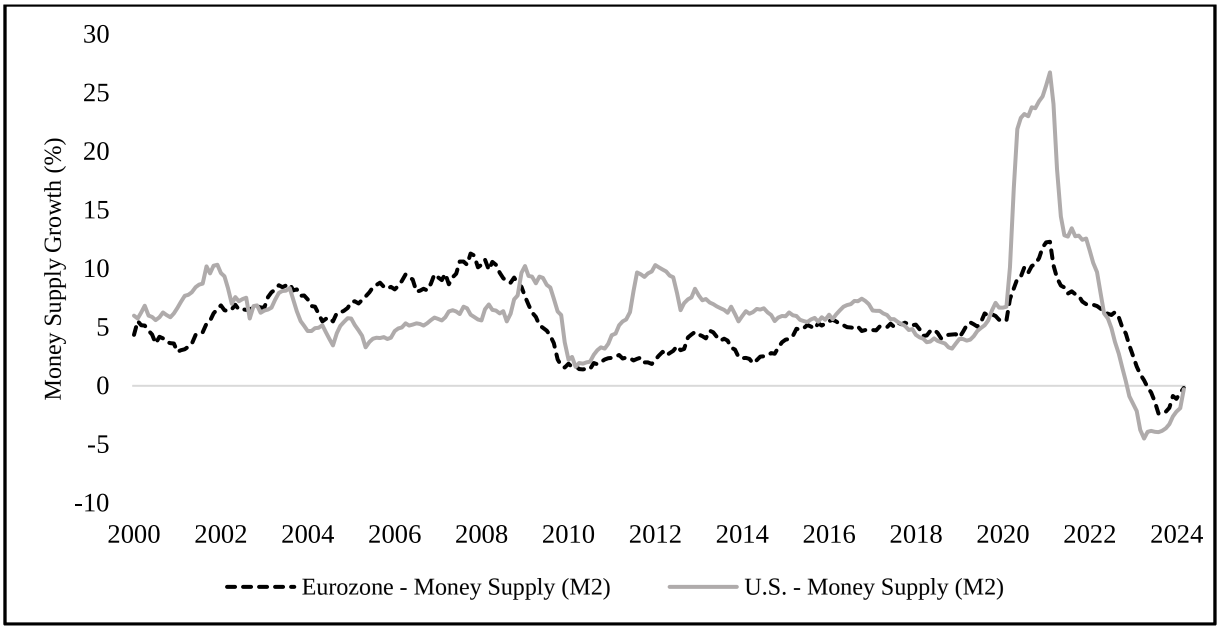
1. Introduction

1.1 Background and Motivation

The current economic landscape seems to be creating a number of challenges and opportunities in the world, which are also being realised on the stock market, for both private and institutional investors. Such environment has provided parts of motivation for this dissertation, particularly related to examining specific challenges that are shaping financial strategies and investment decisions today, especially when related to the listed real estate sector. Some of these challenges include the recent inflation acceleration affecting the cost of living and diminishing the real value of money; climate change and the extensive social adjustments required to address its impact; and the increasing importance of the relationship between the performance of public real estate companies and the rental sector, which highlights the growing importance of tenants structure.

As noted above, one of these major challenges is the recent resurgence of inflation, which troubles both capital markets and households. In a large part the acceleration of inflation was initiated by extensive central banks' monetary stimulus, the quantitative easing (QE), which expanded the money supply following the Global Financial Crisis (GFC) and persisted with loosened monetary policies in response to the COVID-19 pandemic. Figure 1.1 illustrates the money supply expansion in the Eurozone and the U.S.. As a response to the GFC of 2008, there was a substantial increase in the global money supply with both the U.S. and the Eurozone leading the monetary expansionary policy, as shown in the graph. This was primarily a policy response to the economic downturn, where central banks significantly expanded monetary bases to stimulate the economy. Particularly, the sharp spikes in growth for the Eurozone around 2015 and for the U.S. around 2020 correspond to periods of renewed monetary easing in response to subsequent economic challenges. Expectations that QE would significantly boost productivity growth did not sufficiently materialise (Duval et al., 2020).

Figure 1.1: Money Supply for the Eurozone and the US



Note: The graph shows the money supply growth for the Eurozone and the U.S.. Data were retrieved from Refinitiv Datastream.

As a consequence, each sector of the economy became increasingly reliant on easy access to cheap capital, enabling many companies and other economic entities to maintain marginal profitability solely through access to inexpensive financing (Woodford, 2016; Bukowski and Gowers, 2018; Ferreira-Lopes et al., 2022; Serranito et al., 2023). This situation, along with recent geopolitical tensions, has led to increases of energy and commodity prices to global costumers. These increases have contributed to higher inflation, therefore, in real terms, reducing disposable income.

The resurgence of inflation also makes it much harder to deal with another challenge which impacts the world: climate change and the social adaptations required to address it. The corporate sector holds substantial responsibilities and obligations regarding their impact on society and the environment. Under these circumstances, investors, lenders, and the other stakeholders are advocating for a greater integration of environmental, social, and governance (ESG) factors into their strategic business choices. This is further strengthened by governments regulations which in certain instances make investors' steering towards such goals mandatory.

In addition to these challenges, the dissertation investigates a third important issue for property managers and investors: the role of tenants' industry sectors in the performance of PRECs. Investors' exploration of the tenants' industry sectors can serve as a valuable indicator of the riskiness of PRECs stocks. Therefore, the risks associated with tenants should not be overlooked by property managers and investors.

Such changing environment is creating significant challenges for listed real estate companies (LRE). This is because, on the one hand, LRE is very responsive to movements of the capital markets, and on the other hand, the majority of the cash flows LRE generates come from the properties they hold (see section 1.2). This dynamic presents several issues. Firstly, stock prices of LRE companies can rapidly react to changes in the economic environment, making them volatile. In contrast, direct ownership of a commercial real estate asset binds a landlord to leasing contracts that cannot quickly adapt to market shifts. Secondly, in periods of inflation acceleration, while the cost side for a landlord, such as capital expenditures and maintenance costs, typically adjusts quickly to rising inflation, the income side, predominantly derived from fixed lease agreements, tends to lag. This asynchronous adjustment can strain the financial performance and valuation of LRE companies. This implies that in times of high inflation, LRE investors should seek to ensure that their portfolios have adequate hedging capabilities. At the same time a structural shift towards implementing ESG-friendly activities has significantly increased companies' commitments to their social and environmental impact, pushing them to improve the relevant sustainability metrics. Such situation, marked by political and macroeconomic turmoil, highlights the need for additional research in these areas to improve the understanding and management of the underlying market dynamics.

This dissertation comprises four Essays, each addressing a specific aspect of the challenges to LRE sectors. It particularly examines the relationships between LRE and economic indicators such as inflation, i.e., LRE's capability to hedge inflation. In addition, it highlights the prevalence of ESG metrics that require a thorough understanding in respect of their impact on the market valuation and intrinsic valuation of LRE. Finally, a more granular perspective is adopted by analysing the tenant structures within LRE, with a particular focus on the industrial sector of tenants. More precisely, the analysis investigates whether the systematic risk associated with the underlying industrial sector is reflected in the returns of LRE.

There exists extensive academic research examining various aspects of LRE, however there are still significant gaps, particularly in relation to the non-linear capabilities of LRE as an inflation hedge as well as in respect of the impact of ESG criteria on valuation. Previous studies often use linear models which do not always adequately capture the complexity of economic cycles and policy changes. Occasionally, those could lead to incorrectly constructed investment strategies in terms of inflation hedging capabilities. Furthermore, while much of the existing research has concentrated on the direct effects of tenants on real estate, it has largely overlooked the broader implications of tenant industry sectors. It is suspected that these sectors may significantly influence the systematic risks associated with real estate returns. The dissertation thoroughly examines how systematic risk associated with tenants' industry sectors influence returns in PRECs, enhancing understanding of the impact of tenant structure on realised returns. Lastly, while the influence of ESG criteria appears to be increasingly recognised across different sectors, the mechanism under which ESG criteria influence market valuation or intrinsic valuation is insufficiently understood. The possibility of a “Halo Effect” in relation to

ESG in the valuation of public real estate companies (PRECs) could therefore exist which is being analysed in more detail.

Summarising this dissertation addresses critical gaps in the existing literature by:

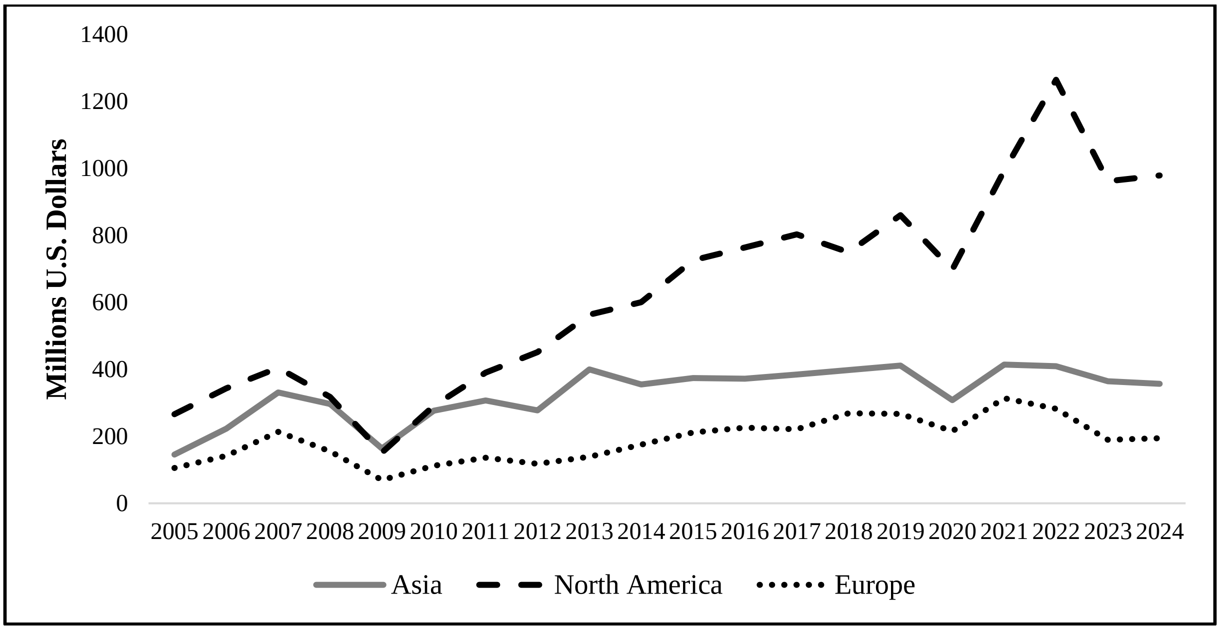
- Exploring non-linear inflation hedging: **Essays 1 and 2** utilise econometric models to examine the non-linear interactions between real estate returns and inflation across multiple national economies, offering deeper insights into effective hedging strategies during different economic conditions.
- Exploring the systematic risk of tenants' industry sectors: **Essay 3** extends the empirical evidence on the relationship between the performance of PRECs and the industrial sector to which their tenants belong.
- Exploring ESG Impact: **Essay 4** analyses the impact of ESG ratings on the market valuation and intrinsic value of PRECs and shed light on the possible presence of an "Halo Effect" regarding ESG in the valuation of PRECs.

1.2 Characteristics of LRE

What is listed real estate? "Listed real estate are real estate companies quoted on an official national stock exchange that derive cash flows from the ownership, trading, and development of income producing real estate assets. Listed real estate allows anyone, starting from private to large institutional investors, to invest in the underlying assets of public quoted companies, the same way as investing in other industries through purchasing shares. Owning shares of a listed public real estate company means earning a part of the income produced through the underlying bricks and mortar" (EPRA, n.d.). LRE has a dual nature which on the one hand implies that these entities are influenced by the broader stock market dynamics, while on the other hand, they also function as real estate entities, deriving a substantial portion of their cash flows from rental revenue. According to the European Public Real Estate Association (EPRA), the combined value of global real estate markets tracked by FTSE, EPRA, and NAREIT is approximately EUR 3 trillion (EPRA, n.d.), underlying the importance of this asset class.

Figure 1.2 illustrates the market capitalization evolution of selected indices over the last two decades of three leading capital markets: Asia, North America, and Europe. While over the considered period the Asian market displays a steady general trend of gradual increase albeit with some fluctuations, the North American market indicates a more pronounced growth, especially since around 2019 onwards, with a notable spike in 2023. During the same period, the European market exhibits less fluctuations than the other two markets, with lower growth but with less of volatility as well.

Figure 1.2: Market Capitalization of LRE



Note: The figure shows the market capitalization of FTSE EPRA NAREIT indexes for Asia (grey solid line), North America (black dashed line), and Europe (black dotted line). Data were retrieved from Refinitiv Datastream.

Since all four Essays are based on LRE this section aims to provide a clear and detailed overview of LRE definitions, aiming to highlight both its potential benefits but also associated risks. LRE refers to real estate properties that are traded on public stock exchanges which is inclusive of Real Estate Investment Trusts (REITs) and real estate companies whose shares are available to the public. LRE offers to investors the opportunity to own a share in real estate assets, typically providing liquidity that is not found with direct real estate investments (Morawski et al., 2008).[1]

Various studies have explored whether REITs, or LRE should in general be considered a “true” real estate asset, recognising the fact that LRE is subject to the general dynamics of both the stock market and the specific trends affecting the direct real estate sector (Pagliari et al., 2005; Li et al., 2009; Oikarinen et al., 2011; Hoesli and Oikarinen, 2012; Hoesli and Oikarinen, 2021; Feng et al., 2022). A higher liquidity relative to the direct ownership of real estate makes LRE more volatile than direct real estate ownership but allowing much easier entry and exit (Brunnermeier, 2009; Ametefe et al., 2016). This means that liquidity is one of the primary advantages of LRE, as shares can be bought and sold during market hours, providing flexibility which is absent from direct real estate ownership (Hoesli and Oikarinen, 2012).

LRE also differs from other stock markets assets in a sense that it often provides a steady income stream through dividends, which are typically higher yielding than those from other equities. This is attributed to the requirement for REITs to distribute most of the taxable income to shareholders (Boudry, 2011). Furthermore, LRE offers diversification benefits to investment portfolios as the correlation coefficient between LRE, other equities, and fixed income assets varies over time (Hoesli et al., 2004; MacKinnon and Al Zaman, 2009). Additionally, being publicly listed entities, LRE are subject to strict regulations, implying a high level of disclosure and transparency standards (An et al., 2011; Boudry, 2011).

[1] REITs were established in the United States in 1960, providing investors with a tax-efficient way to invest in real estate portfolios. In Germany, REITs, were introduced in 2007 to stimulate investment in the German real estate market. The rollout of REITs in Germany hasn't been particularly successful. Currently, there are only five operational REITs in the country: alstria office REIT-AG, Fair-Value REIT-AG, HAMBORNER REIT-AG, Deutsche Industrie REIT-AG, and Deutsche Konsum REIT-AG.

Like any other type of asset, LRE assets are subject to market risk which can cause fluctuations of investment values. The performance of LRE can be influenced by factors such as interest rates, economic growth, or changes in real estate demand and supply (Ewing and Payne, 2005). The performance of LRE can furthermore be affected by the financial health and stability of its tenants. Tenant defaults or vacancies can significantly impact revenues (Liu and Liu, 2013, Lu-Andrews, 2017, Liu et al., 2019), while changes in real estate or tax regulations can affect the profitability and operational mode of LRE (Ghosh and Petrova, 2021).

1.3 Basic Concepts and State of Research

1.3.1 Inflation and Inflation Hedging (Essay 1 and 2)

Following Parkin (2008), inflation refers to the ongoing increase in prices, or in other words, the continuous decline in the effective value of money. The common method to quantify inflation is by using the Consumer Price Indices (CPIs) (Arnold and Auer, 2015). Despite of certain challenges that use of CPI implies, such as lagged announcements, variations in CPI calculation across different countries, and the possibility that CPI estimates do not fully capture the price changes that may be relevant to investors, it remains the most commonly utilised indicators of inflation (Arnold and Auer, 2015). As an alternative to CPI, certain research efforts employ the other means to capture inflation such as Production Price Indices (PPI) (Ely and Robinson, 1997; Beckman and Czudaj, 2013), Wholesale Price Indices (WPI) (Jaffe and Mandelker, 1976; Guletkin, 1983), Retail Price Indices (RPI) (Barkham et al., 1996; Hoesli et al., 2008), or GDP deflators (Ely and Robinson, 1997). In empirical studies, the frequency of data can vary, with inflation rates calculated as monthly, quarterly, semi-annual, or annual basis (Arnold and Auer, 2015).

Arnold and Auer (2015) summarise three inflation hedging definitions based on the study by Bodie (1976). A financial instrument like stocks, bond, or LRE is an inflation hedge if it diminishes or minimises the chance that the real return on the financial instrument will drop below a certain threshold value. In addition, the hedging capacity of a financial instrument is measured as the proportional decrease in the variance of real returns on a default-free asset, which is achieved by pairing the two assets. Arnold and Auer (2015) also note, that a financial instrument serves as an inflation hedge if its real return does not depend on the inflation rate, indicating existence of a positive correlation between the nominal return of the asset and inflation. When this correlation reaches 1, it is described as a perfect hedge, since increases in prices are fully offset by equivalent growth of returns from the asset. If an asset does not offer a perfect hedge, its value can still be enhanced by a stable positive correlation between returns and inflation, as appropriate hedge ratios can theoretically allow for effective hedging under such circumstances. However, since hedging based on hedge ratios can result in high transaction costs for small investors (Bekaert & Wang, 2010), high co-movement values are of greater practical use than small leveraged values (Arnold and Auer, 2015).

Fisher's 1930 research established the Fisher Effect, under which the nominal interest rates can be decomposed into the combination of an expected real return and a predicted rate of inflation (Arnold and Auer, 2015). This concept has been instrumental for understanding adaption of interest rates to expected inflation changes, maintaining a relatively stable real interest rate over time (Fisher, 1930). Expanding on this framework, Fama and Schwert (1977) delved into researching effectiveness of various asset classes, especially stocks and bonds, function as hedges against inflation. Their analysis indicated that although stocks did not provide perfect hedges, they in general offered a better protection against inflation than bonds did. Furthermore, their research achieved to shed some light on the distinct impact of inflation on different asset types. These results subsequently enabled a more informed strategic assets allocation in respect of possible future inflation conditions.

It has been often perceived that real estate is an asset class which has the capability to deliver an adequate inflation hedge due to two of its characteristics: (1) Rent or lease payments (tenant leases contain rent escalation clauses and/or pass expense increases through to tenants) and (2) Land values and building costs typically tend to rise with inflation (Ruhmann and Woolston, 2011). However, empirical evidence, especially in case of listed real estate, is mixed. **Essays 1 and 2** summarise and highlight the existing literature and position the paper within the current academic discourse framework.

1.3.2 Systematic Risk and Tenant Industry Sector (Essay 3)

In general, systematic risk is unpredictable and unavoidable. While it cannot be reduced through diversification, some of its components could be managed through hedging or appropriate asset allocation strategies (Geltner et al., 2007). Systematic risk is influenced by wide-reaching economic factors such as changes in interest rates, inflation, recessions, and geopolitical events, which typically impact the entire market. Although diversification among sectors such as real estate, healthcare, and cybersecurity can distribute industry-specific risk, it does not shield investors against systematic risk. To manage this type of risk, a portfolio should be diversified across different asset classes, including bonds, cash, commodities and real estate, since each of them respond differently to broad economic changes (Clarke et al., 2002). For instance, when interest rates rise, the value of existing bonds decreases because fixed interest payments associated with those bonds become less attractive compared to new bonds emissions issued at higher rates. This can also lead to a decline in some company stock prices, as higher borrowing costs can reduce corporate profits. However, having a portfolio with high-yield securities can help offset the decline in value of certain stocks due to their higher interest payments.

In the same way, the industry sectors of tenants can represent a systematic risk. Since, LRE income derives from tenant rent collection, the economic link between tenant and LRE performance is rather obvious.[2] The tenant-related information may play an important role in the valuation of real estate companies. For instance, everything else being equal, a retail real estate company's performance could be substantially different, depending on whether tenants tend to be mainly engaged in selling personal and household goods, travel and leisure, or any other type of retailing activity. LRE in general, own a large property portfolio which as a result could imply a mixed structure in respect of industry sectors to which tenants belong (Muckenhaupt et al., 2023b). According to diversification theory, idiosyncratic risk can be mitigated and thus is not reflected in stock returns. Consequently, the focus shifts to the systematic risk associated with the industry sectors in which the tenants operate. While strategies that diversify tenant mix can help neutralise individual tenants' unique risks, the inherent systematic risk of each sector persists. Second, the fundamental performance of each tenant, especially when the tenant is a private firm, is not always observable (Chen et al., 2020). In this case, the volatility of the industry sector can provide some information on the changes in the market valuation of individual tenants, especially when the detailed market valuation information is not observable. **Essay 3** highlights the existing literature and categorises the Essay within the existing academic literature.

1.3.3 ESG and LRE Valuation (Essay 4)

The ESG principle is a framework that encompasses environmental (E), social (S), and governance (G) factors. The Principles for Responsible Investment (PRI) define responsible investment as a strategy and practice that incorporates these ESG factors into both investment decisions and active ownership (PRI, 2024; Zhang and Wang, 2024).[3] Therefore, ESG is

[2] A well-known example of an industry-focused office market is Aberdeen, Scotland. Aberdeen's primary sector is Oil and Gas, nevertheless there is a noticeable shift as many traditional oil and gas companies are transitioning into renewable energy sectors. The office market in Aberdeen has benefited from a stable oil price, consistently above $75 per barrel over the past two years. This stability has led to increased activity from energy firms and their service providers, driving demand for office space in the city (Knight Frank, 2024).

[3] Principles for Responsible Investment is an independent nonprofit organization supported by, but not part of the United Nations (Hill, 2020).

commonly used as a criterion and strategy by investors to assess corporate practices and anticipate financial performance. As a method for evaluating a company's sustainability, the three fundamental aspects of ESG are important in the analysis and decision-making process of investments (Li et al., 2021).

ESG ratings attempt to make investors' sustainability efforts quantifiable and measurable. As already indicated, environmental factors refer to a company's impact on the environment, such as its carbon footprint, energy efficiency, and resource management practices. In addition to the environmental component, the social and governance aspects of ESG also significantly influence investors' decision-making processes. Social factors pertain to a company's influence on societal aspects, including its employment standards, record on human rights, and involvement with local communities. Conversely, governance factors concern the internal governance and administrative practices of a company, such as the structure of its board, management remuneration, and levels of transparency. ESG has become an increasingly important area of focus for investors, as it is believed that companies that score well on ESG criteria are more likely to be sustainable, have lower risk and may perform better over the long-term (Ernst & Young, n.d.; McKinsey, 2023).

The existing literature includes numerous studies exploring the relationship between ESG metrics and LRE (Feng and Wu, 2021; Aroul et al., 2022; Chacon et al., 2022). A large body of literature has focused on ESG information disclosure, such as the relationship between ESG information disclosure and REIT leverage and company value (Feng and Wu, 2021) or fund performance (Devine et al., 2022). Other work investigated the inclusion of ESG in a real estate portfolio and studied the impact of ESG commitment on the firm's financial performance (Cajias et al., 2011).

Focusing on the single components, the environmental metric of ESG was heavily researched in studies such as (Fuerst and McAllister, 2011; Eichholtz et al., 2019; Morri et al., 2021; Hedemann et al., 2022, etc.). Fuerst and McAllister (2011) measure the effects of environmental certification on office values. Eichholtz et al. (2019) examine the relationship between the environmental performance of institutional assets and the performance of commercial real estate, while Morri et al. (2021) explore the connection between greenness and the operating performance in 50 European REITs.

The social component was focused by further studies as well (Cannon and Vogt, 1995; Newell and Lee, 2012; Erol et al., 2023; etc.). Newell and Lee (2012) investigate the influence of the CSR factors and financial factors on REIT performance in Australia. Erol et al. (2023) study the causal relationship and the sign of the association between financial and corporate social performance for REITs. They assess the social impact hypothesis of the stakeholder theory of the corporation and the neoclassic trade-off argument to investigate corporate social responsibility and the market valuation of REITs.

The analysis of the corporate governance is also gaining in importance (Bianco et al., 2007; Bauer et al., 2010; Anglin et al., 2013; Campbell et al., 2011; Lecomte and Ooi, 2013; etc.). Anglin et al. (2013) survey the impact of corporate governance on the quality of investor information. Campbell et al. (2011) investigate the connection between acquirer external and internal corporate governance mechanisms and announcement abnormal returns. They discover that bidder returns are higher for REITs with smaller boards, more experienced CEOs, and shorter tenure. The returns of acquirers' announcement are also significantly positive related to higher ownership by their CEOs and board directors. Lecomte and Ooi (2013) examine the relationship between corporate performance and make-up of corporate governance among externally managed Singaporean REITs. A detailed analysis of the existing literature can be found in **Essay 4**.

1.4 Applied Methods

The four Essays adopt different methodologies, subject on the topic and context. This section delivers an overview of the applied methods in the underlying dissertation. The sections of the corresponding Essays provide more information on the adopted methodologies, and their outcomes. All four Essays are conducted by the implementation of advanced quantitative techniques. While **Essays 1** and **Essay 2** use time series analysis on index data, **Essay 3** and **Essay 4** use panel data analysis based on the company level.

Essay 1 examines the inflation-hedging capability of listed real estate (LRE). In the case of the U.S., monthly LRE and macroeconomic variables data were used covering the period from 1975 to March 2023, while in the cases of the other three economies - the U.K., Japan, and Australia - data was available over the time span from 1990 to 2023. Macroeconomic variables were sourced from Refinitiv Datastream, while LRE monthly total return indexes were obtained from the European Public Real Estate Association (EPRA). The quantitative methodology used is a Markov-Switching Vector Error Correction Model (MS-VECM). There were several reasons for adopting such an approach. The VECM models have the capability to distinguish the long-term equilibrium relationship between multiple non-stationary time series variables, by comprehending both the long-term co-integrating relationships and the short-term adjustment dynamics that correct deviations from this equilibrium. In **Essay 1** those short-term relationships were combined with a Markov-Switching algorithm, with an aim to explore transitions paths between the different regimes within a dataset (Hamilton, 1989). In addition, inflation-hedging portfolios are constructed by using an expected short-fall measure. The case of an investor with an objective to hedge inflation over the investment horizon with a minimum target return was examined. The optimal allocations are determined by minimizing the shortfall probability under the constraint that real returns exceed the investor’s desired target (Brière and Signori, 2012).

Essay 2 also investigates the inflation-hedging capability of LRE and uses similar data and a similar quantitative technique. Data were compiled for a panel of six economies: France, Germany, Sweden, Switzerland, the U.K., and the U.S. The five European countries have the largest LRE market capitalization in Europe, while the U.S. LRE market is the largest in the world. In this research a monthly data set is used, starting from 1990 until the end of 2023. LRE returns were obtained from EPRA. Stock market data and macroeconomic variables were obtained from Refinitiv Datastream. Again, a Markov-switching process is combined with a VECM, but this time in a Panel model context. Differently to **Essay 1,** such set up allows for switching in the short- and long-term. Additionally, Cumulative Impulse Response Functions and Variance Decomposition techniques were applied as well. The impulse responses help understanding the behaviour of LRE in terms of inflationary shocks. The variance decomposition further illustrates in what ways the LRE performance is affected by other shocks, such as GDP or interest rates shocks.

Essay 3 and **Essay 4** differ to **Essay 1** and **Essay 2**, in a sense that they do not observe LRE index data, but individual PRECs panel data which implied that the methodology needed to be adjusted. In both cases an unbalanced panel regression was implemented. **Essay 3** aims to explain the relationship between the performance of PRECs and the industrial sector of their tenants. The Essay uses data of 205 European PRECs spread over twelve countries, including Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the U.K. observed over a period from 2010 to 2019. The data was compiled from S&P Global Market Intelligence Data. The list of firms is taken from the S&P Global

Market Intelligence Database, formerly known as SNL Financials. The methodology is based on an unbalanced panel regression to identify whether the sector risk is capitalised in PREC returns. Furthermore, it is shown how to generate benchmark-adjusted returns (also known as alphas) on PREC portfolios according to the tenant sector risk. The results of the unbalanced panel regression are tested on robustness by applying several tests, such as dropping the public sector, stock beta modifications, tenant sector alpha, anchor tenant and tenant diversification, rating dummy construction, and individual tenant performance.

Essay 4 examines the impact of ESG ratings on the market valuation and intrinsic value of PRECs across 38 countries over the period from 2015 to 2021. Data on ESG is obtained from Bloomberg Professional, while the data on company characteristics are obtained from the S&P Global Market Intelligence Database, formerly known as SNL Financials. The additional data on control variables such as firm size, firm age, financial leverage, and asset growth are compiled from Refinitiv Datastream. Similarly to **Essay 3,** an unbalanced panel regression was employed aiming to identify whether ESG has a significant impact on the market value or intrinsic value of listed real estate firms. To further bolster the results, the potential endogeneity of the ESG performance variable is taken into account, considering that firms with higher financial performance, or higher market valuation may pay more attention to sustainability issues. The country's sustainability policy development is used as the instrument. Furthermore, it is acknowledged that only 30% of PRECs have an ESG score, which may raise concerns that the sample is not randomly distributed, i.e., larger PRECs are more likely to focus on more developed ESG-conscious real estate markets. To account for the potential selection bias, a Heckman correction based on a two-stage model is conducted.

1.5 Contribution and Results

Essay 1 examines whether LRE can be utilised to protect against inflation. All in all, the study confirms the existence of desired inflation-hedging properties of LRE. The most important results can be summarised as it follows.

I. LRE can be considered as an effective hedge against inflation, especially against expected inflation and over the long-run. The long-term hedging ability of LRE arises mainly from the value appreciation. Furthermore, due to the long-term nature of most commercial leases, the hedging potential of LRE assets is especially notable over the long-run. Over the long-term, LRE appears to offer a more effective inflation protection than stocks.

II. In economically turbulent times, the short-term hedging capability of LRE can become negative. While in stable conditions, LRE effectively guards against inflation, during periods of turbulence, this capability may reduce to zero or become negative. Conversely, if deflation occurs during these turbulent periods, the performance of LRE is not likely to suffer from deflationary effects. Therefore, it is clear that from investors vantage point, the effectiveness of LRE as an inflation hedge is strongly influenced by the investment horizon time frame.

III. The LRE capability to hedge against inflation appears to differ between different countries. While LRE appears to consistently offer long-term protection against expected inflation, it fails to effectively hedge against unexpected inflation. In certain instances it even indicates the presence of perverse hedging effects. The most significant long-term correlation between expected inflation and real estate equity returns is observed in Japan, with an elasticity of 11.18%. In the U.S., the U.K., and Australia LRE over the short-term exhibits positive hedging against expected inflation, resulting in increases of 0.43%, 4.63%, and 1.32%, respectively, with a one percent increase in expected inflation.

IV. When inflation is broken down into its categories such as energy, food, core, and housing CPIs, in case of Japan it is evident that LRE effectively hedges against inflation related to core, food, and housing. In Australia, LRE shows positive hedging traits against energy inflation. Conversely, in the U.S., there are adverse hedging effects concerning food and core inflation, and in the U.K., similar negative hedging is observed with energy inflation.

V. The findings indicate that over the long-term, the hedging quality of LRE primarily stems from value appreciation rather than income returns. Conversely, in the short-term, it was observed that price returns hedge against expected inflation, while income returns provide a hedge against unexpected inflation.

VI. Robustness tests using a rent-adjusted inflation index demonstrate enhanced hedging capabilities for LRE compared to results using a standard, unadjusted inflation index. This suggests that previous studies, which relied predominantly on an unadjusted index, may have underestimated the hedging effectiveness of LRE.

VII. Inflation-hedging portfolios provide more balanced and realistic allocations to listed real estate than those derived using the standard mean-variance method. The mean-variance methodology tends to measures risk through variance magnitude, which may not fully align with investor objectives. Alternatively, inflation-hedging portfolios utilise the expected shortfall as the risk metric, concentrating on the risk of returns significantly deviating below the anticipated real return (i.e., the downside risk). These portfolios include a diverse mix of assets such as LRE, stocks, oil, gold, silver, agricultural commodities, and inflation-linked government bonds. Listed real estate plays a crucial role, with average allocations in the portfolios for the U.S., U.K., Japan, and Australia 8.32%, 10.87%, 8.55%, and 32.15% respectively, highlighting the benefits of including listed real estate in investment strategies. These portfolios also demonstrate notable performance, achieving higher Sharpe ratios than mean-variance portfolios in the U.K., Japan, and Australia, along with a reduced probability of shortfall in the U.S., U.K., and Australia, and superior average expected returns in all four regions. Although the Lower Partial Moment (LPM) portfolio often shows comparable performance, the inflation-hedging portfolio typically presents a lower likelihood of failing to meet the minimum target return, except in Japan, thus emphasizing its value for investors aiming to hedge against inflation and minimise the risk of not achieving target returns.

Essay 2 extends the literature of assets' capability to hedge against inflation not only by considering non-linear features of inflation hedging in the short-term, but also in the long-run. The most important results can be summarised as follows.

I. Using a panel of monthly return data for LRE companies for six countries including, France, Germany, Sweden, Switzerland, the U.K., and the U.S. – from 1990 to 2023, this research reveals that the response of LRE returns to inflation shocks is strongly regime-dependent. During periods of economic stability, LRE returns consistently show a positive relationship with inflation shocks, observable in both the short- and long-term. A one standard deviation inflation shock results in a 20% rise in LRE returns three months following the shock, and an increase of up to 320% within 60 months. This response is persistent, with the inflation shock accounting for nearly 20% of the variations in LRE returns three months after the shock, and this influence slightly declines to 14% after 60 months. Conversely, during periods of economic instability, the influence of inflation shocks on LRE returns can be noticeably negative in the short-term, with a one standard deviation shock resulting in a 13% decrease in LRE returns three months following the shock. During such turbulent times, inflation shocks explain only about 4% of the variations in LRE returns, indicating a minimal impact on LRE performance in the short-term. However, over the long-term, the explanatory power of inflation shocks on LRE returns increases to approximately 14%.

II. Furthermore, LRE demonstrates greater hedging effectiveness over the long-term compared to the short term. In periods of turbulence, there is a notable negative inflation hedging coefficient in the short-term. Yet, over extended periods, a consistently positive correlation exists between LRE returns and inflation. This long-term relationship is significantly stronger, with the response of LRE to inflation shocks being more pronounced over 60 months than over 3 months. This pattern is underscored by the variation decomposition results, which show that while the impact of inflation shock is less than 4% in the short-term during periods of crisis, it accounts for around 14% of the variations in both stable and turbulent times over the long-term.

III. The Essay successfully highlights how the inflation-hedging capabilities of LRE shift during economic downturns, such as those seen during the dotcom bubble, the global financial crisis, the COVID-19 pandemic, and the onset of the conflict in Ukraine. These periods are distinctly marked in the regime-switching analysis, emphasizing the need to account for economic contexts when evaluating the inflation-hedging attributes of LRE. The effectiveness of LRE as an inflation hedge from an investment standpoint is strongly influenced by the investment duration. Notably, the adaptability of LRE’s hedging efficacy during crises is also evident in the long-term dynamics when incorporating a regime-switching approach into the long-term equilibrium equation, suggesting that changes during crises occur not only through adjustment speed but also in the long-term equilibrium itself.

IV. The direct real estate market typically shows a lagged yet significant reaction to inflation, with impacts becoming apparent six months after a shock. This delay is attributed to factors such as market illiquidity, the duration of real estate leases, and information asymmetries. The effect of inflation on direct real estate exhibits minimal short-term consequences but a pronounced long-term impact.

Essay 3 extends the literature on the risk-return relationship of PRECs by showing that the tenant sector risk is capitalised in REIT stock returns. The most important results can be summarised as follows.

I. While prior research has focused on assessing real estate firms' asset quality based on tenant creditworthiness or asset location, this study proposes adding the systematic risk of the industries in which tenants operate as a new factor in assessing PRECs' risk. The findings indicate that the systematic risk of tenant industry sectors is reflected in the equity returns of PRECs, with firms that lease to tenants in more volatile industries experiencing higher returns. Additionally, a one-standard-deviation increase in the sector beta of tenants correlates with a 6.18% rise in equity returns.

II. To explore the practical implications of these findings, a hypothetical trading strategy was tested, focusing on the tenant sector risk. This strategy, involving long positions in stocks of companies with high tenant sector risk and short positions in those with low risk, yielded a benchmark-adjusted annual return of 3.68%. These results underscore the significance of tenant characteristics - specifically the industry risk factor - on the stock performance of real estate firms. This suggests that systematic risk in tenant industries should be considered an additional factor influencing PRECs’ risk assessments. Therefore, the risks associated with tenants should not be ignored by property managers and investors.

Essay 4 advances the understanding of the relationship between ESG ratings and the market and intrinsic valuations of PRECs, by utilizing metrics such as Tobin's Q for market valuation and examining cash flow, idiosyncratic, and systematic risks for intrinsic value. The most important results can be summarised as follows.

I. The study employs an instrumental-based methodology, specifically the Two-Stage Least Squares (2SLS) method, to address endogeneity issues, which is further enhanced by a Heckman two-stage correction for robustness. The analysis, which encompasses PRECs from 38 countries from 2015 to 2021, identifies a positive association between comprehensive ESG metrics (including sub-components) and the market valuations of firms. For intrinsic value, the impact of ESG is primarily observed through the cash flow channel, showing significant links between ESG factors and financial measures such as EBIT and net operating income. However, the influences on idiosyncratic and systematic risks are relatively minor. The systematic risk channel initially displays a negative impact from ESG in the 2SLS framework, but this effect vanishes after adjusting for potential selection bias.

II. These results imply a “Halo Effect” from robust ESG practices, where an improved corporate reputation favourably influences investor perceptions, potentially leading to increased investment and higher valuations for companies with strong ESG scores. Such perceptions might also lead investors to anticipate greater growth opportunities for these firms, affecting market efficiency and the rational allocation of resources. The study also uncovers differences in the roles of ESG components. Both Environmental (E) and Social (S) scores significantly correlate with positive impacts on Tobin's Q, enhancing market valuation. In contrast, Governance (G) scores do not show a significant effect on market valuation. Additionally, the Social (S) score demonstrates a significant negative relationship with systematic risks, suggesting that higher S scores can boost a firm's intrinsic value by reducing equity risk. This indicates that the S component plays a crucial role in shaping fundamental values through the valuation channel, rather than merely influencing stock prices.

1.6 Structure

The remainder of this dissertation is structured around the four Essays, each representing an individual research project. The **first two Essays** explore the realm of listed real estate and its role in protecting against inflation, aiming to ensure that investors can realise a return at least in the amount of inflation. **Essays 3 and 4**, while also focusing on listed real estate, delve more directly into company-specific dynamics. First, **Essay 3** deals with the performance of listed real estate and if it is influenced by systematic risk within tenant industry sectors. Last, **Essay 4** analyses sustainable aspects in the form of ESG. More specifically, how the market and intrinsic valuations of listed real estate are affected when considering ESG metrics and their sub-components.

The subsequent chapters follow the structure of Table 1.1, which provides an overall view of the topic, methodology, as well as findings and practical contributions. Subsequently, the key findings from the four Essays are summarised and concluded with Section 6. Thus, limitations and avenues for further research are provided, along with a final remark. After that, additional information is included in the appendix for the four Essays.

Table 1.1: Overview of Essays

Essay Characteristics	**Essay 1 (cf. Section 2)**	**Essay 2 (cf. Section 3)**	**Essay 3 (cf. Section 4)**	**Essay 4 (cf. Section 5)**
Research Question	How does the inflation-hedging capability of LRE companies vary across different economic conditions and time periods in the U.S., U.K., Japan, and Australia, and what are the optimal portfolio allocations to maximise this hedging capability?	To what extent can LRE serve as a hedge against inflation in both the short- and long-term, during crisis and non-crisis periods, and how does it compare to other asset classes, particularly in terms of protecting against inflation shocks?	Is the tenant industry risk capitalised in real estate company equity returns?	How do ESG ratings influence the market valuation and intrinsic value of Public Real Estate Companies?
Research Approach and Data	MS-VECM; LRE index data and macroeconomic indicators	MS-VECM; LRE index data and macroeconomic indicators	Unbalanced Panel Regression; Performance indicators of European PRECs	Unbalanced Panel Regression; Performance indicators of Internation PRECs
Findings	LRE's short-term hedging against inflation diminishes during turbulent periods but is effective in stable times and superior to stocks in the long-term; strategies to minimise shortfall are also identified.	LRE is an effective hedge against inflation in the long-run, both in crisis and non-crisis periods. In the short-term, listed real estate only hedges against inflation in stable periods.	Systematic risk in the tenants' industry sectors is capitalised in real estate company equity returns.	ESG ratings positively affect the market valuation of PRECs. High Social scores in ESG ratings can boost a firm's intrinsic value by lowering equity volatility and systematic risks.
Practical Implications	The proposed strategy is suitable for long-term institutional investors, especially pension funds with inflation-linked liabilities, and individual investors focused on preserving capital in real terms.	This approach is well-suited for long-term institutional investors, such as pension funds facing inflation-linked liabilities, and for individual investors aiming at minimum real-term capital preservation.	The risks associated with tenants should not be ignored by property managers and investors.	Investors can boost market valuation and mitigate risks in Public Real Estate Companies by focusing on their environmental and social ESG metrics.

Note: This table sums up the four essays in the dissertation, giving readers a clear and simple overview.

2 Listed Real Estate as an Inflation Hedge Across Regimes

Abstract

This paper examines the inflation-hedging capability of listed real estate (LRE) companies in the U.S. from 1975 to 2023, and in three other economies - the U.K., Japan, and Australia - from 1990 to 2023. By using a Markov switching vector error correction model (MS-VECM), we identify that the short-term hedging ability moves towards being negative or zero during turbulent periods. In stable periods, LRE provides good protection against inflation. In the long-term, LRE offers a good hedge against expected inflation and shows a superior inflation hedging ability than stocks. Additionally, we identify inflation-hedging portfolios by minimizing the expected shortfall. This inflation-hedging portfolio allocation methodology suggests that listed real estate stocks should play a significant role in investor portfolios.

Keywords: Inflation Hedging, Listed Real Estate Companies, Markov-Switching, VECM, Inflation-Hedging Portfolio

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[4] Author contributions based on CRediT roles: Conceptualization, data curation, software, formal analysis, methodology, validation, visualization, and writing – both the original draft and review & editing – were conducted by Jan Muckenhaupt. Supervision was provided by Martin Hoesli and Bing Zhu.

[5] Full paper presentation at the 29th ERES Conference in London; Full paper presentation at the E-CREDA 2023 Conference in Paris.

[6] This dissertation contains content from a manuscript published by Springer Nature in the Journal of Real Estate Finance and Economics, available at https://link.springer.com/article/10.1007/s11146-023-09964-x.

2.1 Introduction

Due to central banks' response to the COVID-19 pandemic and a huge stimulus that increased levels of money supply, together with the subsequent consequences of military confrontations, the world is experiencing large price swings in energy and commodity markets and a possibility of a global recession. In September 2022, the year-on-year U.S. inflation rose to 8.2%. In response, Central banks, such as the Federal Reserve or the Bank of England, quickly tightened their monetary policy, attempting to curb the massive inflation by imposing higher interest rates. As of the end of 2022, the engaged policies did not appear to be adequate in terms of curbing inflationary pressures; hence further tightening is likely. With those inflationary pressures, it becomes more important to take a fresh look at real estate's inflation hedging capability by using state-of-the-art estimation techniques. Against this background, this paper aims to broaden our understanding of the inflation-hedging characteristics of real estate relative to other asset classes. Such properties should particularly benefit long-term institutional investors (especially pension funds, which usually operate under inflation-linked liability constraints) and individual investors, for whom real-term capital preservation is a minimal objective.

Some assets are more suited to hedging inflation than others, depending on the country, sector, or time horizon. Real estate has often been perceived as the asset class which can deliver an adequate inflation hedge due to its two mechanisms: (1) Rent or lease payments (tenant leases contain rent escalation clauses and/or pass expense increases through to tenants) and (2) Land values and building costs typically rise with inflation (Ruhmann and Woolston, 2011). However, empirical evidence, especially for listed real estate, is mixed. Gyourko and Linneman (1988) find that REITs may protect against expected inflation but not against unexpected inflation. In contrast, Park et al. (1990) find that equity REITs are negatively associated with expected and unexpected inflation. Titman and Warga (1989) argue that REITs act as a paradoxical hedge against inflation because they are catalysts rather than reactants to a change in inflation rates. In particular, the contemporaneous return on equity REITs anticipates future inflation rates.

This paper extends the literature in two ways. First, we allow for non-linear inflation-hedging characteristics. Most previous literature combines the Fama and Schwert (1977) framework (which distinguishes the expected and unexpected inflation components) and the cointegration technique (which differentiates long-term equilibrium and short-term dynamics) (e.g., Hoesli and Hamelink, 1997; Liu et al., 1997; Hoesli et al., 2008; and many others). However, all these studies assume a stable relationship, which may be violated by the change in monetary policy and business cycles. For instance, Glascock et al. (2002) show that the relation between REIT returns and inflation can be influenced by monetary policies. Demary and Voigtländer (2009) argue that the office sector partially protects against inflation because worsening economic perspectives (inflation) alleviate the demand for office space. National and Low (2000) find that the inflation-hedging characteristics of assets differ in distinct inflationary environments, indicating time-varying inflation-hedging characteristics. Given the long-lasting low-interest-rate environment and the increased uncertainty in the global economy, the inflation-hedging characteristics of real estate may differ from previous periods.

Second, this project compares the hedging characteristics across asset classes, including real estate, stocks, silver, and gold, using an inflation-hedging portfolio. The hedging ability of other assets, such as infrastructure (Bitsch et al., 2010; Wurstbauer and Schäfers, 2015), stocks (Bodie, 1976), gold (Lucey et al., 2017), and white precious metals (Bampinas and Panagiotidis, 2015; Bilgin et al., 2018) has been intensively studied in the literature. Regarding real estate, many studies also exist, as highlighted above, and the literature has often focused on whether differences exist across property types (Hoesli, 1994; Ganesan and Chiang, 1998; National and

Low, 2000). However, there is still a lack of conclusive evidence regarding the inflation-hedging capabilities across different asset classes, i.e., in a diversified portfolio. Most of the research has been done within a mean-variance framework. However, using variance as the risk measure may not be what corresponds best to investors' objectives, as variance treats both upside and downside risk as the same. Because investors usually consider the upside risk to be favorable, the use of variance appears to be unsuitable (Sukcharoen and Leatham, 2016). In reality, listed real estate returns are non-normal (Hutson and Stevenson, 2008; Giannotti and Mattarocci, 2013). Using listed real estate (LRE) performance in the EU area, Lizieri et al. (2022) also show that the mean-variance approach often yields extreme and unrealistic asset allocations to listed real estate. Given that investors may only consider downside risk, we use a more realistic measurement of risk – the expected shortfall, which focuses on the risk of being far below the expected real return (i.e., the downside risk). A shortfall probability risk measure for portfolio optimizations has been conducted before, for example, by Leibowitz and Henriksson (1989), Leibowitz and Kogelman (1991), Lucas and Klaassen (1998), Smith and Gould (2007), and Brière and Signori (2012). In this paper, we apply this measurement to construct an inflation-hedging portfolio.

Using 1975 to 2023 data for LRE companies in the U.S., and data for 1990-2023 for three other economies – the U.K., Japan, and Australia –, our paper confirms the effectiveness of listed real estate to hedge against inflation. First, LRE assets provide a reliable hedge against inflation in the long-term, but mainly against its expected component. In all four regions, listed real estate shows positive long-term inflation-hedging capability against expected inflation. Second, in stable periods, LRE may provide an adequate level of protection against inflation in the short-term. However, the level of protection decreases during periods of economic turmoil. Third, the inflation-hedging ability largely comes from the capital value increase rather than the dividend yield. Fourth, when we use the housing rent adjusted inflation index (Ambrose et al., 2022), LRE shows a better hedging ability compared to using the classic unadjusted inflation index. This indicates that the hedging ability of listed real estate may have been underestimated in the literature, as prior studies mainly use an unadjusted inflation index, which tends to underrepresent rent changes between leases and underestimate the volatility due to valuation smoothing and significant time lags[7] in the official rent measure (Ambrose et al., 2022).

Finally, we demonstrate that LRE can play a significant role in the inflation-hedging portfolio of an investor, even when inflation-linked government bonds are included. The average allocations to LRE for the U.S., U.K., Australia, and Japan over the entire period are 8.32%, 10.87 %, 32.15%, and 8.55%, respectively. Those weights are higher than those in the mean-variance portfolio for all countries and higher than those in lower partial moment portfolios for the U.S., Japan, and Australia. The inflation-hedging portfolio also provides a higher risk-adjusted return than when the mean-variance approach is implemented for the U.S. and Japan.

The remainder of the paper is organised as follows. Section 2.2 discusses the literature. We next discuss the data and methods that we use to test the inflation-hedging ability of the various asset classes, followed by the presentation of our results. We then present a battery of robustness tests. The subsequent section discusses inflation-hedging portfolios and compares those with traditional mean-variance and lower partial moment portfolios (Byrne and Lee, 2004). A final section concludes.

2.2 Literature Review

There have been numerous studies examining various aspects of LRE's ability to serve as an inflation hedge. One strand of the literature focuses on protecting against expected and

[7] Ambrose et al. (2015) indicate that the BLS rent index lags the contemporaneous market rent by approximately one year because of its sampling and index construction method.

unexpected inflation in the short-run (e.g., Chen and Tzang, 1988; Gyourko and Linneman, 1988; Murphy and Kleiman, 1989; Titman and Warga, 1989; Chan et al., 1990; Park et al., 1990; Yobaccio et al., 1995; Hardin et al., 2012; Fang et al., 2022; and Connolly and Stivers, 2022), while others investigate the long-term relationship using cointegration techniques (e.g., Chatrath and Liang, 1998; Glascock et al., 2002; Bahram et al., 2004; Hoesli et al., 2008; Lee and Lee, 2012; Lee et al., 2011; and Fehrle, 2023).[8] The findings are mixed. For instance, Chen and Tzang (1988) show that REITs can protect against inflation expectations up to some extent. Glascock et al. (2002) find significant negative coefficients for general and expected inflation and a negative but non-significant coefficient for unexpected inflation. They find evidence of cointegration between REIT returns and the generic CPI as well as with its expected and unexpected components. Innovations in REIT returns lead to negative changes to both expected and unexpected inflation (which would be consistent with a real output model for a given level of money). In contrast to this, Chatrath and Liang (1998) and Bahram et al. (2004) support the traditional notion that REITs do not hedge against inflation (in contrast to direct real estate).

Lee et al. (2011) investigate the long-run inflation-hedging properties of real estate stocks in East Asian developing countries. They report that LRE was not capable of hedging inflation in the long-run. Fehrle (2023) investigates the hedging ability of equity and housing against inflation. He concludes that the hedging ability is strongly time dependent. Further, he notes that housing is superior, albeit only marginally, to equity in terms of hedging against inflation capability. The study by Fang et al. (2022) decomposes inflation into energy, food, and core components and finds that these components have markedly different properties concerning asset pricing. They demonstrate that traditional inflation hedging instruments such as stocks, currencies, commodities, and REITs only succeed in hedging energy inflation, while in the case

[8] A comprehensive summary of the existing literature can be found in Arnold and Auer (2015).

of core inflation they tend to be less successful. Following Fang et al. (2022), Connolly and Stivers (2022) find the existence of a complex relationship between REIT equity returns. The authors establish a strong negative relationship during phases of weaker economic growth, such as periods in the 1980s and early 1990s when stagflation was more of a concern.

The mixed results may be explained by different observation periods. Considering the structural break in the U.S., Hardin et al. (2012) split the sample period into two subperiods (1980–1992 and 1993–2008). Based on dividend yield composition, the authors demonstrate that, although inflation illusion and hedging effects exist in REITs, inflation illusion appears to predominate throughout the entire sample period. Similar to Hardin et al. (2012), Lee and Lee (2012) demonstrate that REITs act as a hedge against expected inflation only after a structural break in 1993, where a tax reform made large-scale investments in REITs more desirable to institutional investors. Moreover, they emphasise that the hedging capability of REITs is driven by large capitalization which implies that small-cap REITs fail to hedge against inflation once isolated from the influence of large REITs.

Our paper extends the literature by combining Vector Error Correction Model (VECM) with a Markov-regime switching process. We follow Beckmann and Czudaj (2013), who analyze whether gold possesses the ability to hedge against inflation but from a new perspective. By using data from four major global economies, they allow for non-linearities while they also discriminate between long-run and time-varying short-run dynamics. A Markov switching vector autoregressive model (MS-VAR) has also been used by Chiang et al. (2020), who observe the dynamic relationships between housing market returns and stocks in the U.S.. They identify a significant regime-dependent autocorrelation between stock and housing returns in both low-volatility and high-volatility regimes.

Our paper is also related to the listed real estate literature on optimal portfolio composition. An abundant amount of literature has investigated portfolio optimizations in a mean-variance framework advocating that real estate holdings improve the mean-variance efficiency of a diversified portfolio (Fogler, 1984; Firstenberg et al., 1988; and Ennis and Burik, 1991). By using U.S. REIT data, several studies demonstrate that the risk-return trade-off for U.S. investors can be mitigated (Burns and Epley, 1982; Miles and McCue, 1982; Ennis and Burik, 1991). Several studies demonstrate the benefits of diversifying into international real estate using a variety of data (Giliberto, 1990; Eichholtz, 1996; Conover et al., 2002).[9] Others focus on the performance of different asset types (Lee and Stevenson, 2005; Chiang et al., 2008; Newell and Marzuki, 2016).

Fewer studies follow the approach of expected shortfall by finding the optimal portfolio (Leibowitz and Henriksson, 1989; Leibowitz and Kogelman, 1991; Lucas and Klaassen, 1998; Smith and Gould, 2007; Brière and Signori, 2012). Only Brière and Signori (2012) determine the allocation of their portfolio by minimizing the shortfall probability, with the constraint that returns are above a minimum target return in an inflation-hedging context. They conclude that the portfolio allocation depends on the time horizon as well as the minimum return target. According to Leibowitz and Kogelman (1991), downside risk is determined by the shortfall probability relative to a minimum return threshold. Providing both a threshold and a shortfall probability allows them to determine the maximum allocation to risky assets based on a shortfall constraint. Additionally, they examine how the risky asset allocation is affected by changes in volatility, equity risk premium, return thresholds, and shortfall probabilities.

[9] A comprehensive summary of the existing literature can be found in Worzala and Sirmans (2003).

2.3 Data and Method

2.3.1 Data Description

Data were compiled for the U.S., the U.K., Japan, and Australia. We use monthly data from 1975 to March 2023 for the U.S., sourced from Refinitiv Datastream. For the three other countries, LRE monthly total return indexes, available from 1990 to March 2023, were obtained from the European Public Real Estate Association (EPRA). Stock total return indexes are obtained from Refinitiv Datastream. Specifically, these are the S&P 500 index for the U.S., the FTSE 250 index for the U.K., the Nikkei 500 index for Japan, and the S&P/ASX 200 index for Australia. Additionally, we also include the price of gold, silver, and oil in U.S. Dollars, along with the total return index of the S&P GSCI Agriculture and the real three-month Treasury Bill rates, which is a proxy for the risk-free rate, as well as the nominal GDP.[10][11] Our key variables, namely expected inflation and unexpected inflation, are derived from the seasonally adjusted consumer price indexes (CPI) obtained from Refinitiv Datastream for the respective countries.

Table 2.1 displays the corresponding summary statistics of our data. The highest average total return is recorded in the U.S. with 10.64% annually, while Australia, the U.K., and Japan follow with annual rates of 8.01%, 4.05%, and 1.31%, respectively. The U.S. faces the highest average expected inflation rate of 1.12% per month, while Japan comes across with the lowest rate of 0.05% per month. In the U.S., the average monthly unexpected inflation rate is -0.007%, while Japan underwent a rate of monthly unexpected inflation of -0.005%.

[10] Because GDP is only available on a quarterly basis, we use temporal disaggregation. Temporal disaggregation methods are used to disaggregate and interpolate a low frequency time series to a higher frequency series. Using real GDP provides similar results.

[11] To obtain the real three-month Treasury Bill rates, we employ a deflation process on the corresponding nominal rates.

Table 2.1: Summary Statistics

	Mean	Std.	Max.	Min.	SP	Obs.
			Panel A: U.S.			
LRE	0.879%	5.819%	31.301%	-45.227%	1975/01	579
Stocks	0.710%	4.786%	17.653%	-34.032%	1975/01	579
Oil	0.338%	8.892%	54.562%	-56.813%	1975/01	579
Gold	0.404%	5.560%	53.507%	-25.277%	1975/01	579
Silver	0.209%	9.658%	51.269%	-63.756%	1975/01	579
Agricultural Commodities	0.012%	5.356%	25.088%	-23.725%	1975/01	579
GDP	0.181%	0.996%	7.922%	-8.452%	1975/01	579
Interest rate	4.323%	3.523%	15.920%	-0.010%	1975/01	579
EI	1.122%	0.871%	6.386%	-4.705%	1975/01	579
UI	-0.007%	0.263%	0.942%	-1.570%	1975/01	579
			Panel B: U.K.			
LRE	0.337%	6.366%	24.851%	-35.632%	1990/01	399
Stocks	0.750%	5.117%	15.311%	-32.469%	1990/01	399
Oil	0.328%	10.926%	46.262%	-80.665%	1990/01	399
Gold	0.397%	4.558%	21.609%	-20.478%	1990/01	399
Silver	0.318%	8.186%	34.912%	-43.663%	1990/01	399
Agricultural Commodities	0.149%	3.918%	15.192%	-12.349%	1990/01	399
GDP	0.140%	1.442%	16.208%	-21.602%	1990/01	399
Interest rate	3.179%	3.168%	15.149%	0.015%	1990/01	399
EI	0.355%	0.278%	1.967%	0.033%	1990/01	399
UI	-0.003%	0.221%	1.591%	-0.832%	1990/01	399
			Panel C: JPN			
LRE	0.109%	8.330%	34.276%	-26.445%	1990/01	399
Stocks	-0.006%	5.773%	36.335%	-22.837%	1990/01	399
Oil	0.328%	10.926%	46.262%	-80.665%	1990/01	399
Gold	0.397%	4.558%	21.609%	-20.478%	1990/01	399
Silver	0.318%	8.186%	34.912%	-43.663%	1990/01	399
Agricultural Commodities	0.149%	3.918%	15.192%	-12.349%	1990/01	399
GDP	0.063%	0.794%	5.386%	-7.958%	1990/01	399
Interest rate	0.886%	1.853%	8.288%	-0.629%	1990/01	399
EI	0.048%	0.060%	0.236%	-0.073%	1990/01	399
UI	-0.005%	0.244%	1.725%	-0.898%	1990/01	399

Panel D: AUS						
LRE	0.658%	5.945%	26.489%	-47.944%	1992/06	370
Stocks	0.734%	4.195%	13.685%	-27.893%	1992/06	370
Oil	0.365%	10.516%	26.103%	-80.665%	1992/06	370
Gold	0.482%	4.617%	21.609%	-20.478%	1992/06	370
Silver	0.416%	8.335%	34.912%	-43.663%	1992/06	370
Agricultural Commodities	0.181%	3.988%	15.192%	-12.349%	1992/06	370
GDP	0.485%	1.050%	4.579%	-8.219%	1992/06	370
Interest rate	3.019%	1.775%	7.343%	0.005%	1992/06	370
EI	0.357%	0.270%	1.576%	-0.725%	1992/06	370
UI	-0.001%	0.119%	0.873%	-0.738%	1992/06	370

Notes: U.S. stands for United States of America, U.K. for United Kingdom, JPN for Japan, and AU for Australia. LRE denotes the FTSE/EPRA/NAREIT real estate stock monthly total return. Stocks denotes for each country the corresponding monthly total return of the stock market. Oil denotes the change of oil price in U.S. Dollars. Gold denotes the change of gold price in U.S. Dollars. Silver denotes the change of silver price in U.S. Dollars. Agricultural Commodities denotes the S&P GSCI Agriculture monthly total return. GDP stands for GDP of each country. Interest rate are the 3-month treasury bill rates. EI and UI stand for the rate of expected and unexpected inflation, respectively. Variables show the first difference, SP denotes the starting point of the time series and Obs. displays the number of observations.

2.3.2 Inflation Decomposition

We decompose the observed inflation (I_t) into expected inflation (EI_t) and unexpected inflation (UI_t). Expected inflation is the inflation element that economic agents expect to arise. It is what they have already embedded in their economic choice. Unexpected inflation is the surprise component of inflation that people haven't incorporated in their pricing and costing. We follow Fama and Schwert's (1977) framework to make the decomposition. We can define inflation based on the prior anticipated inflation rate, adjusted for differences between actual inflation and the prior expectation for each period. This leads to a univariate time series approach using Box-Jenkins / ARIMA (1,0,1) procedures to inflation:

Equation 2.1: Inflation Decomposition (ARIMA Model)

$$EI_t = \alpha + \rho I_{t-1} + \varepsilon_t,$$

Equation 2.2: Residuals of Equation 2.1

$$\varepsilon_t = \Theta\varepsilon_{t-1} + e_t.$$

where α, ρ, and Θ are parameters. The fitted value for EI_t is taken as the expected inflation and the residual, e_t, is interpreted as unexpected inflation.

Reasons for changes in unexpected inflation can be manifold. Examples are changes in monetary policy. If a central bank abruptly changes its monetary policy – such as altering interest rates or money supply – this can lead to unexpected inflation (Fisher, 1930). But also supply and demand shocks (Blanchard and Quah, 1989), fiscal policy changes (Sargent and Wallace, 1981), exchange rate fluctuations and economic forecasts can affect the unexpected component of inflation (Taylor, 2000). Unexpected inflation is considered to be more costly to the economy because investors may request a higher premium for high uncertainty in the future (Fama and Schwert, 1977).

When we look at crises such as the COVID-19 pandemic, which caused a supply and demand shock, or the global financial crisis (GFC), which caused a period of massive turbulence in global financial markets and banking systems, we notice a significantly increased volatility of expected and unexpected inflation. This is also shown in Appendix A, where the decomposition of inflation is illustrated. Between 2007 and 2008, the standard deviation of expected inflation in the U.S. stood at 1.90%, while that of unexpected inflation was 0.52%. Compared to the overall observation period, these figures indicate that the volatility of both expected and unexpected inflation during 2007-2008 was approximately twice as high. The fluctuations in both expected and unexpected inflation highlight the complexities policymakers encounter when adjusting their strategies. Stabilizing these indicators during crises is vital for upholding economic confidence and stability.

Appendix A further shows that the average of expected inflation is always higher than the average of the unexpected component in each country. While the U.S. experienced the highest average of expected and unexpected inflation, Japan realised the lowest inflation numbers.

2.3.3 Stationarity and Cointegration

Using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for stationarity, we show that all U.S. series are I(1), indicating stationarity in first differences. Similarly, the series for the U.K., Japan, and Australia are I(1) and therefore, in first-difference stationary. The results are shown in Appendix B. Considering that the variables are I(1) series, we further perform the cointegration test using the trace test.

The trace test investigates the null hypothesis of *r* cointegrating vectors against the alternative hypothesis of *n* cointegrating vectors. To determine ranks and estimate coefficients, maximum likelihood estimation is used. Accordingly, likelihood ratio tests are as follows:

Equation 2.3: Trace Test for Cointegration

$$\lambda_{Trace} = -T \sum_{i=1}^{k} \ln(1 - \lambda_i)$$

where T is the sample size and λ represents the estimated eigenvalues of the reduced rank of the matrix π.[12] In the process, the sequential test strategy begins with $r = 0$ and is continued until the null hypothesis for the 5% significance level cannot be rejected for the first time. The related

[12] The coefficients of the co-integrating relationships (co-integration vectors) and of the error correction term are contained in the matrix π, with $\pi = \alpha\beta'$, where β represents a (n×r) matrix of the r co-integrating vectors. The (n ×r) matrix α contains the so-called loading parameter, i.e., those coefficients that describe the contribution of the *r* long-term relationships in the individual equations. $\zeta_t = Y_t - \beta X_t$, where ζ_t is called the error correction term. The coefficient β is the cointegrating coefficient, and it represents the long-term relationship between X_t and Y_t.

value of *r* ultimately corresponds to the cointegration rank. In this way, there are (*n*-*r*) stochastic trends in the system.

2.3.4 Markov-Switching Vector Error Correction Model (MS-VECM)

Markov-switching models are key tools for exploring transitions between different states within a dataset, especially time series data with non-stationary traits (Hamilton, 1989). This study focuses on financial indicators, such as returns of various assets, and economic indicators like the short-term treasury bill rate, GDP, and inflation. These variables function as regime indicators, capturing shifting dynamics within the data. Whether observed or latent, these indicators encapsulate changes in the underlying economic context and can instigate switches between the model's different regimes.[13] Following Beckmann and Czudaj (2013), a MS-VECM is used to examine the relationship between the price of assets and expected and unexpected inflation.

The parameters of this model are designed to take a constant value in each regime and to shift discretely from one regime to the other with different switching probabilities. Switches between states are assumed to follow an exogenous stochastic process. Consider an M-regime *p*th order MS-VECM, which in general allows for regime shifts in the vector of intercept terms, the autoregressive part, the long-run matrix, and the variance-covariance matrix of the errors:

Equation 2.4:MS-VECM

$$\Delta Y_t = v(s_t) + \Gamma(L)(s_t)\Delta Y_{t-1} + \Pi(s_t)Y_{t-1} + \varepsilon_t,$$

[13] We use the Expectation-Maximization (EM) algorithm to estimate the parameters of the Markov-switching model and to identify the different states or regimes by maximizing the data likelihood function. In our case, the EM algorithm is used to estimate the parameters that govern the probability of switching from one state (or regime) to another, as well as the parameters of each individual state.

where Δ denotes the difference operator, Y_t represents a K-dimensional vector of time series, $Y_t = [R_t, EI_t, UI_t, X_t]$ and R_t is a vector of asset returns, including stocks, LRE, commodities, silver, and gold. X_t are economic control variables such as GDP, real interest rates, and oil prices. $v(s_t)$ denominates a K-dimensional vector of regime-dependent intercept terms. ε_t is a vector of error terms with a regime-dependent variance-covariance matrix $\sum(s_t)$, $\varepsilon_t \sim NIID(0, \sum(s_t))$. $\Gamma(L)(s_t)$ is the K×K matrix for the state-dependent short-run dynamics. (Beckmann and Czudaj, 2013). The stochastic regime-generating process is assumed to be an ergodic, homogenous, and irreducible first-order Markov chain with a finite number of regimes, $s_t \in \{1, \dots, M\}$, and constant transition probabilities:

Equation 2.5:Transition Probabilities

$$p_{ij} = \Pr(s_{t+1} = j | s_t = i) \, , p_{ij} > 0, \sum_{j=1}^{M} p_{ij} = 1 \;\; \forall i, j \in \{1, \dots, M\}$$

The first expression of Equation 2.5 gives the probability of switching from regime i to regime j at time t + 1 which is independent of the history of the process. p_{ij} is the element in the ith row and the jth column of the M × M matrix of the transition probabilities P. In this paper, we consider two regimes.

2.4 Empirical Results

2.4.1 Long-Term Hedging Properties

Based on the Johansen cointegration test, we identify three cointegration relationships in the U.S. and Japan, and two cointegration relationships in the U.K.. For Australia, no rank could be determined, hence Australia does not have a co-integrating relationship. Table 2.2 reports long-term relationships (β-vectors). In each model with a cointegration matrix, the first vector is normalised to the LRE returns, while the second vector is normalised to the general stock market performance.

We find significant long-term relationships between the performance of listed real estate markets and expected inflation in the U.S., U.K., and Japan (Table 2.2). In the long-term, LRE can positively hedge against expected inflation in these countries. A one percent increase in expected inflation is related to a 1.754 percent, a 1.711 percent, and a 11.182[14] percent increase in the LRE total return in the U.S., the U.K., and Japan, respectively.

In the U.S., the U.K., and Japan, LRE is not significantly related to unexpected inflation in the long-term relationship. This is consistent with most prior literature, which also finds mixed results in terms of the hedging ability of real estate against unexpected inflation. For instance, Limmack and Ward (1988) found that office and retail properties offered no significant hedge against unexpected inflation.

Moreover, we find a significantly negative long-term coefficient between stock returns and expected and/or unexpected inflation, indicating that general stocks do not provide an effective long-term hedge against inflation. This finding is in line with previous literature. For instance, using Swiss data, Hoesli (1994) shows that real estate hedges better in the long-run than stocks. When the inflation rate is divided into expected and unexpected inflation, stocks exhibit negative coefficients for both expected and unexpected inflation. Meanwhile, the coefficient for expected inflation is positive for real estate.

[14] The large coefficient in Japan is caused by the low standard deviation of expected inflation in that country. If we use economic interpretation by multiplying the coefficient with the standard deviation of the variable, we can conclude that a one standard deviation increase in expected inflation leads to an increase in LRE returns by 0.868 standard deviation.

Table 2.2: Long-Term Equilibrium Relationships (β-Vectors)

Country	Rank	$r_{LRE,t-1}$	$r_{stock,t-1}$	$r_{oil,t-1}$	$r_{gold,t-1}$	$r_{silver,t-1}$	$r_{agri,t-1}$	GDP_{t-1}	ir_{t-1}	EI_{t-1}	UI_{t-1}
U.S.	3	1.000	0.000	0.000	-0.227	-0.509	0.580	-0.021***	-0.236***	1.754**	-1.026
		(0.000)	(0.000)	(0.000)	(0.892)	(0.695)	(0.915)	(0.010)	(0.076)	(1.038)	(5.568)
		0.000	1.000	0.000	0.446	-2.032	4.781**	0.031	1.017***	-3.891*	-13.145
		(0.000)	(0.000)	(0.000)	(2.016)	(1.569)	(2.067)	(0.022)	(0.175)	(2.345)	(12.576)
		0.000	0.000	1.000	0.204	0.887	-4.272***	-0.028***	-0.550***	1.807	-7.354
		(0.000)	(0.000)	(0.000)	(0.906)	(0.705)	(0.929)	(0.010)	(0.077)	(1.054)	(5.652)
U.K.	2	1.000	0.000	0.350*	-0.556	-0.209	-0.304	-0.052***	-0.161***	1.711**	-11.070
		(0.000)	(0.000)	(0.203)	(0.353)	(0.299)	(0.490)	(0.011)	(0.032)	(0.868)	(12.499)
		0.000	1.000	-0.127	-0.112	-0.370**	0.886***	-0.030***	-0.065***	-1.571***	-25.827***
		(0.000)	(0.000)	(0.122)	(0.211)	(0.179)	(0.294)	(0.007)	(0.019)	(0.520)	(7.482)
JPN	3	1.000	0.000	0.000	-0.556*	-0.282	-0.217	-0.132***	-0.228***	11.182***	6.190
		(0.000)	(0.000)	(0.000)	(0.337)	(0.279)	(0.418)	(0.018)	(0.058)	(4.136)	(5.908)
		0.000	1.000	0.000	-1.109***	0.485	-0.193	-0.068***	-0.396***	1.192	-24.117***
		(0.000)	(0.000)	(0.000)	(0.473)	(0.391)	(0.586)	(0.025)	(0.082)	(5.805)	(8.291)
		0.000	0.000	1.000	-1.618	0.464	0.350	0.028	-0.396***	4.673	-7.153
		(0.000)	(0.000)	(0.000)	(1.168)	(0.964)	(1.446)	(0.061)	(0.047)	(14.315)	(20.445)

*Notes: U.S. stands for United States of America, U.K. for United Kingdom, JPN for Japan. The analysis of the U.S., U.K., and Japan is conducted by using an unrestricted constant. $r_{LRE,t-1}$ denotes the FTSE/EPRA/NAREIT real estate stock total return index. $r_{stock,t-1}$ denotes for each country the corresponding total return of the stock market index. $r_{oil,t-1}$ denotes the oil price in U.S. Dollars. $r_{gold,t-1}$ denotes the gold price in U.S. Dollars. $r_{silver,t-1}$ denotes the silver price in U.S. Dollars. Australia is not reported because the rand of listed real estate, stocks, oil, gold, silver, agricultural, GDP, interest rate, expected and unexpected inflation in Australia is zero, indicating that these variables are not co-integrated. $r_{agri,t-1}$ denotes the total return index of S&P GSCI Agriculture. GDP_{t-1} stands for GDP of each country. ir_{t-1} are the 3-month treasury bill rates. EI_{t-1} and UI_{t-1} stand for expected and unexpected inflation, respectively. Rank denotes the rank of π matrix. Standard errors are included in the parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively. $\zeta_t = Y_t - \beta X_t$, where ζ_t is called the error correction term. The coefficient β is the cointegrating coefficient, and it represents the long-term relationship between X_t and Y_t.*

Concerning other long-term equilibrium relationships, we find a positive long-term relationship between LRE returns and oil prices in the U.K.. Furthermore, we observe a negative long-term relationship between the gold price and LRE returns in Japan. Moreover, we find a negative long-term elasticity of interest rates on LRE returns in the U.S., the U.K., and Japan, which can be explained by the fact that increasing capital costs lead to lower demand for real estate and, therefore, to lower returns. Besides, we find a negative relationship between LRE returns and GDP in the U.S., the U.K., and Japan.[15]

2.4.2 Short-Term Hedging Properties

The MS-VECM representation given in Equation 2.3 has been estimated for each country while enabling each parameter to switch between two regimes, including the intercept, the autoregressive elements, the residual variance-covariance matrix, and, most notably, the adjustment parameters to deviations from long-run relationships.

The short-term relationships and the matrices of transition are reported for both regimes in Table 2.3. The MS-VECM model identifies the transmission matrix from one regime to another for each country. In the U.S., the probability of staying in Regime 1 is 94.1%, while the probability of switching to Regime 2 is 5.9%. It suggests the dominance of the first regime. Switching from Regime 2 to Regime 1 shows a probability of 20.6%, while staying in Regime 2 shows a probability of 79.4%. The associated probabilities for the U.K., Japan, and Australia are comparable.

[15] The negative long-term relationship between GDP and LRE is contradictory to our expectation, which may be due to the merged crises during the sample period. To test our argument, we add a crisis dummy into the long-term relationship equations, and the coefficients for GDP become positive. However, the coefficients for expected and unexpected inflation in the long-term relationships remain very robust. So, we keep our baseline model as the one without a crisis dummy. Detailed results are available upon request.

Table 2.3: Short-Term Coefficients and Transition Probability Matrix

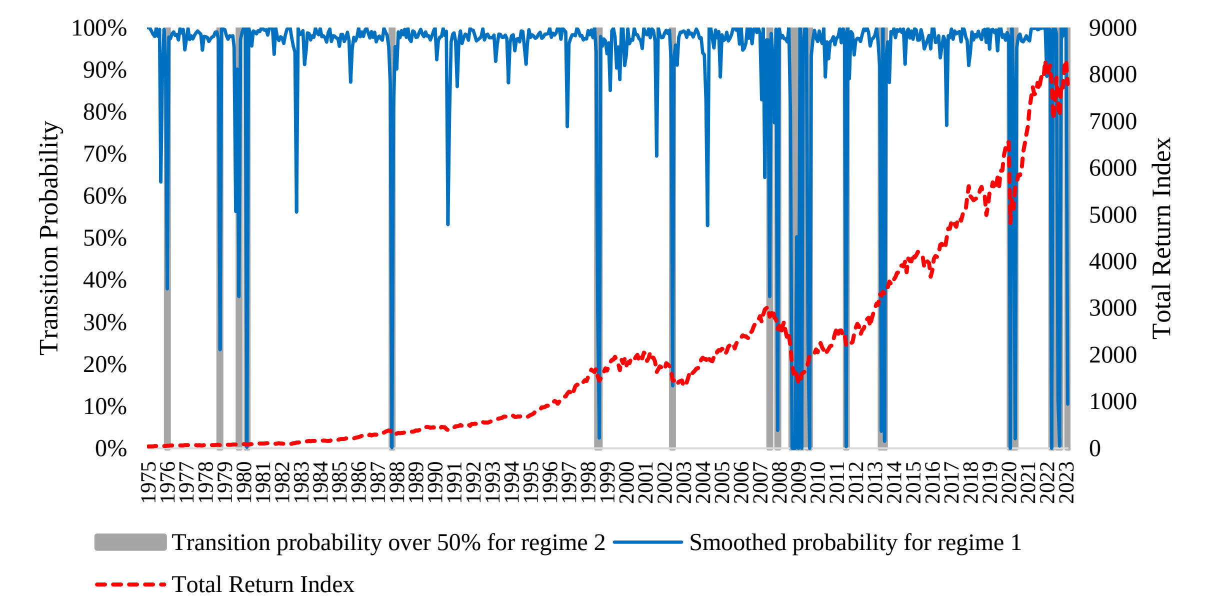
		Short-term coefficients for Regime 1 and 2													Transition probability matrix P		
Country		$\Delta r_{LRE,t-1}$	$\Delta r_{stock,t-1}$	$\Delta r_{oil,t-1}$	$\Delta r_{gold,t-1}$	$\Delta r_{silver,t-1}$	$\Delta r_{agri,t-1}$	ΔGDP_{t-1}	Δir_{t-1}	ΔEI	ΔUI	ECT1	ECT2	ECT3		Regime 1	Regime 2
U.S.	Regime 1	-0.119*** (0.033)	0.112*** (0.043)	-0.028 (0.023)	0.053 (0.041)	-0.072*** (0.024)	0.022 (0.029)	0.0001 (0.000)	-0.009** (0.003)	0.430* (0.230)	-1.410* (0.720)	-0.004 (0.009)	-0.001 (0.008)	0.004 (0.010)	Regime 1	0.941	0.206
	Regime 2	0.044 (0.106)	0.775*** (0.417)	0.417*** (0.111)	-1.596*** (0.322)	0.734** (0.323)	0.805*** (0.1181)	0.001 (0.002)	0.003 (0.056)	-0.900 (1.430)	-30.430*** (7.020)	-0.081* (0.048)	-0.036 (0.057)	-0.010 (0.094)	Regime 2	0.059	0.794
U.K.	Regime 1	-0.153** (0.075)	0.015 (0.083)	0.029 (0.028)	-0.078 (0.053)	0.008 (0.044)	0.089 (0.063)	0.003* (0.001)	-0.063*** (0.012)	4.630* (2.660)	-3.630*** (1.240)	0.022 (0.014)	0.014 (0.026)		Regime 1	0.773	0.410
	Regime 2	0.029 (0.147)	0.377* (0.216)	0.094 (0.085)	-0.231 (0.201)	-0.155 (0.135)	-0.083 (0.228)	0.007 (0.008)	0.047 (0.078)	-3.880 (5.340)	-5.580 (5.530)	-0.054 (0.039)	0.058 (0.061)		Regime 2	0.227	0.590
JPN	Regime 1	-0.116* (0.070)	0.452*** (0.119)	-0.058 (0.058)	0.158 (0.144)	-0.127 (0.099)	-0.127 (0.172)	-0.009 (0.009)	-0.065 (0.064)	60.010** (26.020)	4.640 (3.050)	-0.282*** (0.048)	0.230*** (0.050)	-0.062*** (0.018)	Regime 1	0.954	0.041
	Regime 2	-0.186*** (0.049)	0.702*** (0.064)	0.102*** (0.033)	-0.368*** (0.088)	0.090** (0.042)	0.110 (0.076)	0.001 (0.003)	-0.056* (0.031)	-17.680*** (3.540)	-1.570 (1.120)	0.001 (0.013)	-0.040*** (0.006)	0.023*** (0.002)	Regime 2	0.046	0.959
AUS	Regime 1	-0.117* (0.061)	0.024 (0.063)	-0.051** (0.020)	-0.069 (0.049)	-0.026 (0.030)	0.029 (0.036)	-0.001** (0.001)	-0.023 (0.014)	1.320* (0.750)	1.830 (1.680)				Regime 1	0.984	0.209
	Regime 2	-0.489** (0.236)	0.642 (0.510)	0.396** (0.172)	-0.467 (0.350)	-0.173 (0.251)	-0.722** (0.337)	0.002 (0.004)	0.425*** (0.138)	-10.290 (8.170)	2.920 (24.660)				Regime 2	0.016	0.791

Notes: U.S. stands for United States of America, U.K. for United Kingdom, JPN for Japan, and AU for Australia. We only report the equation for LRE returns. $r_{LRE,t-1}$ denotes the FTSE/EPRA/NAREIT real estate stock total return index. $r_{stock,t-1}$ denotes for each country the corresponding total return of the stock market index. $r_{oil,t-1}$ denotes the oil price in U.S. Dollars. $r_{gold,t-1}$ denotes the gold price in U.S. Dollars. $r_{silver,t-1}$ denotes the silver price in U.S. Dollars. $r_{agri,t-1}$ denotes the total return index of S&P GSCI Agriculture. GDP_{t-1} stands for GDP of each country. ir_{t-1} are the 3-month treasury bill rates. EI_{t-1} and UI_{t-1} stand for expected and unexpected inflation, respectively. ECT1, ECT2, and ECT3 are the coefficients of error correction terms. Regime 1 and 2 are reported. The transition matrix P reports the transition probabilities of the stochastic process.

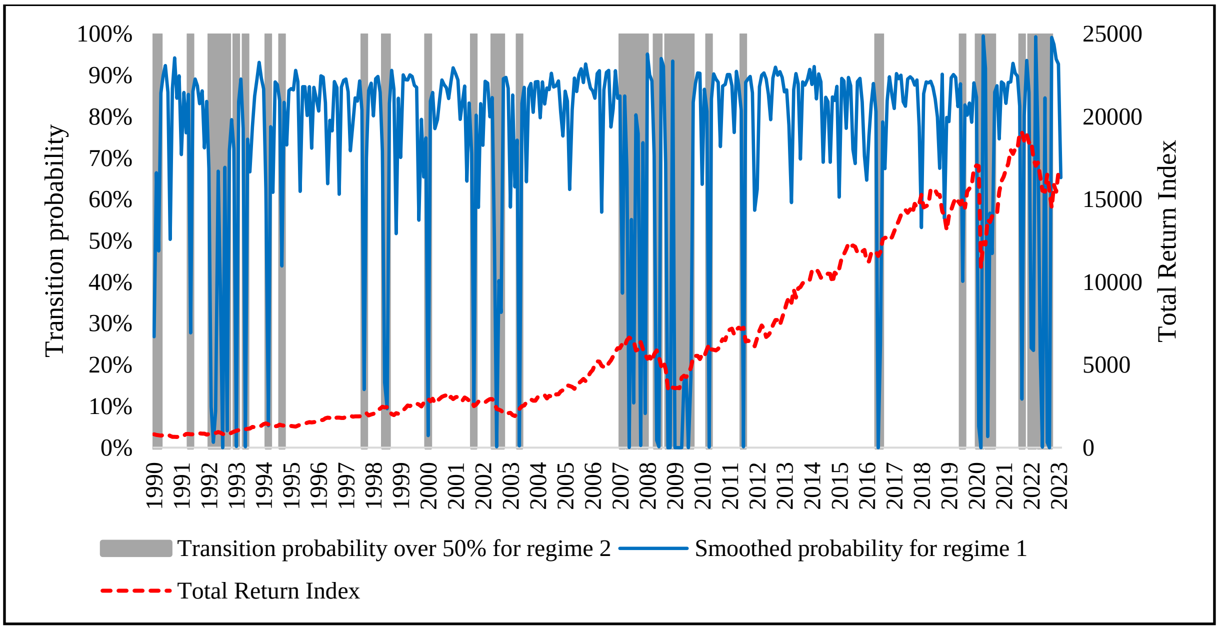
To better understand the two regimes, Figure 2.1 illustrates the switching process for the U.S., U.K., Japan, and Australia. The blue line shows the probability of switching to Regime 1, and the grey area indicates that the probability of Regime 1 is larger than 50%. For comparison purposes, we also illustrate the LRE return in each graph (dashed line). As shown in Figure 2.1, it is quite obvious that Regime 1 captures the stable periods and Regime 2 the times of turbulence, particularly for the U.S., the U.K., and Australia. For instance, turbulent periods like the 1979 oil crisis, the GFC, the dot-com bubble, or the COVID-19 pandemic appear to lead to a switching process to Regime 1. Meanwhile, we also see a remarkable decrease in LRE returns in Regime 2. However, for Japan, we see that this is not obvious. In the case of Japan, specific economic development can provide an explanation. The collapse of the asset price bubble in Japan in 1991 resulted in a period of economic stagnation. Between 1995 and 2007, the nominal GDP fell from 5.33 trillion to 4.36 trillion U.S. Dollars. From the early 2000s, the Bank of Japan set out to encourage economic growth through quantitative easing, which indicates the special role of Japan as an economy. Additionally, in 2006, the Bank of Japan concluded its quantitative easing strategy and increased the operating target for money market operations from essentially zero percent to approximately 0.25 percent. This move marked the end of a five-year period of zero interest rates.

Figure 2.1: Transition Probability and Total Returns

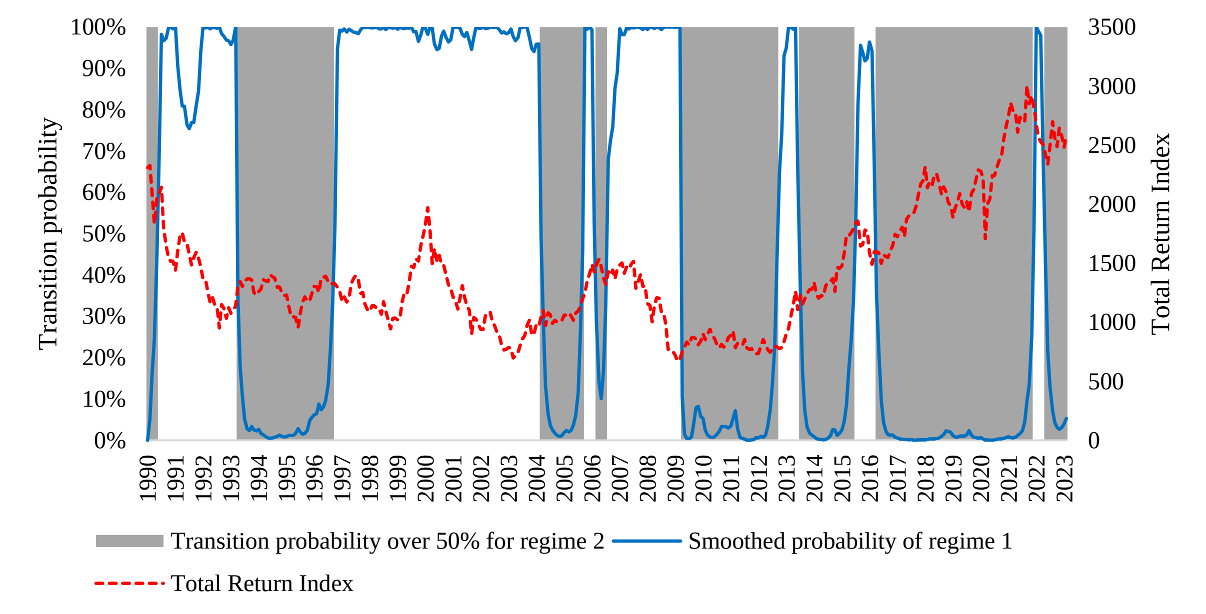
a. U.S. Smoothed Probability of Regime 1



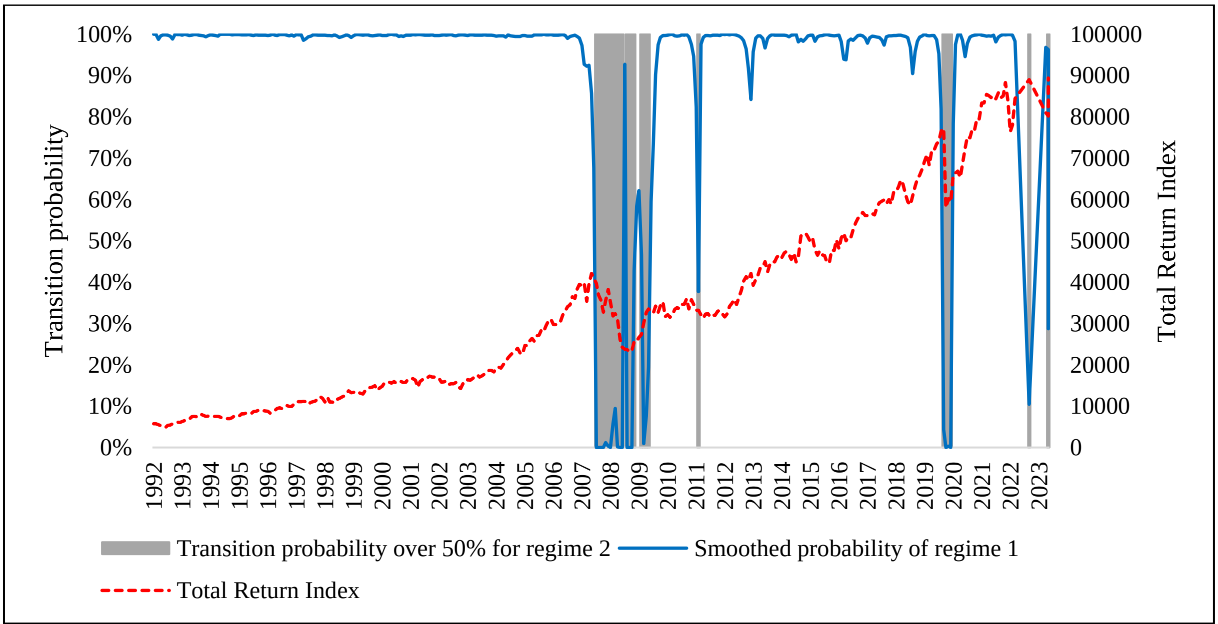
b. U.K. Smoothed Probability of Regime 1



c. JPN Smoothed Probability of Regime 1



d. AUS Smoothed Probability of Regime 1



We report the estimation coefficients in Table 2.3. For the U.S., we see a significant positive short-term impact of expected inflation on LRE performance in Regime 1 (stable periods), but the impact becomes insignificant during the turbulent period. In contrast, unexpected inflation has a significant negative impact on LRE returns in both Regime 1 (stable periods) and Regime 2 (turbulent periods). But the impact is more negative during the turbulent period. In the U.K., expected inflation has a significant positive impact on LRE returns in the short-term in Regime

1 (stable periods), but a non-significant impact in Regime 2 (turbulent periods). The hedging ability is accordingly lost in times of turbulences. For Japan, we see a positive significant short-term impact of expected inflation on LRE in Regime 1, but perverse hedging capabilities in Regime 2. For Australia, we see a positive significant short-term impact of expected inflation on LRE in Regime 1, but no hedging attributes in Regime 2.

To provide a better intuitive overview, we illustrate the restricted[16] time-varying short-term impact of expected and unexpected inflation on LRE returns based on the smoothed transmission probability and the coefficient in each regime:

Equation 2.6: Restricted Time-Varying Short-Term Impact of Expected Inflation

$$EI_t = p_1 * coefEI_1 + (1 - p_1) * coefEI_2$$

Equation 2.7: Restricted Time-Varying Short-Term Impact of Unexpected Inflation

$$UI_t = p_1 * coefUI_1 + (1 - p_1) * coefUI_2$$

We depict the time-varying coefficients if at least one coefficient in Equation is significant in Regimes 1 and 2. Hence, we show the time-varying coefficients of expected and unexpected inflation in the U.S. (Figures 2.2a and 2.2b), those of expected and unexpected inflation in the U.K. (Figures 2.2c and 2.2d), that of expected inflation in Japan (Figure 2.2e), and that of expected inflation in Australia (Figure 2.2f).

First, in the U.S., U.K., Japan, and Australia, we find that during stable periods, LRE provides good protection against expected inflation in the short-term. However, the relationship becomes

[16] If the estimated coefficient is statistically insignificant, we restrict this coefficient to be zero.

negative or zero during turbulent periods. As shown in Figure 2.2a, the coefficient in the U.S. varies between 0.45 and 0.00 for expected inflation. In Regime 1 (stable periods), the coefficient remains positive. But in Regime 2 (e.g., 1979, 2007 and 2009-2010), the coefficient becomes negative or zero. In the U.K., as shown in Figure 2.2c, the coefficient of expected inflation varies from 4.50 to 0.00 and behaves similarly to that for the U.S.. While in Regime 1 (stable periods) the coefficient remains positive, Regime 2 leads to coefficients of zero (e.g., 1992, 1993, and 2007-2009). Figure 2.2e shows the coefficient of expected inflation in Japan, varying between -20 and 60.[17] While in Regime 1 (stable periods) the coefficient remains positive, Regime 2 leads to negative coefficients (e.g., 1993-1997). As illustrated in Figure 2.2f, in Australia, the coefficient of expected inflation varies from 1.40 to 0.00. While in Regime 1 (stable periods) the coefficient remains positive, Regime 2 leads to zero coefficients (e.g., 2008-2009 and 2020).

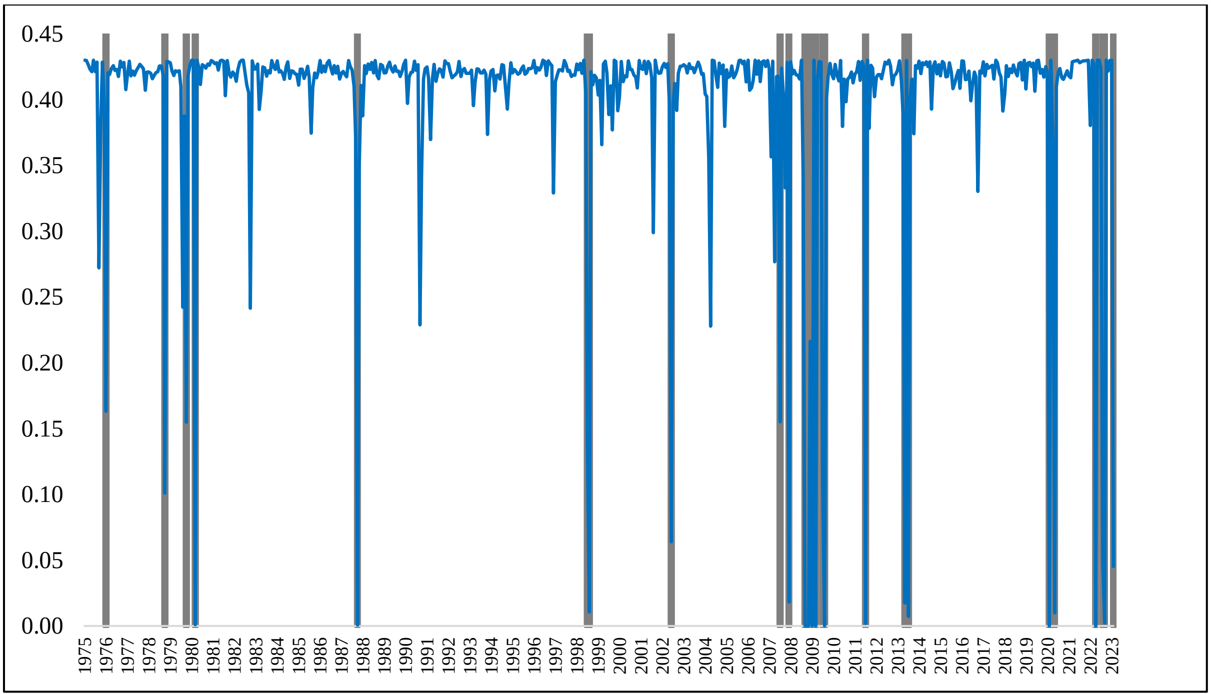
Overall, our analysis shows that the short-term inflation-hedging ability of LRE can be perverse during turbulent periods. During the more steady environment of stable periods, the change in the inflation rate is largely determined by the expected component. LRE provides good inflation hedging because 1) the rental income can be adjusted according to inflation; and 2) the spreads between the cap rate and base rate often narrow because investors perceive a lower risk in investing in real estate due to the general belief that real estate assets can hedge against inflation.[18] However, during turbulent times, due to the high levels of uncertainty, investors normally charge a higher risk premium. As a result, the asset value will decrease, and the short-term inflation-hedging ability of LRE will become insignificant or even negative.

[17] The extreme large coefficient in Japan is caused by the low standard deviation of expected inflation in Japan. An increase in expected inflation by one standard deviation might lead to an increase in LRE returns by 0.429 standard deviations.
[18] Our analysis based on dividend yields and price appreciate index confirm these arguments. The detailed results and discussions are in 4.3.2.

Of course, because each country has different turbulent periods due to their different economic conditions, the coefficients look different. Additionally, varying levels of inflation across countries also play a significant role. For example, Japan has undergone a prolonged period of low inflation. Moreover, the divergent growth of the LRE market and differences in lease contract practices can contribute to distinct responses to inflationary shocks.

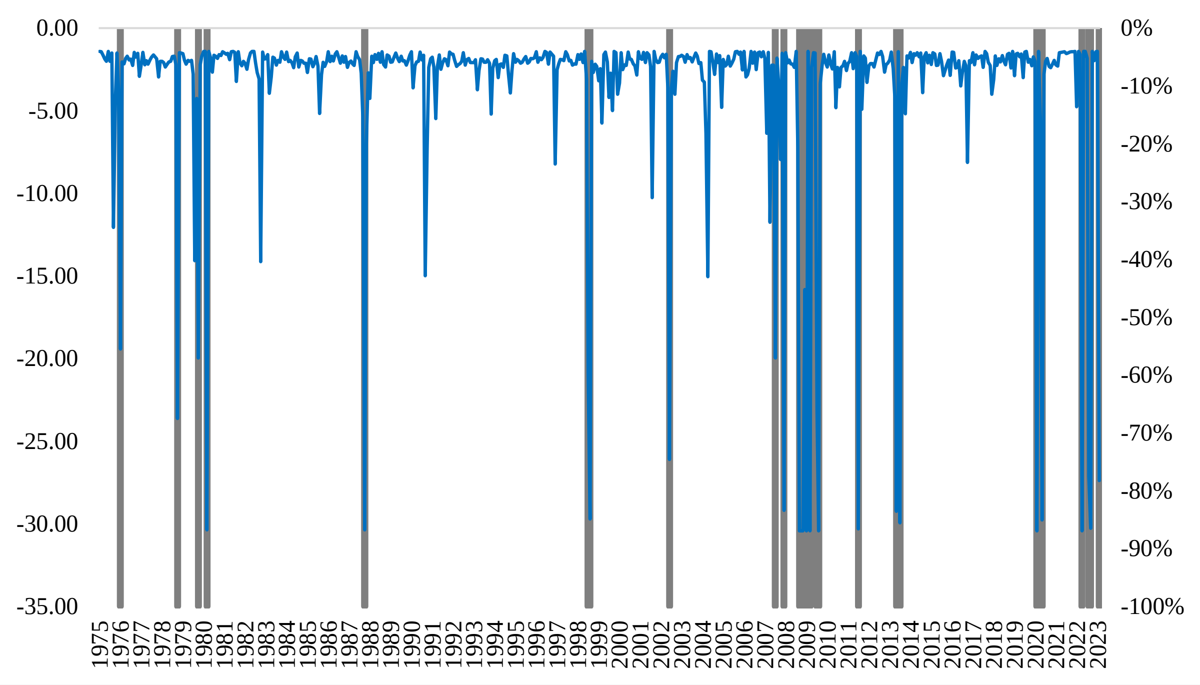
Figure 2.2: Time-Varying Short-Term Impact of Inflation on Real Estate Equity Returns

a. U.S. Time-Varying Coefficient of EI



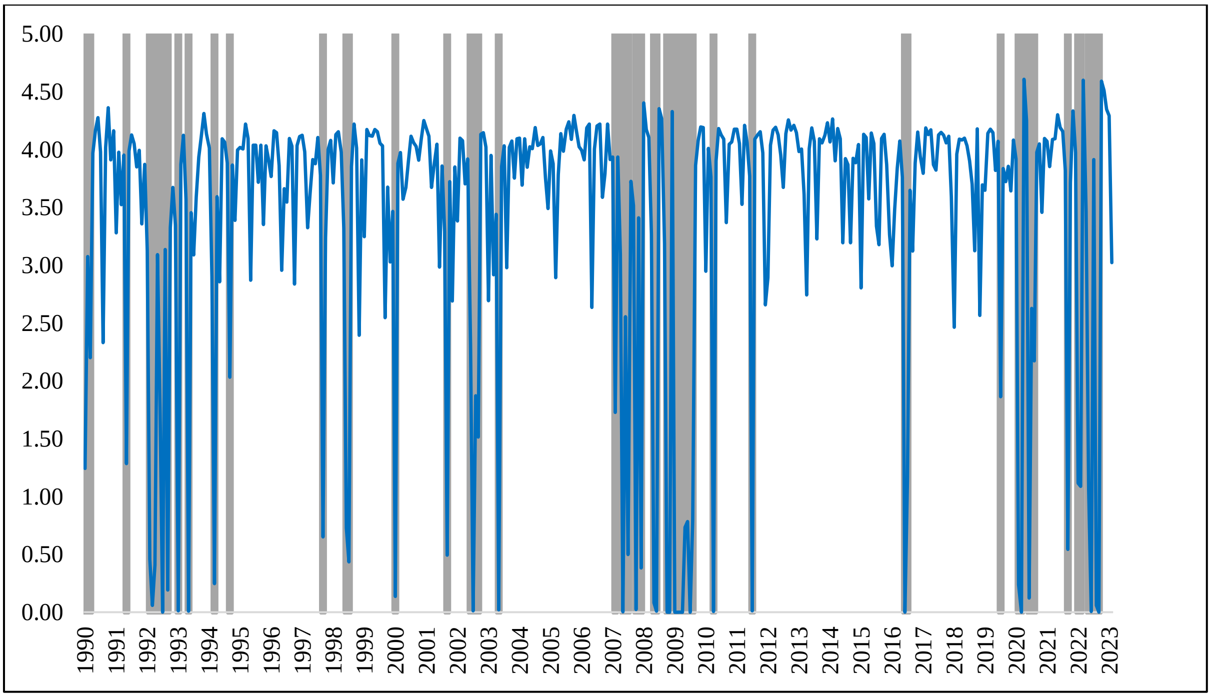
Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

b. U.S. Time-Varying Coefficient of UI



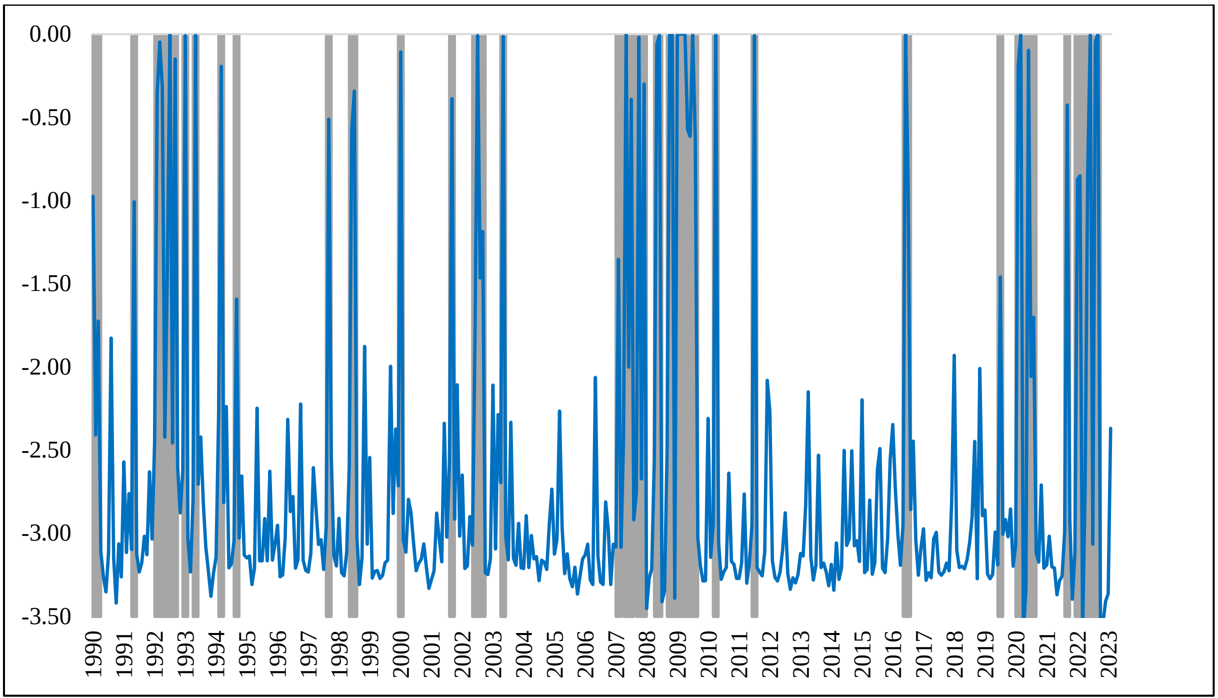
Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7). An increase in unexpected inflation by one standard deviation would lead to a decrease in real estate returns by 1.396 standard deviations.

c. U.K. Time-Varying Coefficient of EI



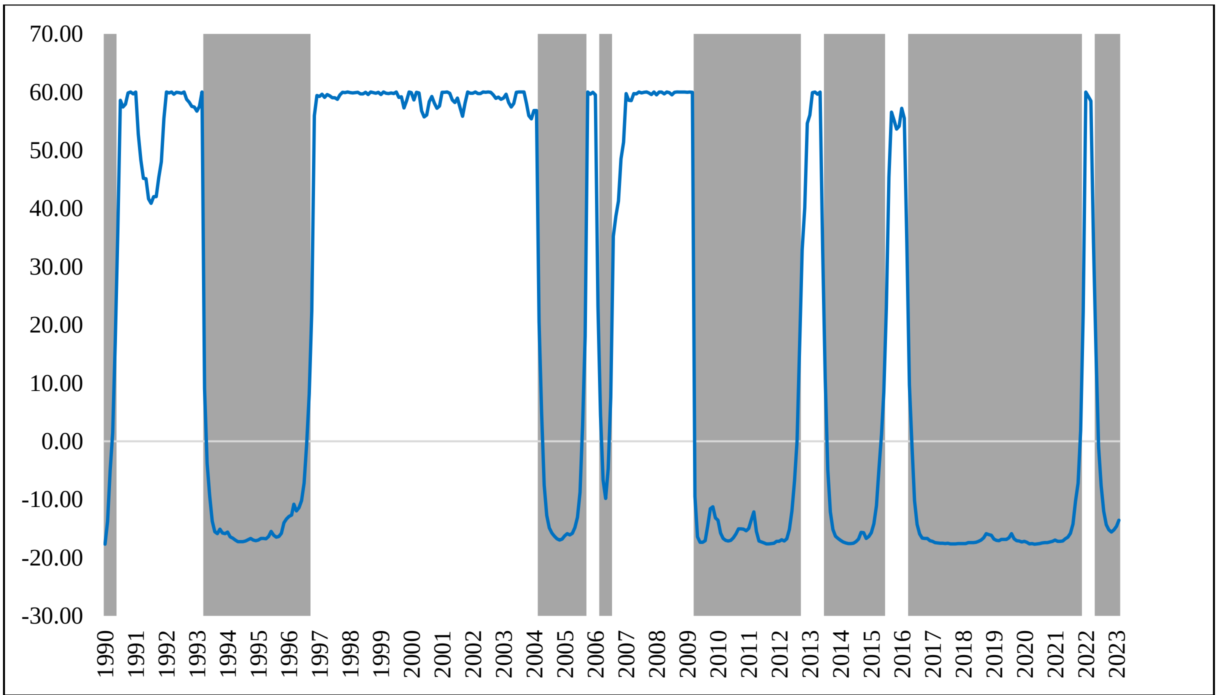
Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

d. U.K. Time-Varying Coefficient of UI



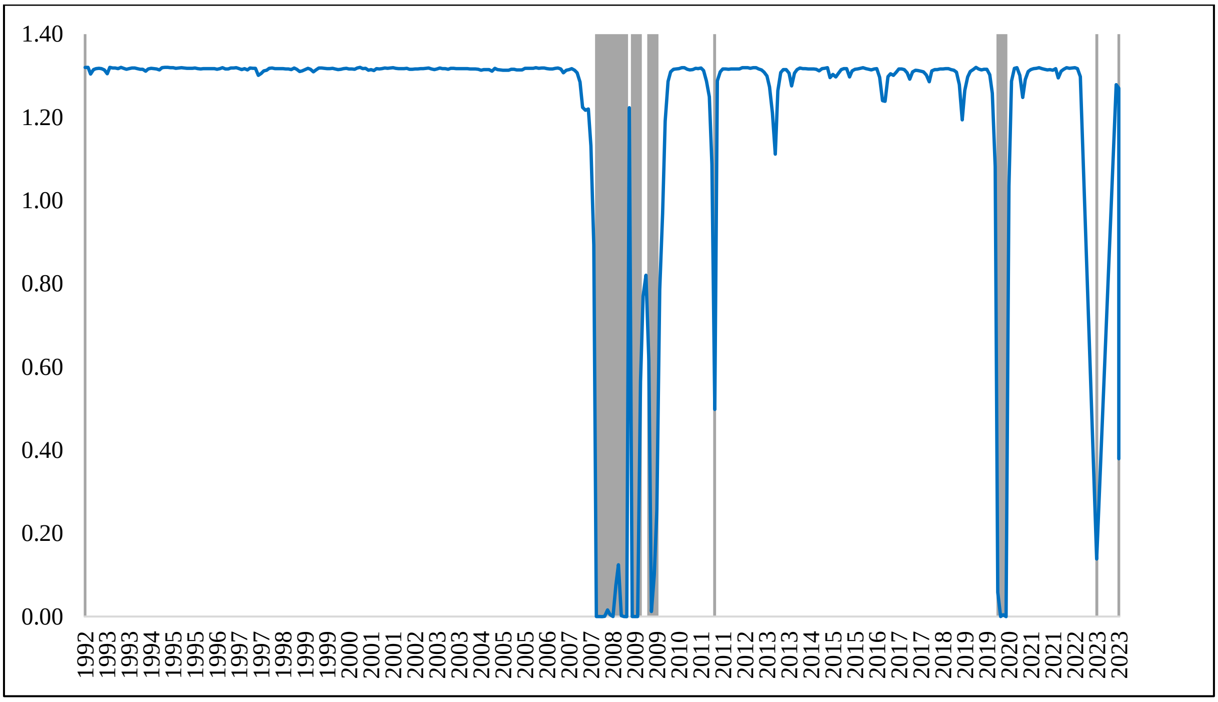
Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

e. JPN Time-Varying Coefficient of EI



Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

f. AUS Time-Varying Coefficient of EI

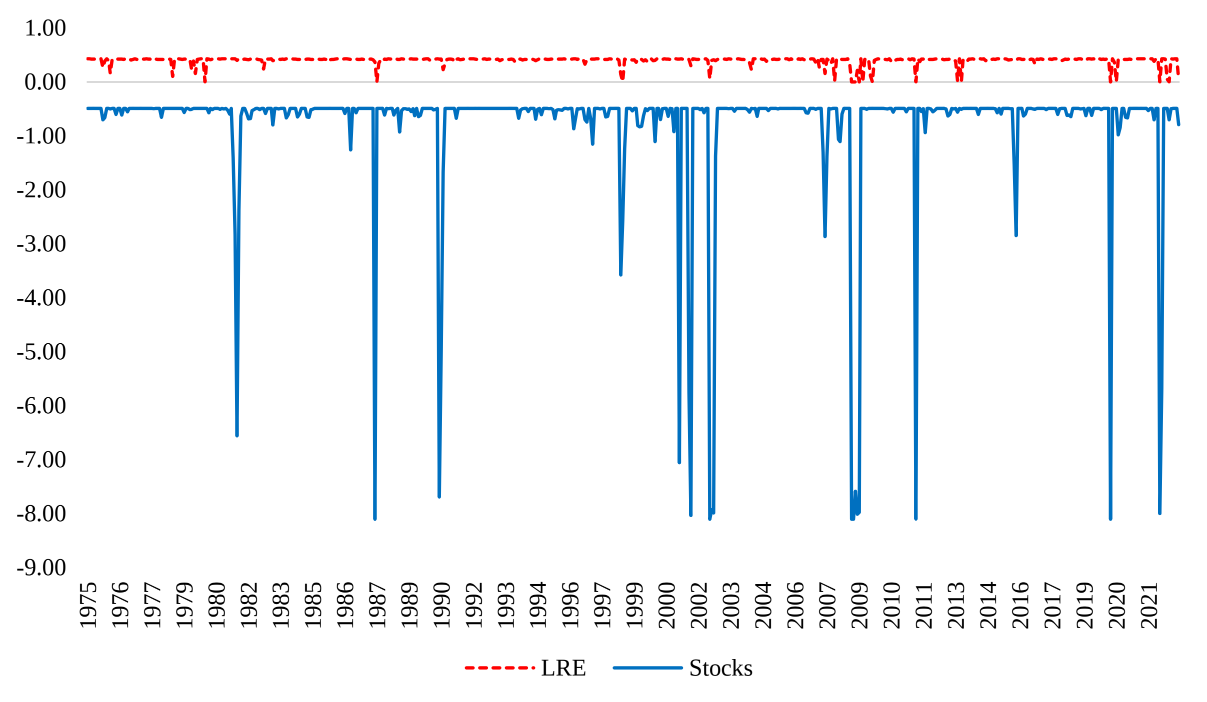


Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

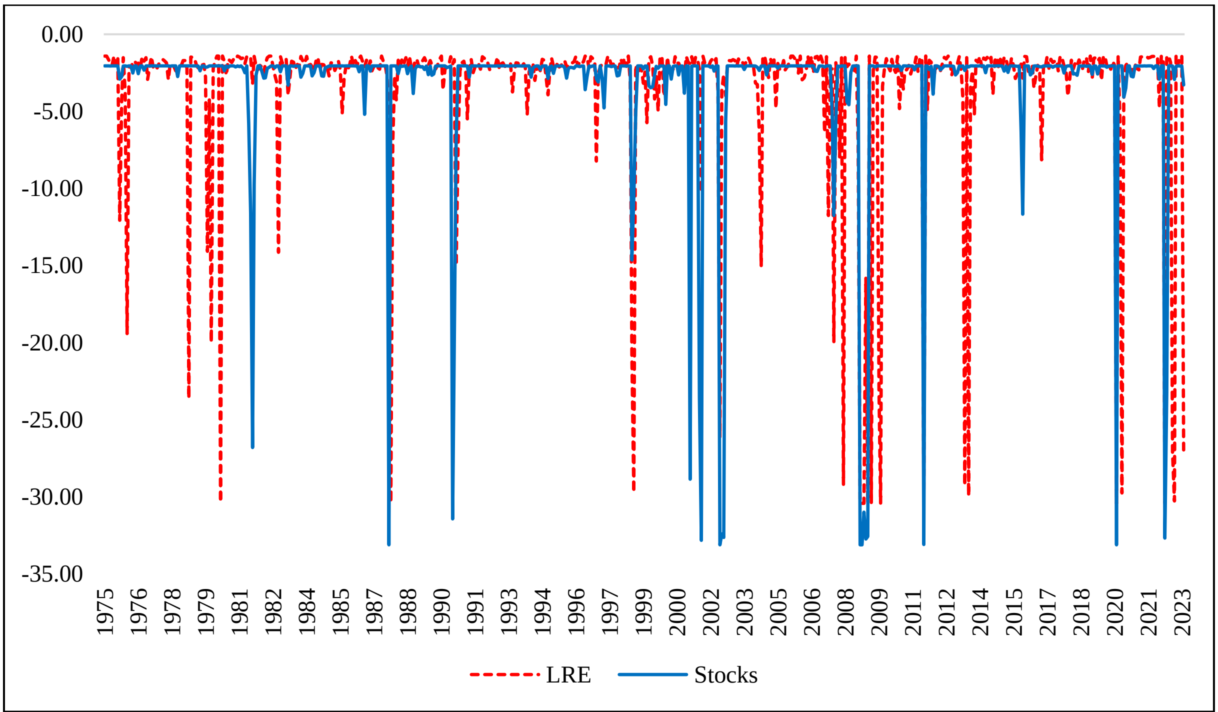
If we compare the short-term hedging ability of LRE with that of stocks, we can see that LRE provides better inflation hedging effectiveness than stocks also in the short-term. Figure 2.3 compares the time-varying coefficients of EI and UI for stocks and LRE returns for the U.S., U.K., Japanese, and Australian markets. The red dotted line shows the coefficient for LRE, and the blue line indicates the coefficient for stocks. In the U.S., compared to stocks, LRE reacts more positively to expected and unexpected inflation, especially during stable periods (Figures 2.3a and 2.3b). We can see a significant positive coefficient for expected inflation for LRE, while stocks show a significant negative impact. Furthermore, the hedging characteristics of LRE is of lesser magnitude than for stocks (Figure 2.3a). In the U.K. (Figure 2.3c), LRE also shows better hedging properties concerning expected inflation, as compared to stocks. Regarding unexpected inflation, LRE and stocks have insignificant relationships, while stocks exhibit larger magnitudes. Overall, LRE provides better inflation-hedging abilities than stocks in the U.S. and U.K.. However, LRE in Japan and Australia show mixed results in the short-term inflation hedging properties compared to stocks.

Figure 2.3: Time-Varying Coefficients of LRE and Stocks

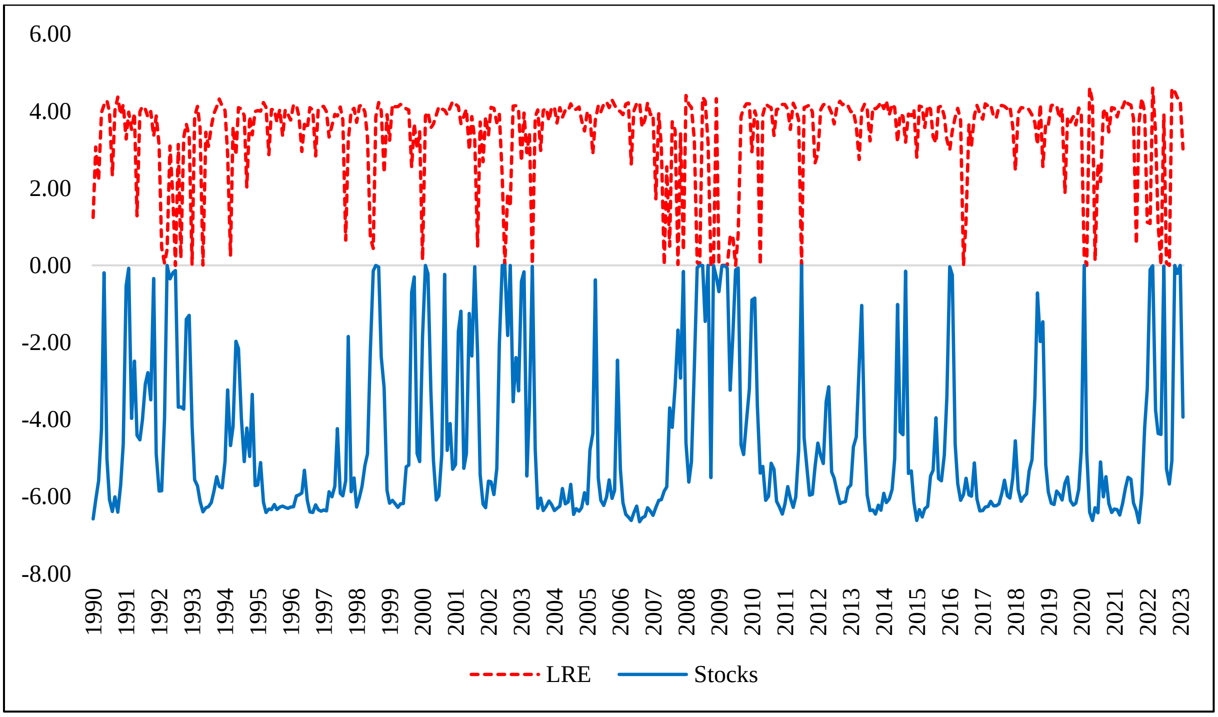
a. U.S. Time-Varying Coefficient of EI



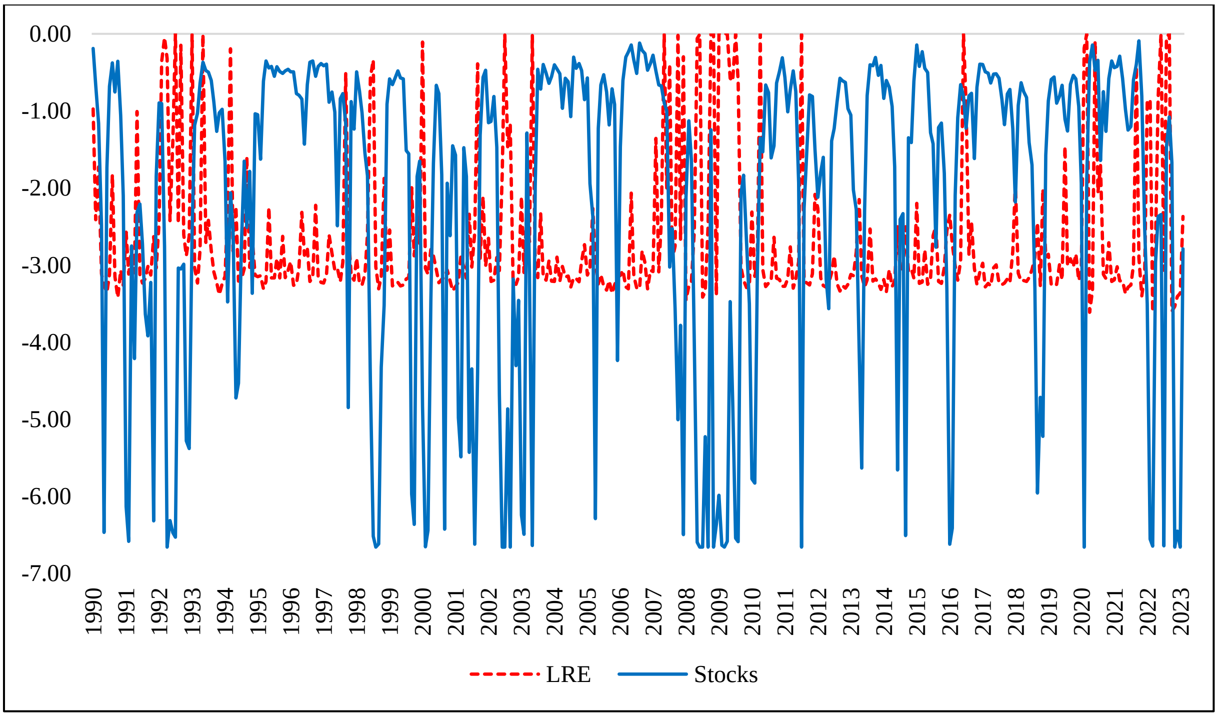
b. U.S. Time-Varying Coefficient of UI



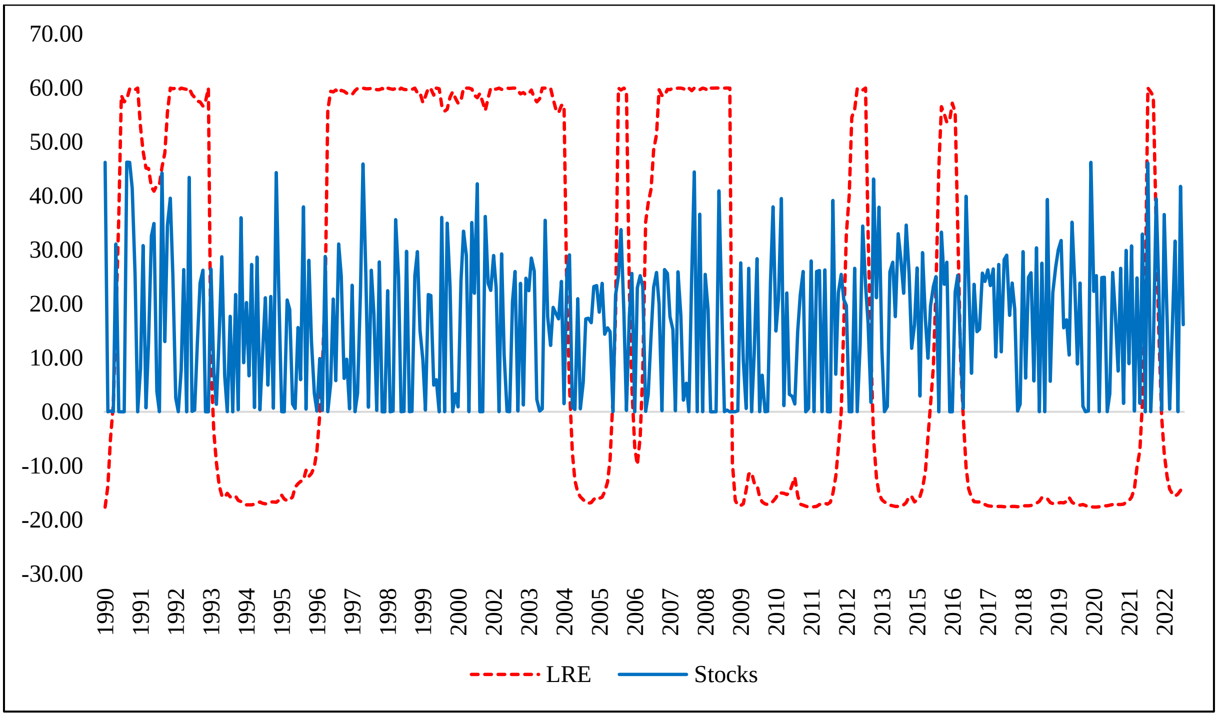
c. U.K. Time-Varying Coefficient of EI



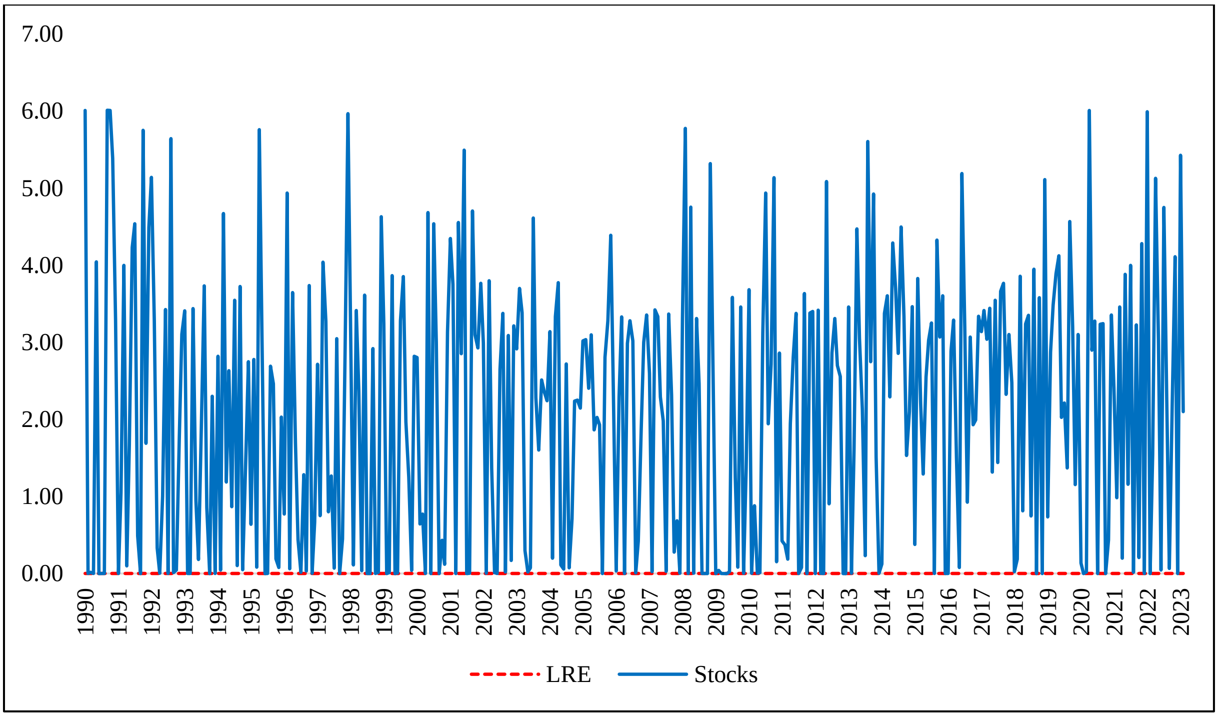
d. U.K. Time-Varying Coefficient of UI



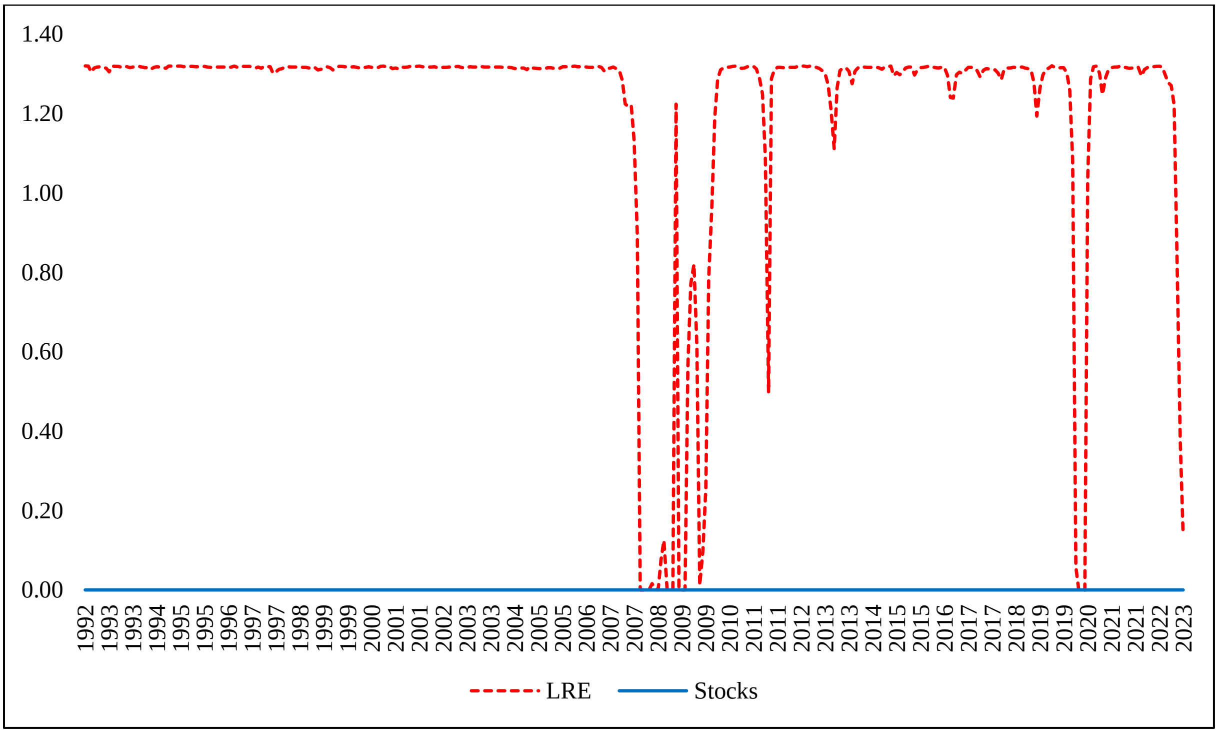
e. Japan Time-Varying Coefficient of EI



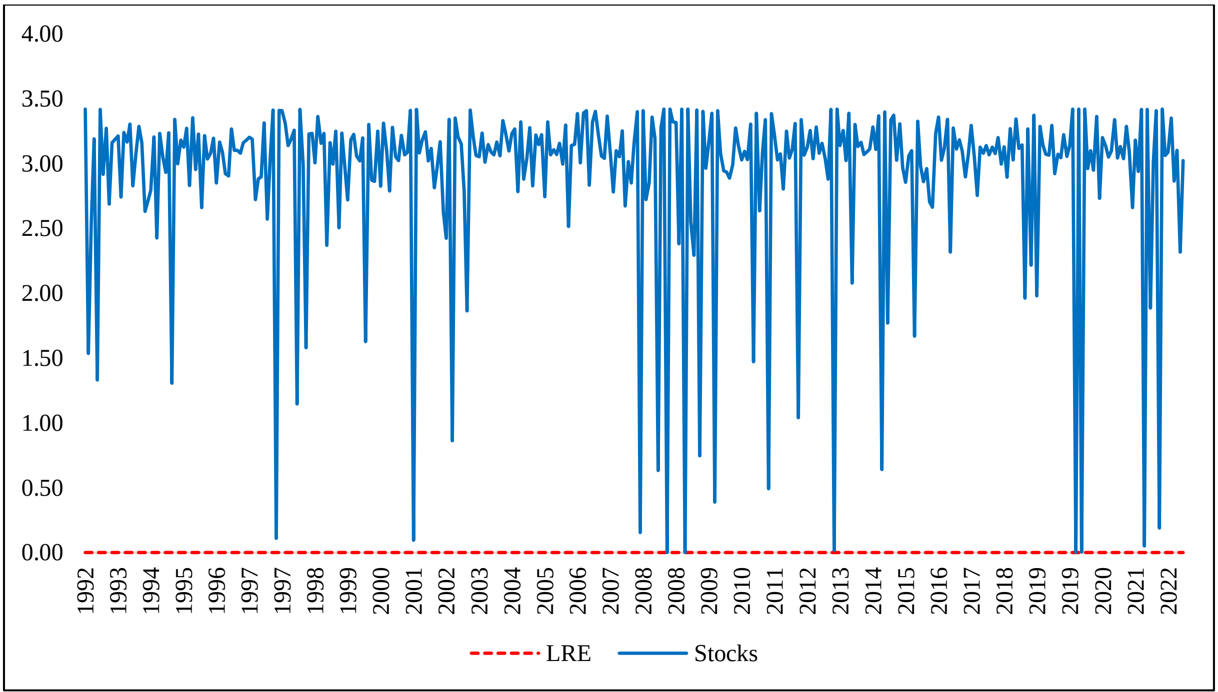
f. Japan Time-Varying Coefficient of UI



g. Australia Time-Varying Coefficient of EI



h. Australia Time-Varying Coefficient of UI



2.4.3 Robustness Tests

2.4.3.1 Alternative Inflation Disaggregation

We also examine the hedging qualities of LRE against four specific manifestations of inflation. Following Fang et al. (2022), we decompose the overhead inflation to Energy, Food, and Core by using their corresponding CPI. Furthermore, we extend those three measurements by using the Housing CPI. By conducting the same methodology as in section 2.3.4, we get results for the long- and short-run. Table 2.4 displays the long-run results, while Figure 2.4 illustrates the short-run effects.

Table 2.4: Long-Term Equilibrium Relationships (β-Vectors) Between LRE and Energy, Food, Core, and Housing CPI

Country	Rank	$EnergyI_{t-1}$	Rank	$FoodI_{t-1}$	Rank	$CoreI_{t-1}$	Rank	$Housing_{t-1}$
U.S.	1	13.990***	1	-2.408	1	-1.523	2	18.569**
		(1.986)		(1.922)		(2.062)		(3.331)
U.K.	1	1.917***	1	3.500***	2	0.338	1	12.453***
		(0.300)		(0.744)		(1.364)		(2.018)
JPN	4	-31.337***	3	6.400***	3	12.862***	1	17.529***
		(7.005)		(1.700)		(3.641)		(6.542)

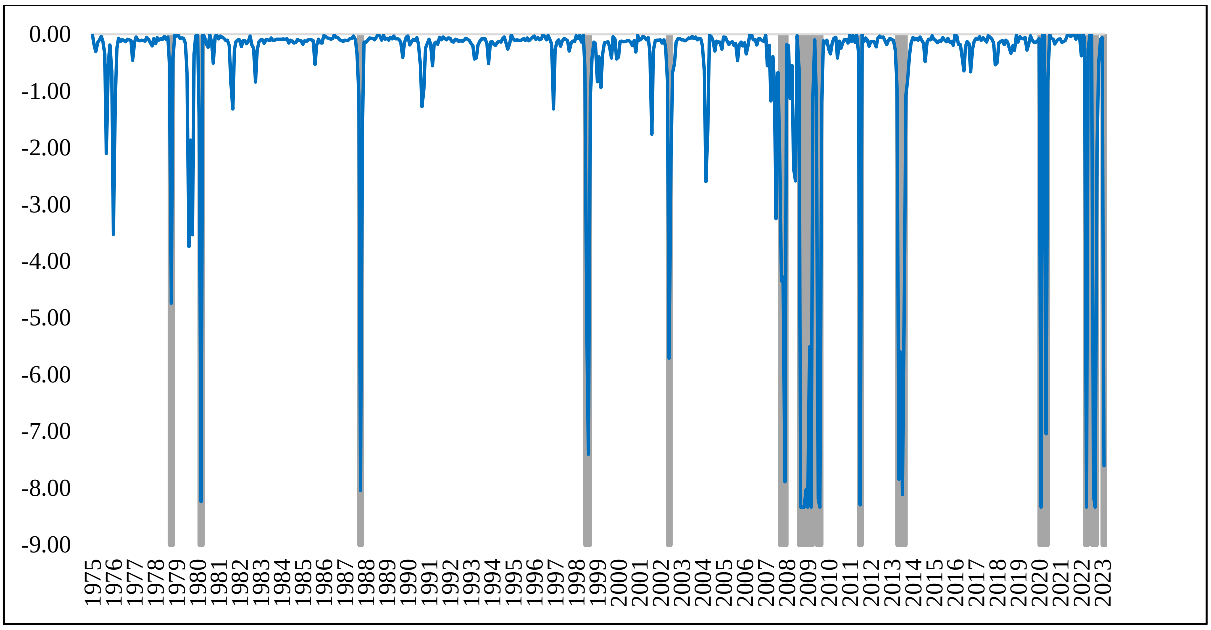
*Notes: U.S. stands for United States of America, U.K. for United Kingdom, JPN for Japan. The analysis of the U.S., U.K., and Japan is conducted by using an unrestricted constant. Rank denotes the rank of the π matrix. Standard errors are included in the parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

In the long-run, LRE is a good hedge against energy inflation. For Japan, the hedging capability against energy inflation is perverse. By investigating the effects of food inflation on LRE, we identify hedging characteristics for the U.K. and Japan in the long-run. In the case of core inflation, LRE might be a good protection in Japan. For the U.S. and U.K., we do not find any significant hedging capability. This is consistent with the work by Fang et al. (2022). They find that currencies, commodities, and real estate also mostly hedge against energy but not core inflation.

Turning to the short-term hedging properties, the hedging capability of LRE is getting negative during stable periods for food and core inflation in U.S.. In Japan LRE provides good protection against energy, food, and housing inflation during stable periods in the short-term. However, for Japan, the relationships become zero or negative during the turbulent period. As shown in Figure 2.4, the coefficient in the U.S. varies between 0.000 and -9.000 for energy inflation. In Regime 1 (stable periods), the coefficient remains zero, but in Regime 2, the coefficient becomes negative.

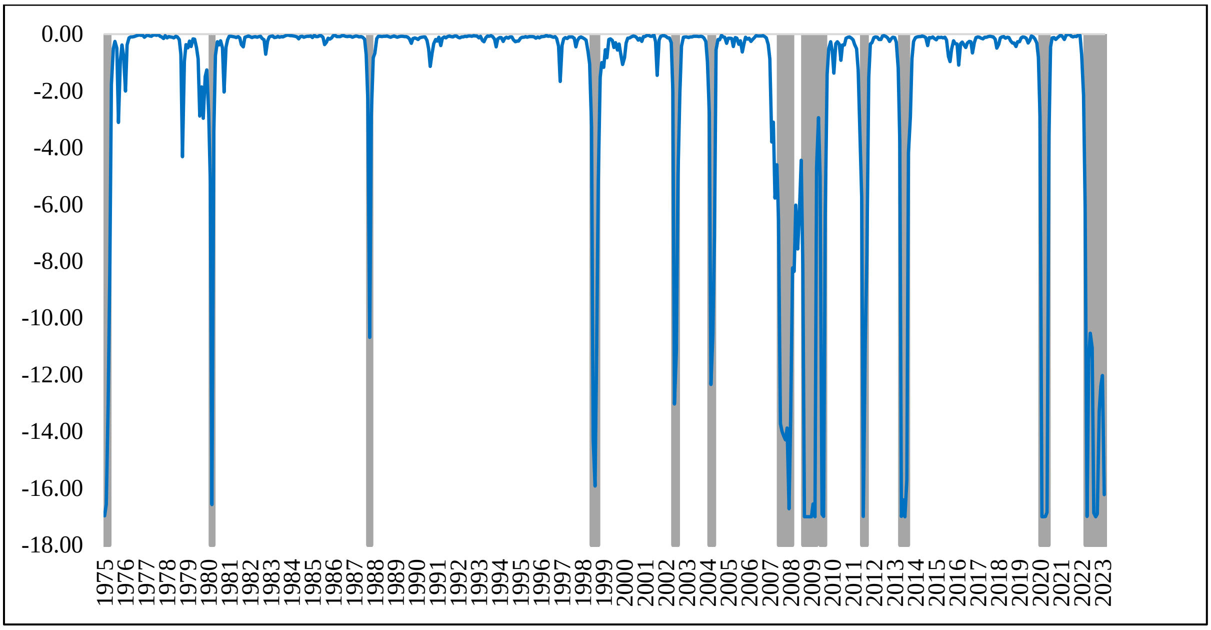
Figure 2.4: Time-Varying Short-Term Impact of Inflation on Real Estate Equity Returns

a. U.S. Time-Varying Coefficient of Food Inflation



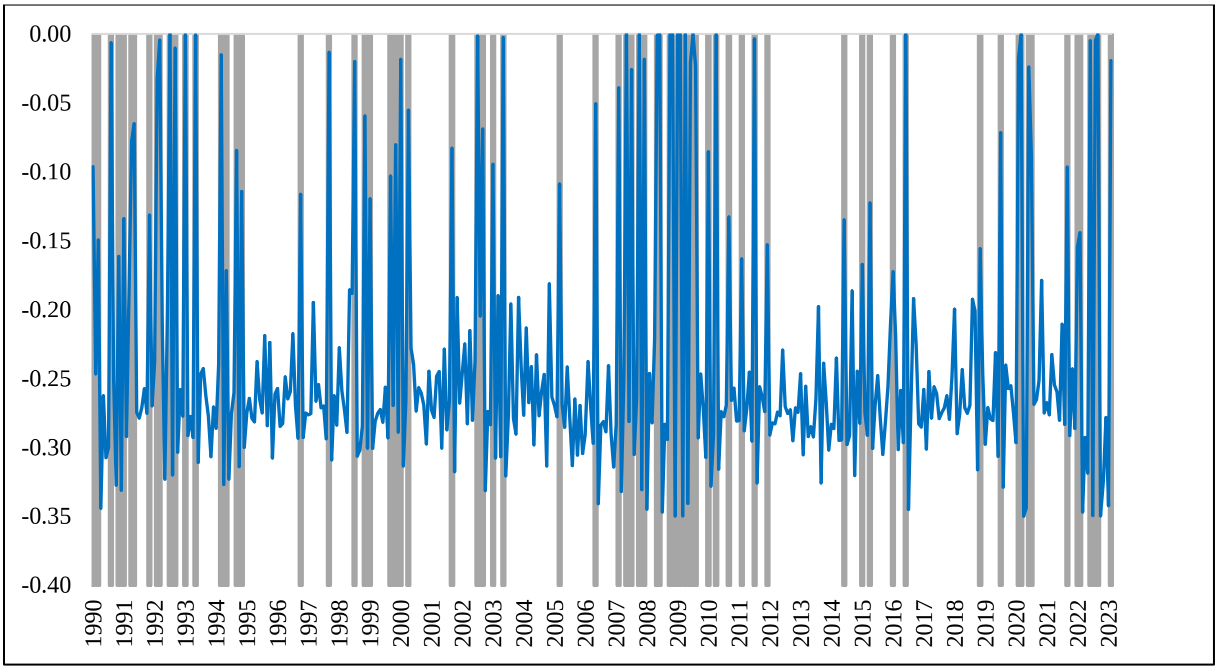
Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

b. U.S. Time-Varying Coefficient of Core Inflation



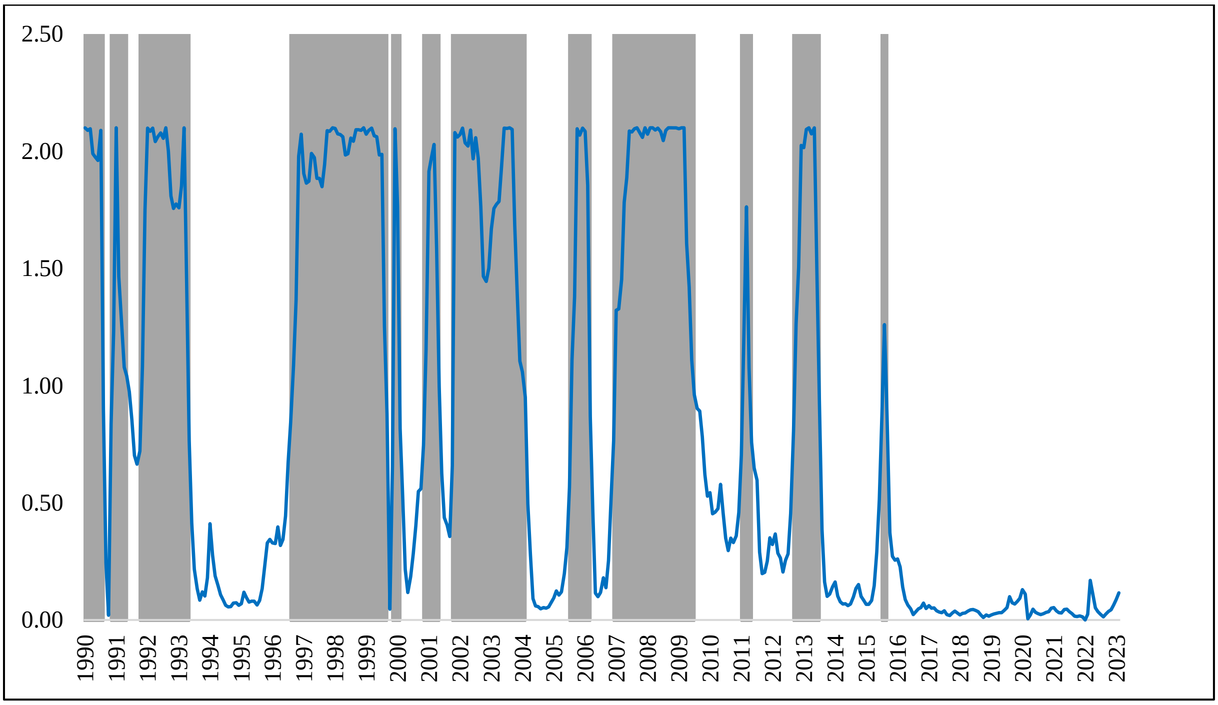
Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

c. U.K. Time-Varying Coefficient of Energy Inflation



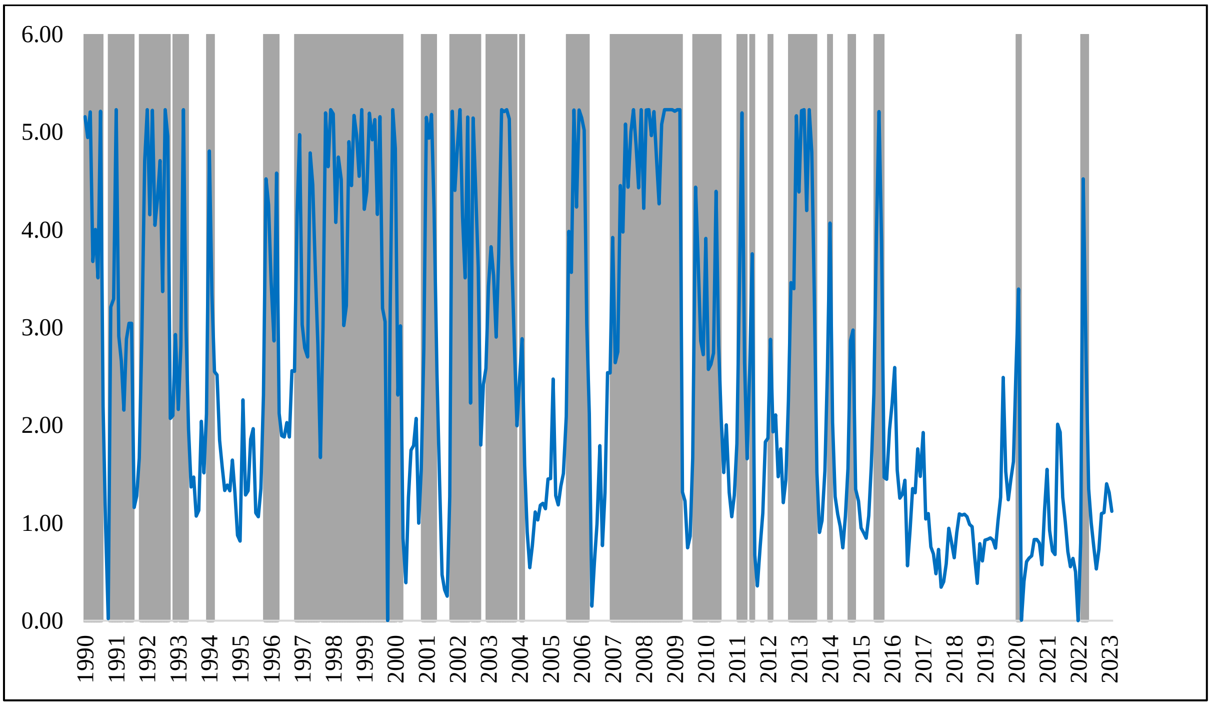
Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

d. Japan Time-Varying Coefficient of Food Inflation



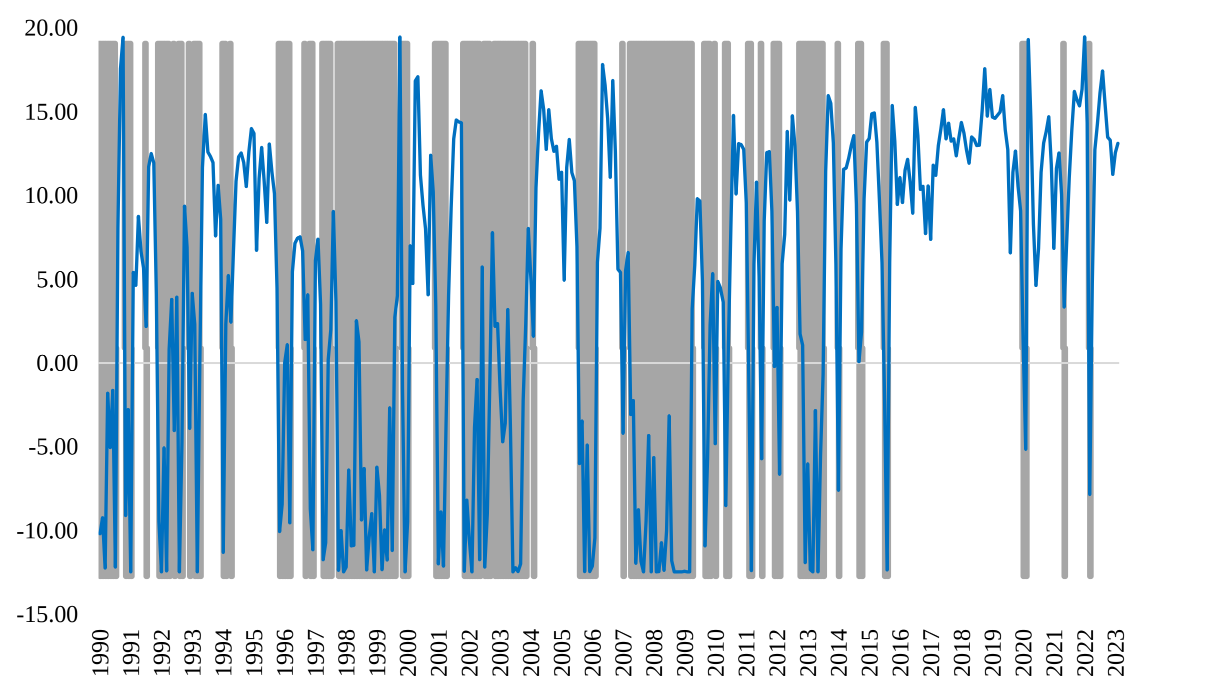
Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

e. Japan Time-Varying Coefficient of Core Inflation



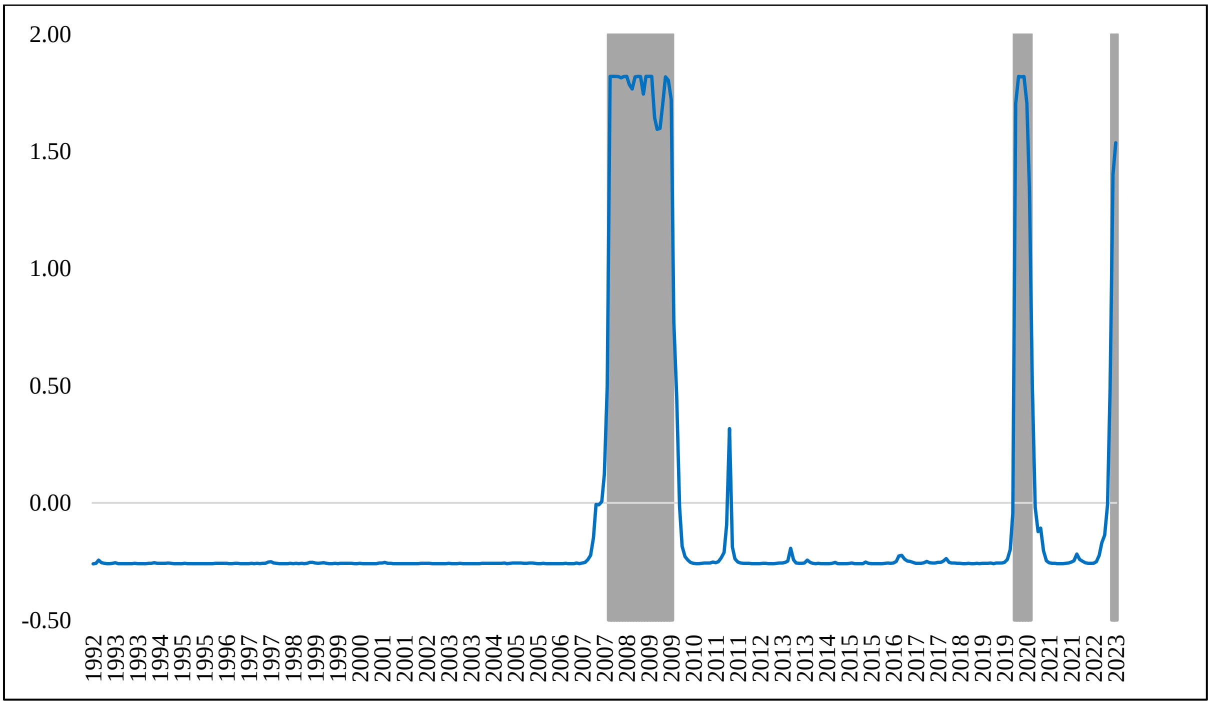
Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

f. Japan Time-Varying Coefficient of Housing Inflation



Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

g. Australia Time-Varying Coefficient of Energy Inflation



Note: The time-varying coefficient is calculated by multiplying the smoothed probability of Regime 1 with the coefficient of expected or unexpected inflation in Regime 1 plus the smoothed probability of Regime 2 multiplied by the coefficient of expected or unexpected inflation in Regime 2. If the estimated coefficient in Equation 2.4 is statistically insignificant, it is restricted to zero in the estimation of time-varying coefficient (Equations 2.6 and 2.7).

As illustrated in Figure 2.4, in the U.K., LRE acts as a significant perverse hedge for energy inflation in the short-term. In Australia, the short-term relationship between energy inflation and LRE is positive. Connecting to Connolly and Stivers (2022), they find that the relation between REIT returns and core-inflation shocks is never significantly different during weaker economic periods.

2.4.3.2 Income and Capital Returns

To dig deeper into the relationship between LRE returns and inflation, we extend our analysis by incorporating two additional variables: capital and income returns. This allows us to examine the relative contribution of income and capital returns in hedging inflationary pressures.

Our analysis reveals that the price appreciation component demonstrates a significant and effective long-term hedge against expected inflation. However, we find no discernible hedging capabilities in the long-run for income returns, as indicated in Table 2.5. This indicates that the long-term hedging ability of LRE comes from capital appreciation. In other words, although sometimes rents may not keep up with inflation due to some restrictions in lease contracts during high inflation periods, the cap rates may compress, or more precisely, the spreads narrow, given investors' expectations regarding future inflation risk. Investors may perceive a lower risk for real estate assets partially as the result of a widespread belief in real estate's inflation-hedging properties when they expect a high inflation risk.

In the short-term, our investigation uncovers hedging capabilities for price returns with respect to expected inflation (Figure 2.5), and for income returns with respect to unexpected inflation (Figure 2.6). Moreover, we observe a negative relationship between the hedging capability of price returns and the unexpected component of inflation, with this negative association becoming more pronounced during periods of heightened turbulence, as depicted in Figure 2.5.

This indicates that rental revenues can protect investors against short-term unexpected inflation risk, given the characteristics of the lease structure. Cap rates may compress when investors expect high inflation in the near future. However, when inflation rises more than expected or becomes more volatile, the cap rate may still increase due to the high uncertainty for the future. As a result, price returns may be negatively related to unexpected inflation, especially during the turbulent period.

Table 2.5: Long-Term Equilibrium Relationships (β-Vectors) Between LRE Price and Dividend Index and EI and UI

Country	Index	Rank	EI_{t-1}	UI_{t-1}
U.S.	Price	3	1.072***	1.430
			(0.525)	(2.817)
	Dividend	4	-2.004	-15.001
			(1.330)	(9.281)

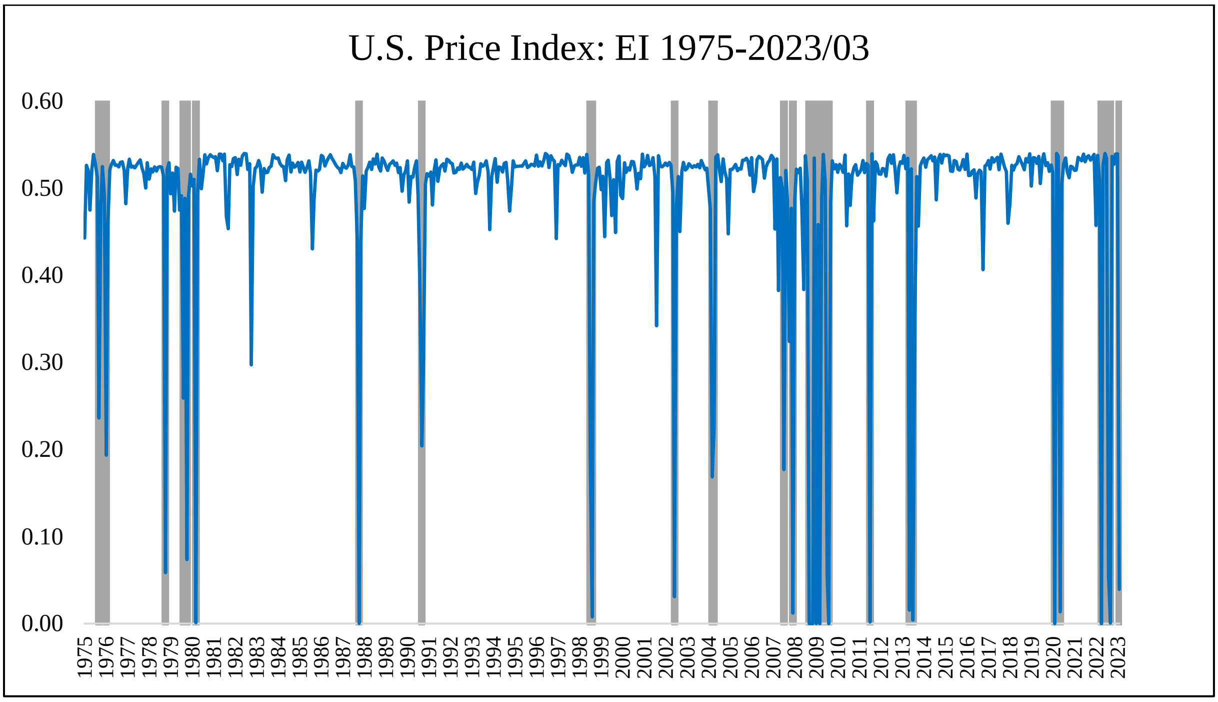
*Notes: US stands for United States of America. The analysis of the US is conducted by using an unrestricted constant. Rank denotes the rank of the π matrix. Standard errors are included in the parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

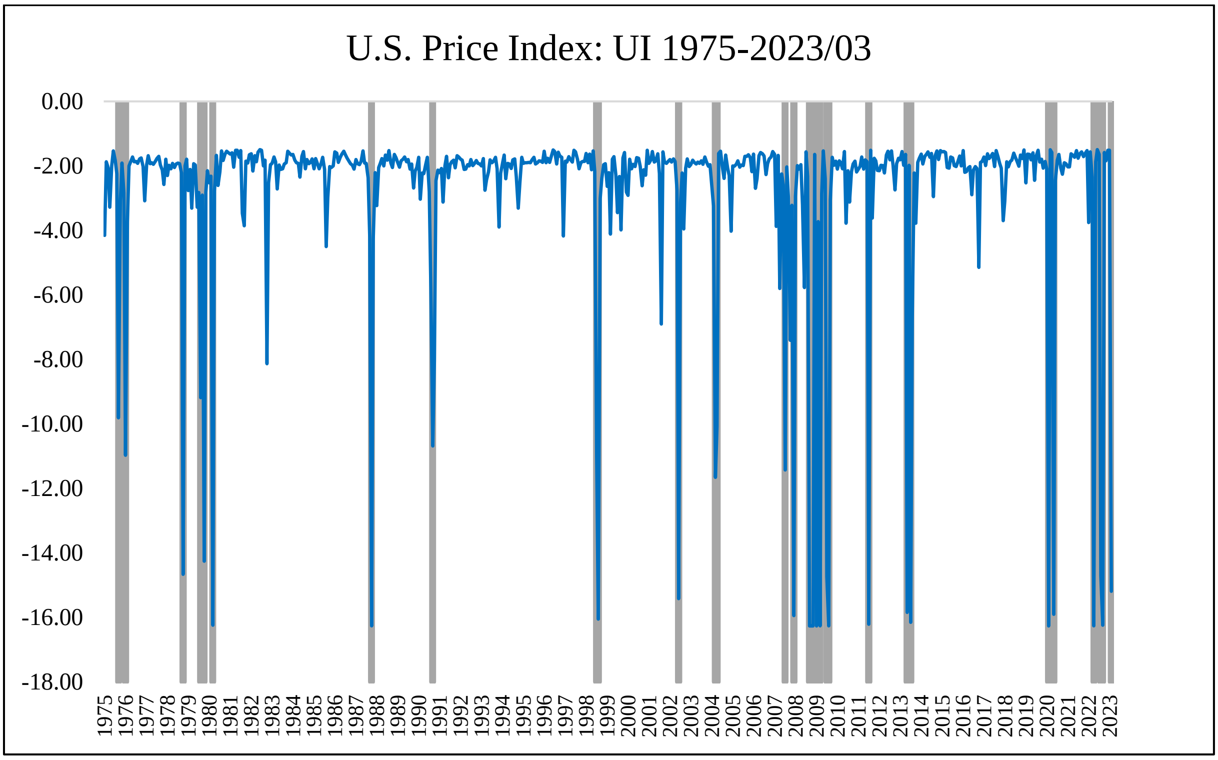
Table 2.6: Long-Term Equilibrium Relationships (β-Vectors) Between LRE and ACY Inflation, Inflation, ACY Core Inflation, and Core Inflation

Country	Rank	$ACY\ mod.C$	Rank	CPI_{t-1}	Rank	$ACY\ mod.CPIC$	Rank	$CPICore_{t-1}$
U.S.	1	19.063***	1	11.073***	1	24.333***	1	11.382***
		(2.484)		(1.169)		(3.227)		(1.177)

*Notes: U.S. stands for United States of America. The analysis of the U.S. is conducted by using an unrestricted constant.. Rank denotes the rank of the π matrix. Standard errors are included in the parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

Figure 2.5: Price Index U.S.

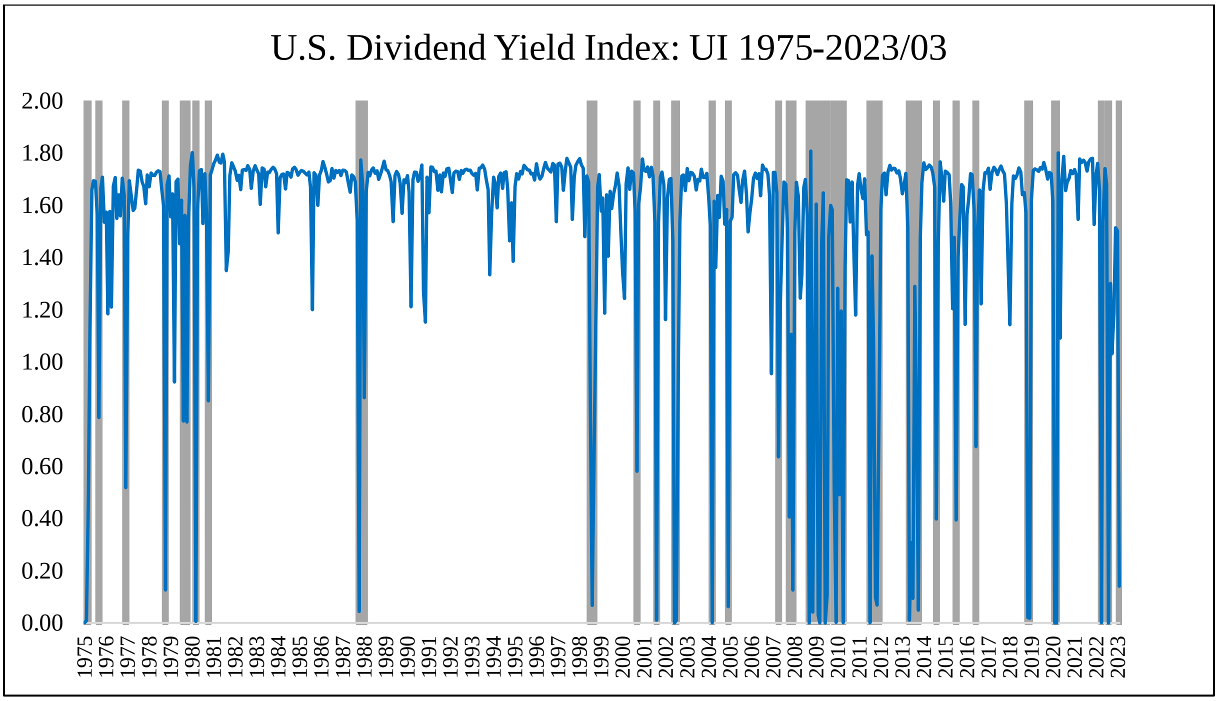




Overall, our results indicate that capital returns effectively hedge against expected inflation both in the long-term and during stable periods in the short-term. Meanwhile, income returns serve as a hedge against unexpected inflation only during stable periods over the short-term.

These findings shed light on the differential hedging characteristics of income and capital return components in relation to inflation, providing valuable insights for investors and policymakers.

Figure 2.6: Dividend Yield Index U.S.

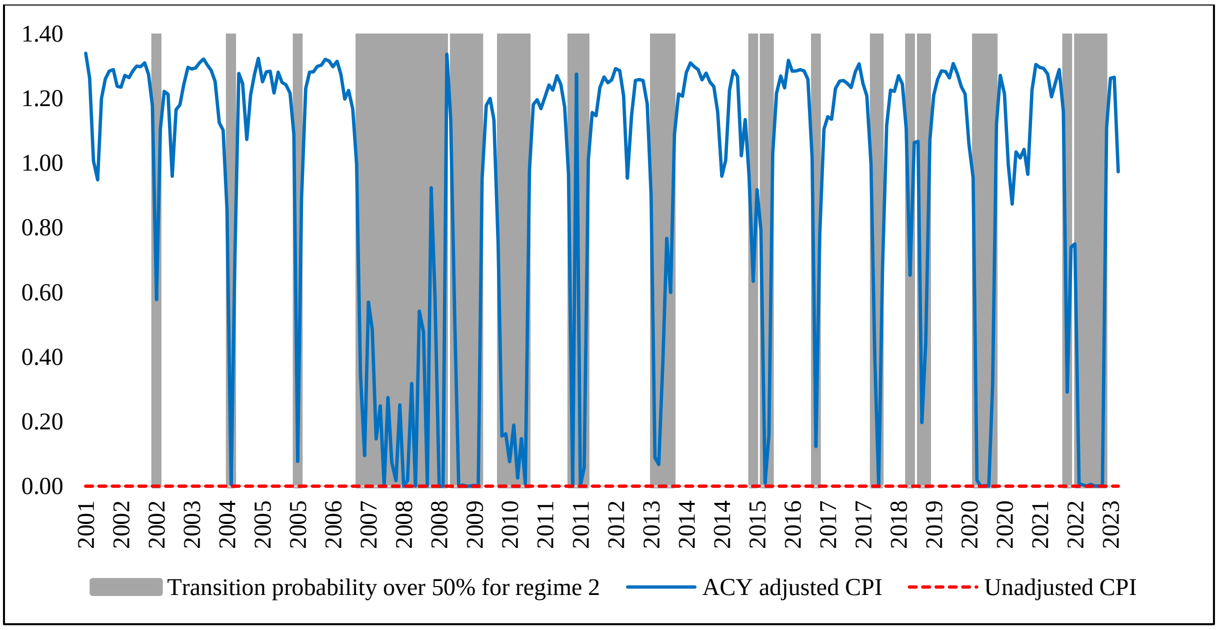


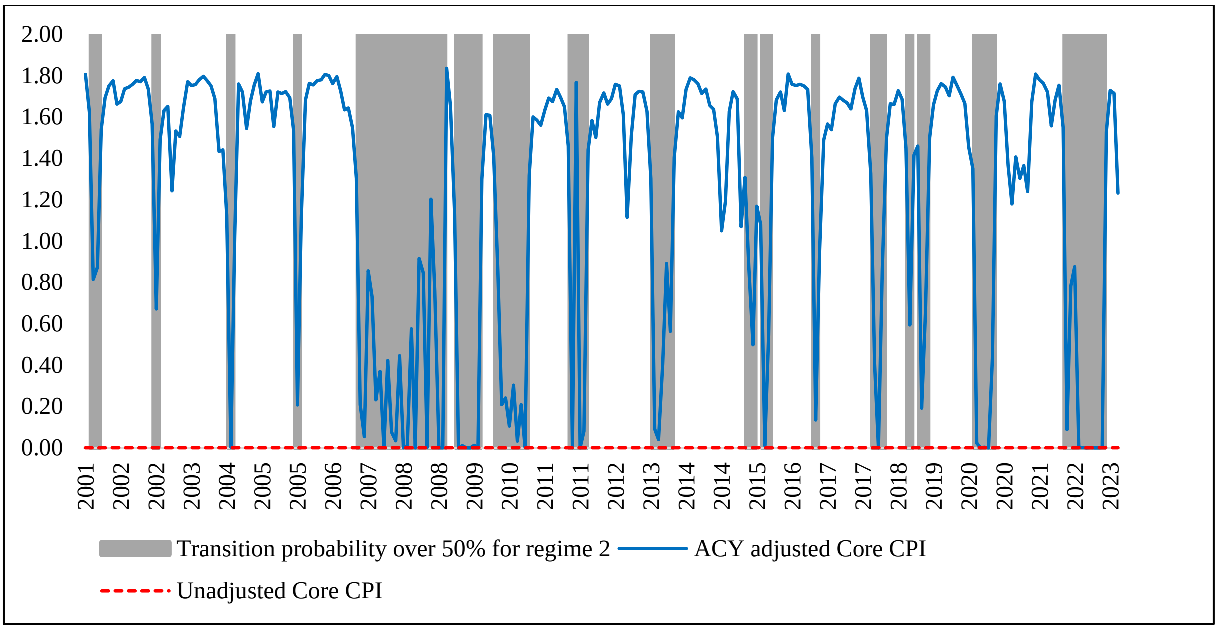
2.4.3.3 Housing Rent Modified Inflation Index

In recognizing the existence of alternative measures of inflation, we employ the Penn State/ACY Alternative Inflation Index as a substitute measure. This index, initially introduced by Ambrose et al. (2015) and subsequently refined by Ambrose et al. (2022), incorporates their Marginal Rent Index, which captures house price changes based on marginal rents, presenting a distinct perspective on inflation dynamics. Although housing rent is the most important component of price indexes (around 33% of CPI), the existing CPI rent index underrepresents rent changes between leases, and also underestimates the volatility due to valuation smoothing and significant time lags (Ambrose et al., 2022). The ACY index is based on a landlord-based net rent income index with several advantages. The NRI is based on market prices, reflects new and existing leases, and is updated monthly. Given data availability, the tests are only conducted for the U.S..

Our findings indicate that LRE exhibits stronger protective characteristics against the ACY inflation index and ACY core inflation index, compared to their unadjusted counterparts. Table 2.6 exhibits the long-term relationships, indicating that the coefficients based on the ACY indices demonstrate a higher degree of hedging for LRE, as compared to the conventional inflation measures. In the short-term, we observe no hedging capabilities when the classic CPI indexes are used to measure inflation. By contrast, there are positive hedging capabilities discernible when ACY indices are used, as depicted in Figure 2.7.

Figure 2.7: Alternative Inflation Measure





This is in line with our expectations. When housing rent is better reflected in the CPI index, LRE shows a better hedging ability. In other words, the hedging ability of LRE may have been underestimated in previous literature due to the problem associated with rent components. This underscores the importance of considering housing rent-adjusted inflation measures when evaluating the inflation-hedging effectiveness of LRE.

2.4.3.4 Lower Frequency Test

To enhance the robustness of our findings, we augment our analysis by including quarterly data for the U.S., spanning from 1975 to the first quarter of 2023. The long-term relationship with expected inflation remains robust, as shown in Table 2.7. A one percent increase in expected inflation is associated with a 2.076 percent increase in the return, higher than the coefficient based on the monthly data. In contrast, the results based on quarterly data also indicate a significant negative relationship with unexpected inflation.

Table 2.7: Long-Term Equilibrium Relationships (β-Vectors) (U.S. Quarterly)

Country	Rank	EI_{t-1}	UI_{t-1}
U.S.	3	2.076***	-38.643***
		(0.637)	(8.112)

*Notes: U.S. stands for United States of America. The analysis of the U.S. is conducted by using an unrestricted constant. Rank denotes the rank of the π matrix. Standard errors are included in the parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

Moreover, in the short-term, our analysis fails to reveal any significant evidence of hedging capabilities against either expected or unexpected inflation. The divergent results may be caused by the reduced number of observations when using quarterly data. The short-term equation encompasses 12 endogenous variables, two to four error correction terms, and two regimes. Given the limited number of observations (around 190) in relation to the numerous endogenous variables, the efficiency of the nonlinear Markov regime-switching model may be compromised, leading to an increase in the standard error of the parameters.

2.5 Inflation-Hedging Portfolios

In this section, we construct an inflation-hedging portfolio. We examine the case of an investor wishing to hedge inflation over her investment horizon with a minimum target return. The optimal allocations are determined by minimizing the shortfall probability under the constraint that real returns exceed the investor's desired target (Brière and Signori, 2012).

Equation 2.8: Minimum Target

$$Min_w \, P\left(\sum_{i=1}^{n} w_i R_{iT} < \pi_T + \overline{R}\right)$$

Equation 2.9: Constraint

$$E\left[\sum_{i=1}^{n} w_i R_{iT} - \left(\pi_T + \overline{R}\right)\right] \geq 0$$

Equation 2.10: Sum of Weights

$$\sum_{i=1}^{n} w_i = 1$$

Equation 2.11. Weight Constraint

$$w_i \geq 0$$

where $R_T = (R_{1T}, R_{2T}, \dots, R_{nT})$ is the annualised return of the *n* assets in the portfolio over the investment horizon T; $w = (w_1, w_2, \dots, w_n)$ is the part of the capital invested in the asset I; π_T is the annual inflation rate during that horizon T; and $\overline{R}$ is the minimum target return in excess of inflation. E is the expectation operator concerning the probability distribution P of the asset returns.

We present optimal portfolios using the shortfall probability approach for the U.S., U.K., Japan, and Australia for a minimum target return of 3% and an investment horizon of T (T = 2 years, rebalancing every two years).[19] Our analysis encompasses a diverse set of assets, incorporating LRE, stocks, oil, gold, silver, agricultural commodities, and inflation-linked government bonds. In refining our investment portfolios, we strategically add inflation-linked government bonds to our existing assets. We use the Bloomberg Global Inflation-Linked Total Return Index for the respective countries. Since the availability of the selected inflation-linked indexes is limited, the portfolios for the U.S. and the U.K. start in 1998, for Japan in 2004, and for Australia in 2012. Figure 2.8 illustrates the calculated weights over time for each country.[20] As expected, the weights for LRE vary over time. In the four regions, we find higher weights for LRE from

[19] The results pertaining to the average weight of LRE in an optimal portfolio composition over a 2-year, 5-year, 10-year, and 30-year investment horizon for the U.S. are shown in Appendix C. In addition, the results for a variety of minimum target returns are presented for the U.S.. As shown in Appendix C, the weight for listed real estate varies between 2.67% and 8.32% as the investment horizon changes.
[20] Appendix D shows the portfolio return distributions for the inflation hedging portfolios for each economy.

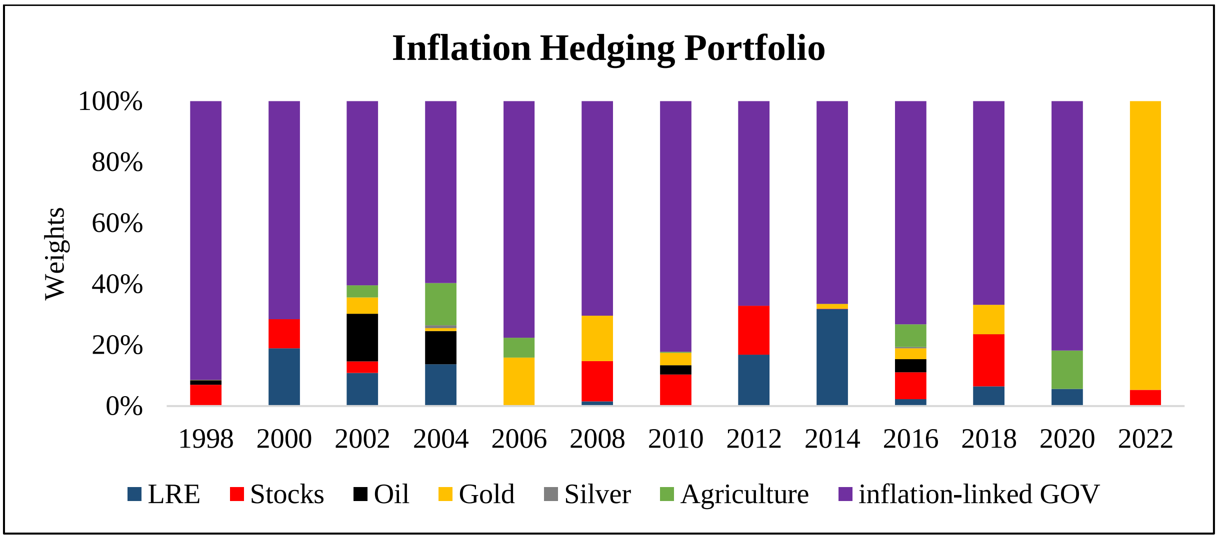
2004 to 2005 and from 2012 to 2015, compared to other periods. This might be explained by the rapid growth of LRE in these regions during the abovementioned periods. It is interesting to note that even in the mean-variance setting, inflation-linked government bonds always play a noticeable role in the portfolio. This can be explained by the fact that inflation-linked bonds can achieve a desirable risk-adjusted return (Campbell et al., 2009; Pflueger and Viceira, 2011).

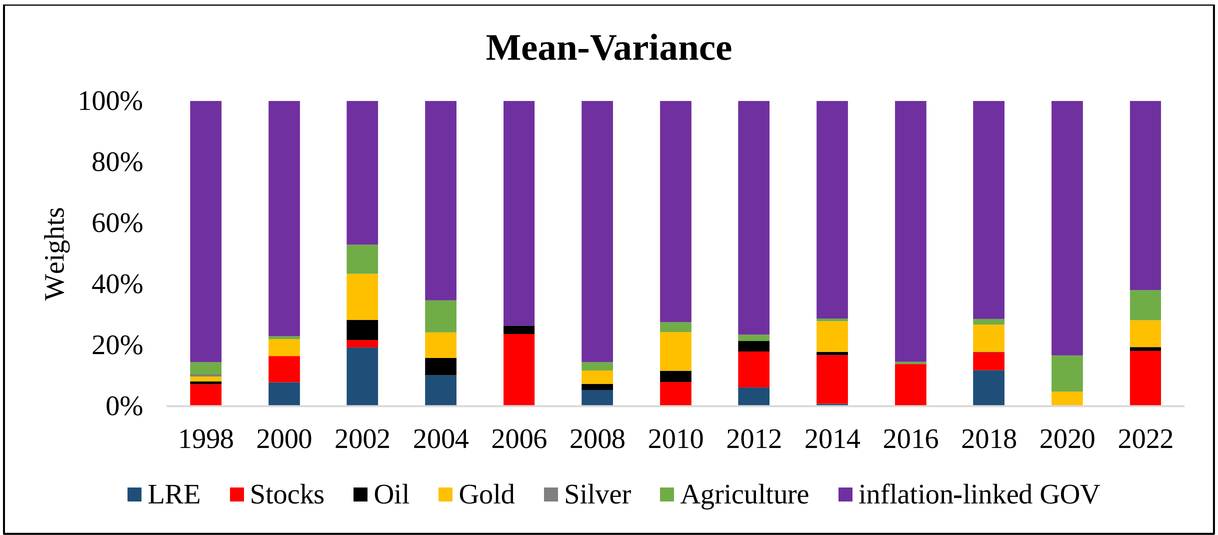
In all four countries, the inflation-hedging portfolio indicates materially higher weights for LRE compared to the standard mean-variance portfolios, while the LPM optimization gives a slightly higher weighting to LRE in the U.K.. This is in line with the desired inflation-hedging properties of LRE. For instance, for the U.S., over the 2012 to 2019 period, the mean-variance portfolio suggests 4.69% for U.S. LRE, but the inflation-hedging portfolio suggests 14.35%. On average, over the entire sample period, the inflation-hedging portfolios indicate 8.32%, 10.87%, 8.55%, and 32.15% weights for the U.S., the U.K., Japan, and Australia, respectively. Meanwhile, the mean-variance portfolios suggest only 4.74%, 8.68%, 1.32%, and 18.65%, respectively, for the four countries.

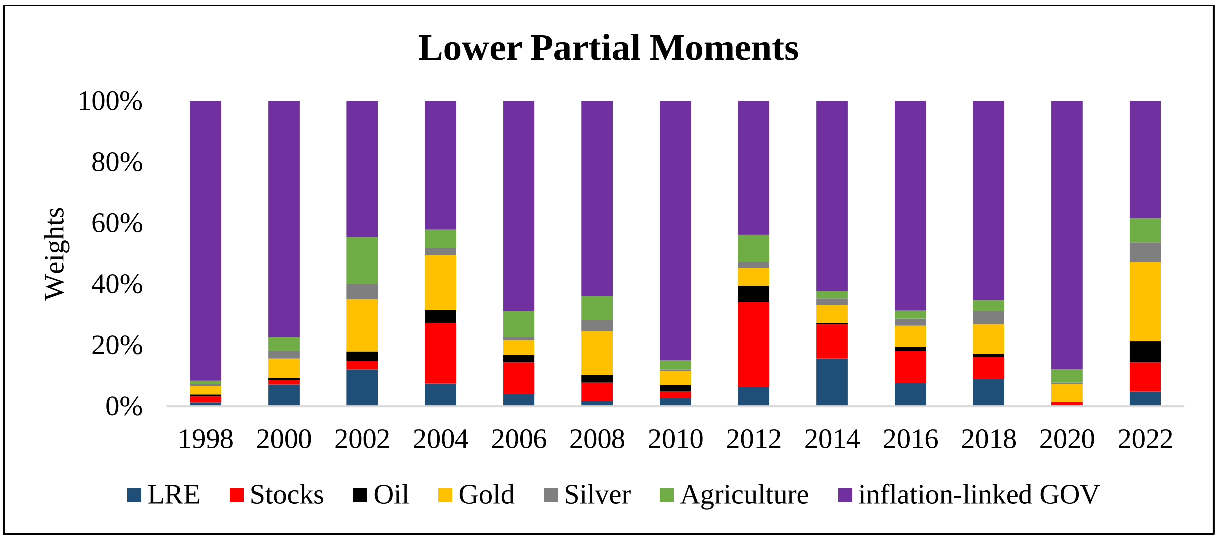
Moreover, the inflation-hedging portfolios provide higher expected returns than the mean-variance portfolios. Table 2.8 reports summary statistics for the portfolios, averaged across all years. As shown in Table 2.8, inflation-hedging portfolios achieve an average annual expected return between 5.67% (Australia) and 8.61% (U.K.), while the average annual expected return of the mean-variance portfolio is less than that of the inflation-hedging portfolios. If we consider risk, as measured by the variance, the inflation-hedging portfolios also achieve a higher Sharpe ratio than the mean-variance portfolios in the U.K., Japan, and Australia. If we measure the risk by the probability of shortfall, as shown in Table 2.8, in the U.S., the U.K., and Australia, the inflation-hedging portfolio achieves a lower probability of shortfall, meanwhile a higher average expected return than the mean-variance portfolio. This can be explained by the fact that the mean-variance portfolio uses variance as the risk measure, which may not be what corresponds best to investors' objectives, as variance treats both upside and downside risk as the same. An inflation-hedging portfolio focuses on minimizing the downside inflation risk, and, therefore, can outperform the mean-variance one.

Figure 2.8: Portfolio Optimizations [Rebalancing Every 2 Years]

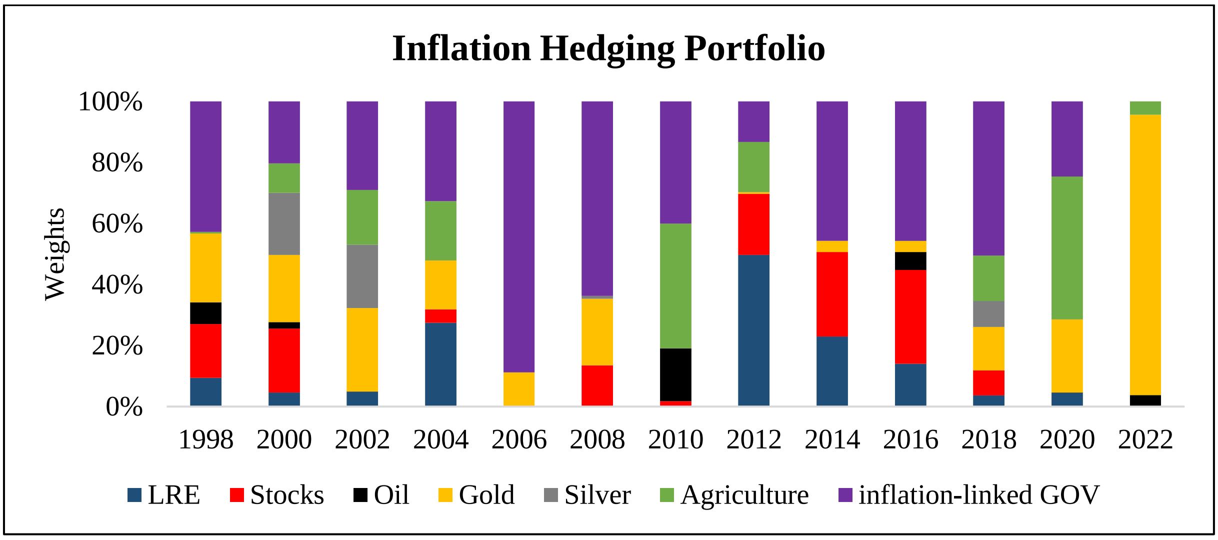
a. Weights of Shortfall Probability, Mean-Variance, and Lower Partial Moments for the U.S.

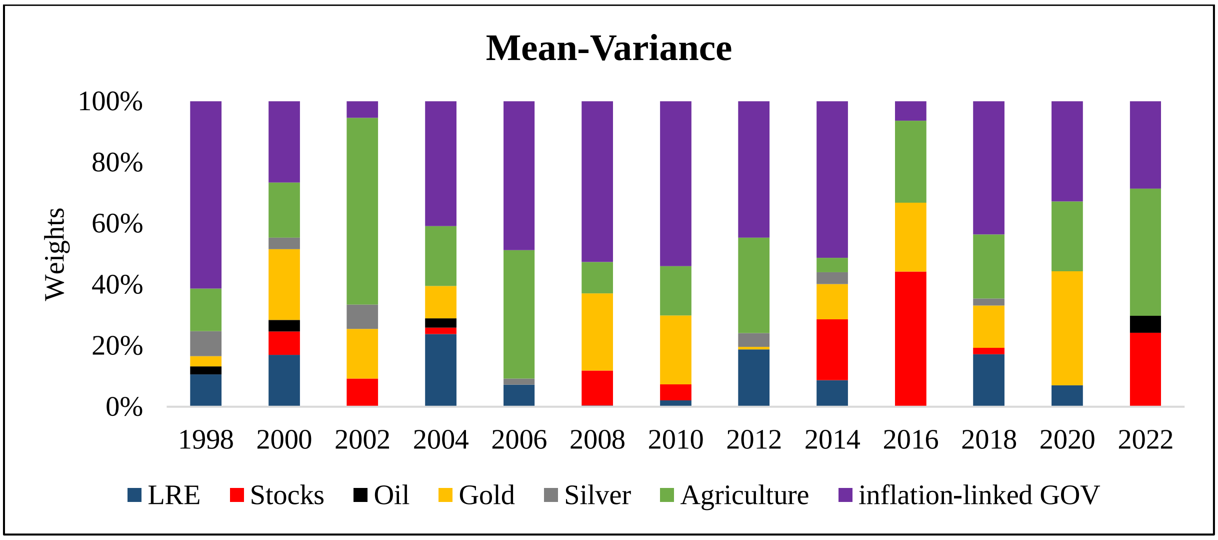


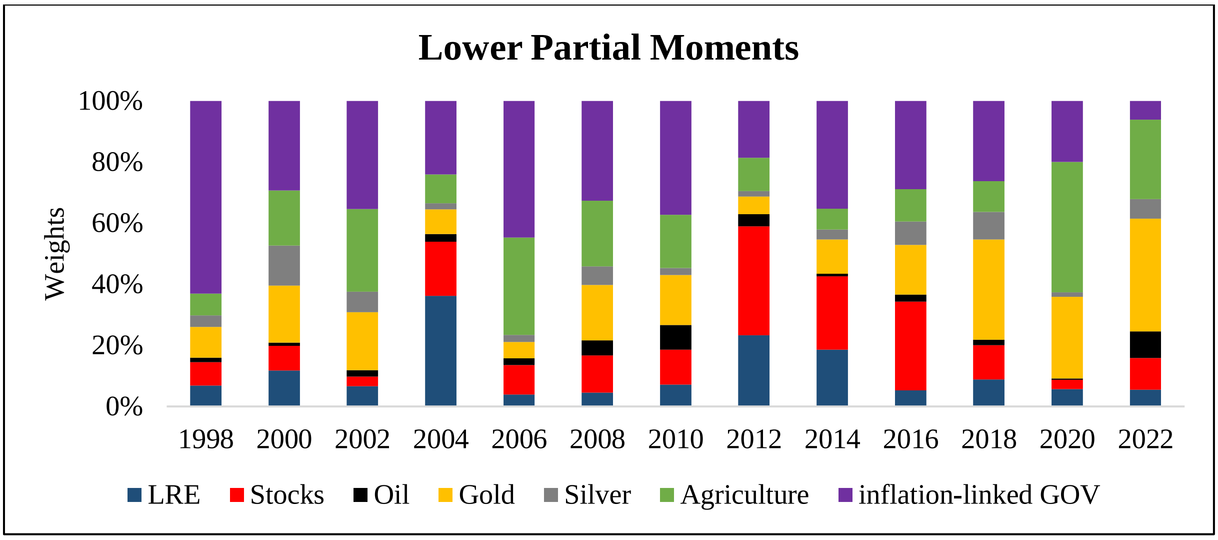




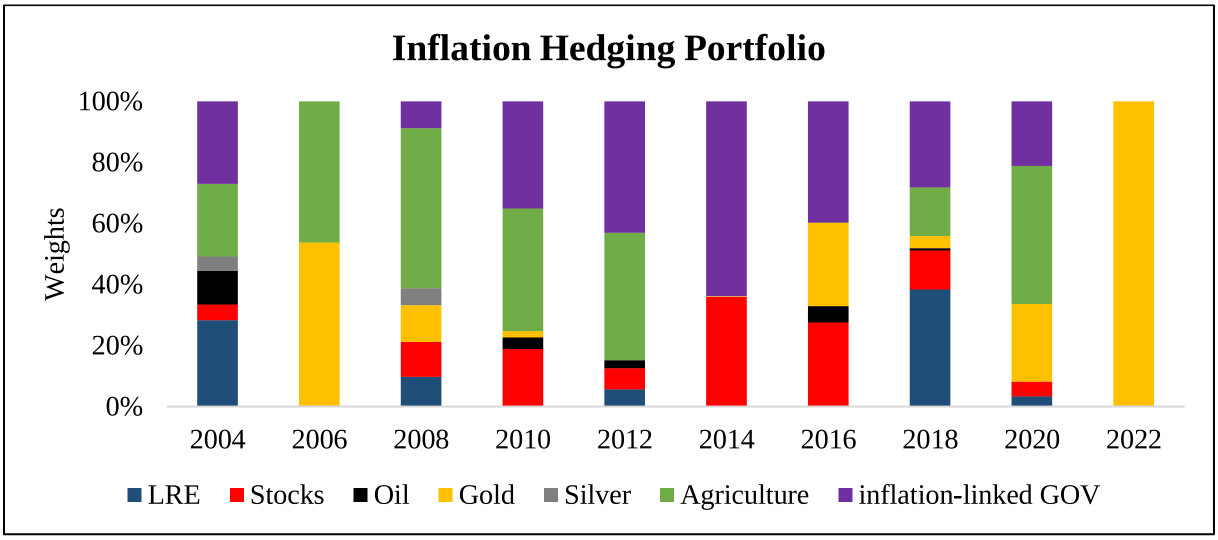
b. Weights of Shortfall Probability, Mean-Variance, and Lower Partial Moments for U.K.

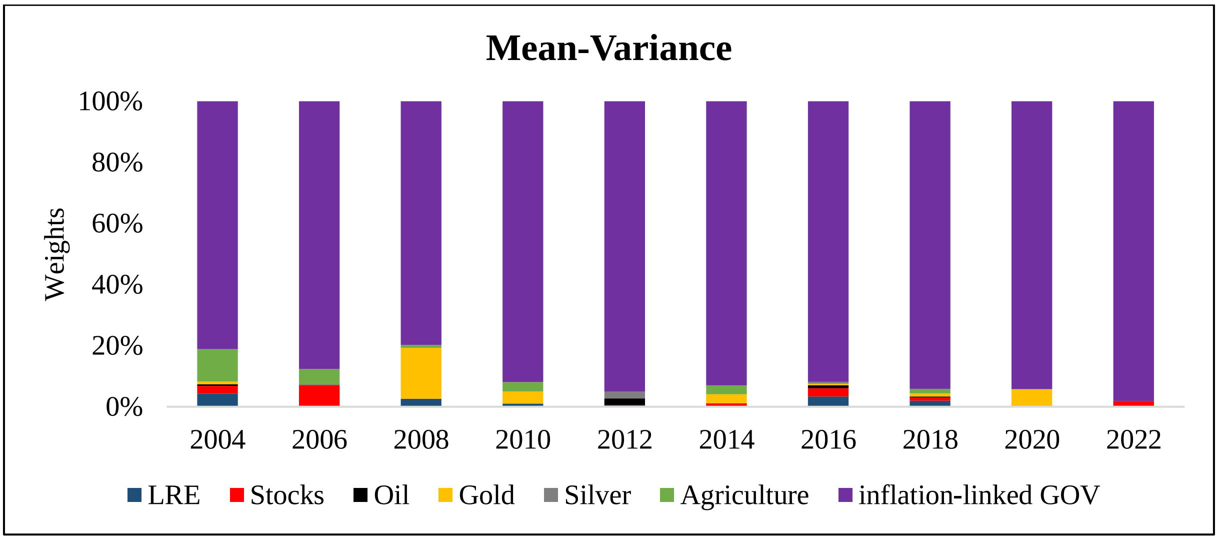


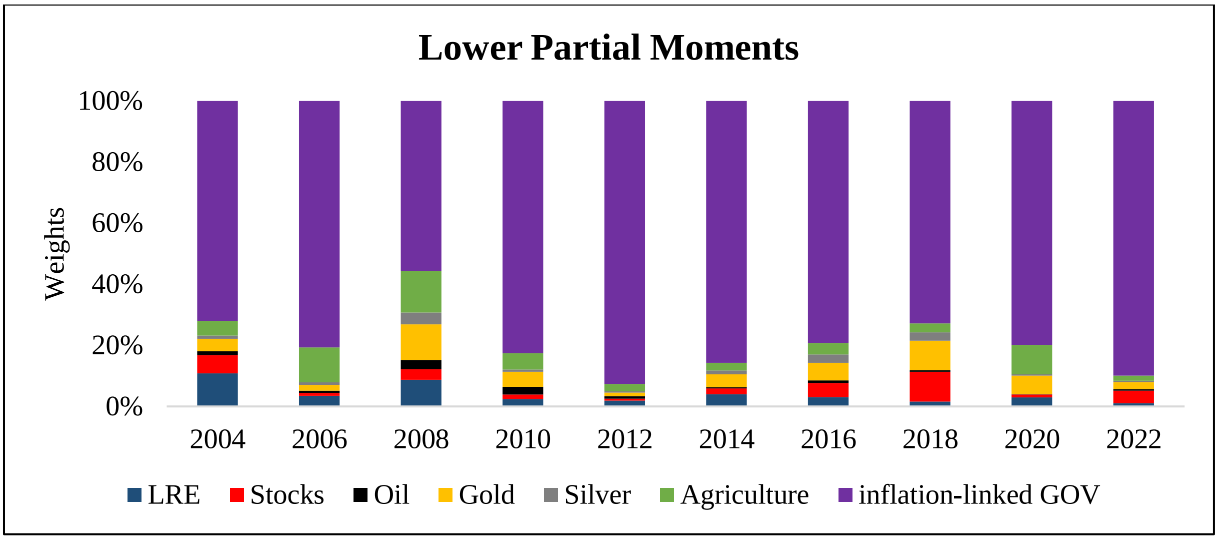




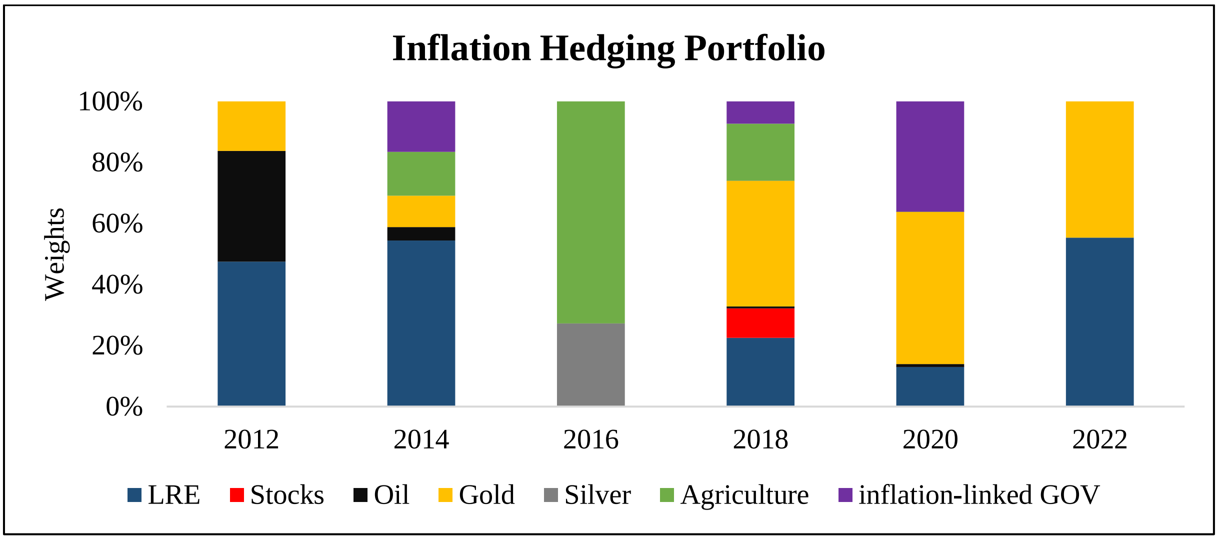
c. Weights of Shortfall Probability, Mean-Variance, and Lower Partial Moments for Japan

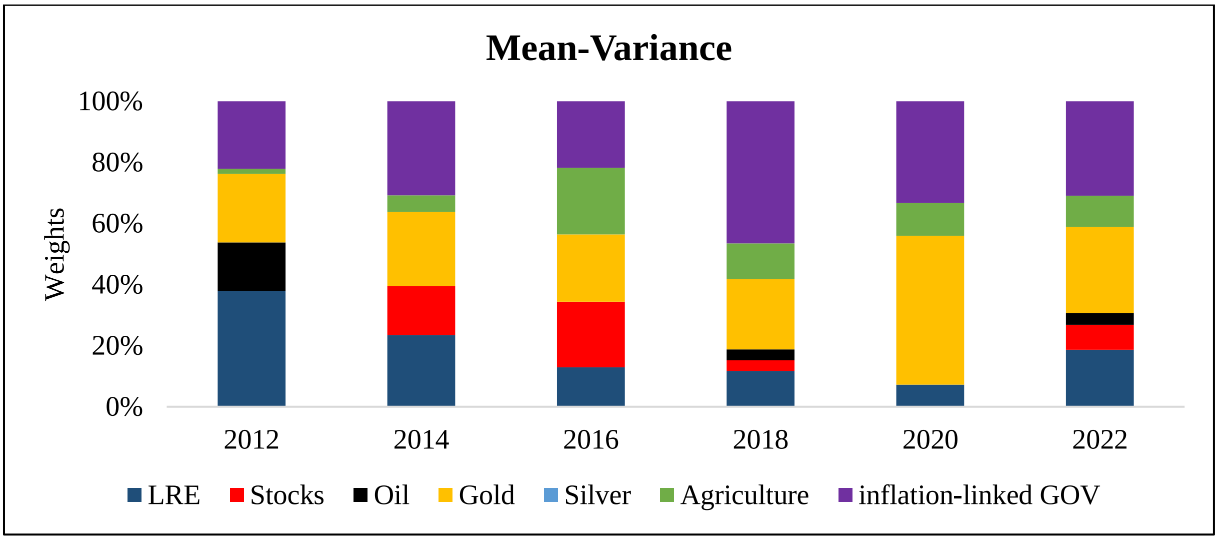


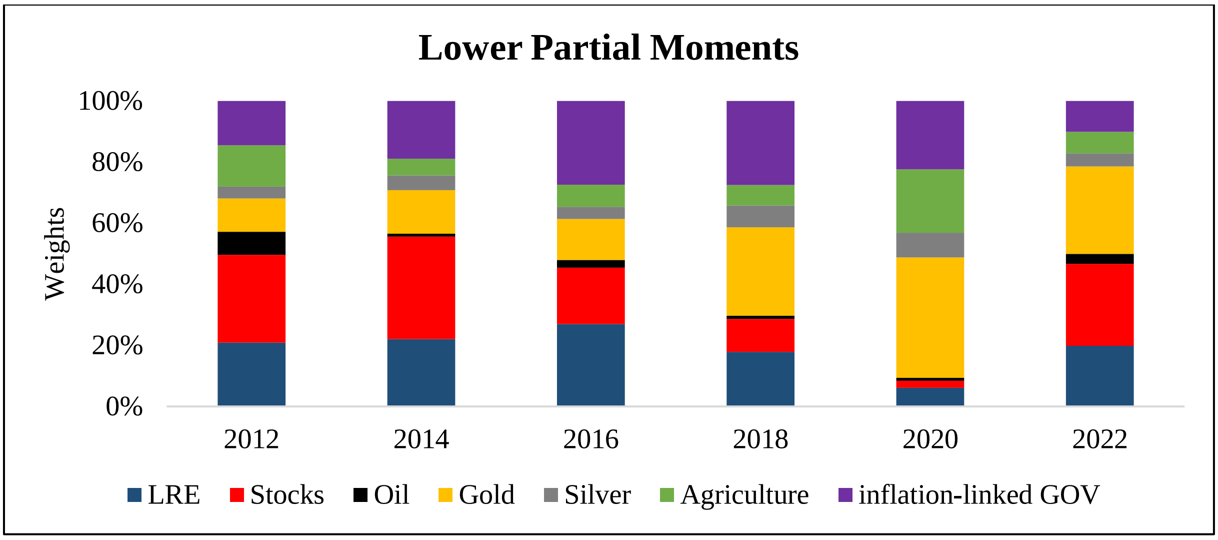




d. Weights of Shortfall Probability, Mean-Variance, and Lower Partial Moments for Australia







When compared to the LPM portfolio, the inflation-hedging portfolio shows a more comparable performance, but the LPM portfolio slightly outperforms the inflation-hedging portfolio. This is in line with our expectations because of the desirable attributes of the LPM portfolio. First, similar to the inflation-hedging portfolio, LPM also separates the analysis of upside and downside risk, focusing on negative returns. Second, LPM additionally provides flexibility by allowing adjustments of risk aversion levels, while an inflation-hedging portfolio does not allow for this. Therefore, LPM proves to be more robust in dealing with non-symmetric or non-normally distributed returns. However, we also find that, except for Japan, the inflation-hedging portfolio achieves a lower likelihood of falling below the minimum target return. Thus, the inflation-hedging portfolio still has merit for investors who want to hedge against inflation and minimise the likelihood of not reaching the minimum target return.

Table 2.8: Summary Statistics of Portfolios with 2-Year-Investment Horizon Over the Entire Sample Period

Portfolio	LRE Weight	Shortfall Probability	Mean	SD	Sharpe Ratio
U.S.					
Inflation Hedging (r=3%)	8.32%	1.74%	6.98%	17.62%	39.65%
Mean-Variance	4.74%	1.98%	5.33%	13.77%	48.41%
Lower Partial Moments	6.20%	2.79%	6.13%	18.75%	41.64%
100% Inflation-linked Bonds	0.00%	2.80%	4.42%	17.82%	24.81%
U.K.					
Inflation Hedging (r=3%)	10.87%	3.09%	8.61%	29.20%	32.29%
Mean-Variance	8.68%	3.54%	5.06%	22.54%	27.64%
Lower Partial Moments	11.10%	4.08%	7.77%	26.87%	34.26%
100% Inflation-linked Bonds	0.00%	6.46%	2.62%	37.77%	6.95%
Japan					
Inflation Hedging (r=3%)	8.55%	3.96%	7.70%	32.21%	29.60%
Mean-Variance	1.32%	1.46%	1.95%	9.22%	24.78%
Lower Partial Moments	4.01%	1.79%	2.69%	11.45%	33.66%
100% Inflation-linked Bonds	0.00%	1.75%	1.58%	10.66%	14.85%
Australia					
Inflation Hedging (r=3%)	32.15%	3.38%	5.67%	29.45%	20.32%
Mean-Variance	18.65%	3.93%	3.99%	24.21%	17.66%
Lower Partial Moments	18.96%	4.24%	6.11%	26.97%	23.19%
100% Inflation-linked Bonds	0.00%	7.61%	-1.29%	42.06%	-3.06%

Note: The weights of LRE, the shortfall probability, the mean of portfolio returns, the standard deviation of portfolio returns (SD), and the Sharpe ratios of portfolios are the average values over the entire sample period.

2.6 Conclusion

Since 2022, inflation has again become a global concern. Hence, investors need to understand the inflation-hedging ability of the different asset classes. Using 1975 to 2023 data for LRE companies for the U.S., and three other economies – the U.K., Japan, and Australia – from 1990 to 2023, our paper analyses whether listed real estate can be used to hedge against inflation.

Overall, our study confirms the desired inflation-hedging properties of LRE. Our main findings can be summarised as follows.

First, listed real estate is a good hedge against inflation, but mainly against expected inflation and in the long-term. We furthermore note, that the long-term hedging ability of LRE comes from value appreciation. Moreover, because most commercial leases are long-term, the hedging capability of listed real estate assets is particularly striking over a long-time horizon. Additionally, in the long-term, LRE provides better hedging against inflation than stocks.

Second, the short-term hedging ability moves toward being negative during turbulent periods. In stable periods, LRE provides good protection against inflation, but the ability becomes negative or zero in times of turbulence. On the other hand, this will also indicate that if deflation happens during turbulent periods, LRE performance will not be adversely affected by deflation. From an investor's perspective, the efficiency of LRE as an inflation hedge is highly dependent on the time horizon.

Third, the inflation hedging ability of LRE also varies across countries. In all four economies, although LRE provides long-term hedging against expected inflation, we see no hedging or perverse hedging characteristics against unexpected inflation. Expected inflation shows the highest long-term elasticity to real estate equity returns in Japan, amounting to 11.182%. In the short-term, LRE in the U.S., the U.K., and Australia provide short-term positive inflation hedging against expected inflation, by a 0.430, 4.630, and 1.320 percent increase, respectively, with a one percent increase in expected inflation.

Fourth, the disaggregation of inflation into energy, food, core, and housing CPIs indicates that LRE is adequately hedged against core, food, and housing inflation in Japan. In Australia, we observe positive hedging characteristics concerning the energy inflation. Furthermore, we observe perverse hedging effects for food and core inflation in the U.S., and energy inflation in the U.K..

Fifth, we show that in the long-run the hedging quality comes from value appreciation and not from income returns. In the short-run, we find hedging capabilities for price returns against expected inflation, for income returns against unexpected inflation.

Sixth, our robustness tests incorporating a rent-adjusted inflation index reveal a superior hedging ability for LRE compared to when an unadjusted inflation index is used. This finding suggests that the hedging potential of LRE might have been downplayed in previous studies, which primarily utilised an unadjusted inflation index.

Finally, our inflation-hedging portfolios provide more realistic and less extreme allocations to listed real estate than when the standard mean-variance approach is used. The mean-variance approach uses variance as the risk measurement, which may not correspond best to investors' objectives. Instead, the inflation-hedging portfolio uses the expected shortfall as the risk measure, which focuses on the risk of being far below the expected real return (i.e., the downside risk). Based on an inflation-hedging portfolio composed of LRE, stocks, oil, gold, silver, agricultural commodities, and inflation-linked government bonds, LRE plays a significant role in an investor's portfolio. The average percentages of the portfolios for the U.S., U.K., Japan, and Australia over the entire period are 8.32%, 10.87%, 8.55%, and 32.15%, respectively, clearly highlighting the benefits of holding listed real estate for investors. The inflation-hedging portfolio also shows a desirable performance. It provides a higher Sharpe ratio than the mean-variance approach for the U.K., Japan, and Australia. It also achieves a lower shortfall probability in the U.S., U.K., and Australia and a higher average expected return than the mean-variance portfolio in all four regions. When compared to the LPM portfolio, the inflation-hedging portfolio shows a more comparable performance, but the LPM portfolio slightly outperforms the inflation-hedging portfolio. However, we also find that, except for Japan, the inflation-hedging portfolio achieves a lower likelihood of falling below the minimum target return. Thus, the inflation-hedging portfolio still has merit for investors who want to hedge against inflation and minimise the likelihood of not reaching the minimum target return.

3. U.S. and European Listed Real Estate as an Inflation Hedge

Abstract

Assets' capability to hedge against inflation has again come to the forefront given the recent surge in inflation. This paper investigates the inflation-hedging capability of an important asset class, i.e., listed real estate (LRE), using data from 1990 to the end of 2023, for the main European countries in terms of LRE market capitalization, but also the U.S. By using a Panel Markov switching vector error correction model (MS-VECM), we identify the hedging ability of LRE in crisis and non-crisis periods, both in the short-and long-term. We additionally compare the hedging ability of LRE with that of other asset classes. Listed real estate provides an effective hedge against inflation in the long-run, both in crisis and non-crisis periods. In the short-term, listed real estate only hedges against inflation in stable periods. LRE effectively serves as a hedge against inflation shocks, particularly protecting against unexpected inflation from the first month and against energy inflation during stable periods. While stocks surpass LRE in long-term inflation protection and LRE has short-term benefits, gold distinguishes itself from LRE by offering reliable long-run protection, but only in economic downturns. The results should provide important insights to investors seeking to allocate resources more efficiently in those turbulent times, both for the short- and long-terms.

Keywords: Inflation Hedging, Listed Real Estate Companies, Markov-Switching, Unexpected Inflation, Impulse Response Functions

Authors: Jan Muckenhaupt, Martin Hoesli, Bing Zhu[21]

Status: Swiss Finance Institute Research Paper No. 24-34

[21] Author contributions based on CRediT roles: Conceptualization, data curation, software, formal analysis, methodology, validation, visualization, and writing – both the original draft and review & editing – were conducted by Jan Muckenhaupt. Supervision was provided by Martin Hoesli and Bing Zhu.

3.1 Introduction

After a long period with virtually no inflation, the topic of inflation hedging again became important in 2022. In response to the COVID-19 pandemic, central banks significantly increased the money supply through extensive stimulus efforts. Alongside the impact of military confrontations, these measures have led to substantial price fluctuations in energy and commodity markets, raising concerns about a potential global recession. By October 2022, this led to a significant rise in inflation in the euro area, reaching 9.9% year-on-year. As a result, central banks, including the Federal Reserve and the European Central Bank, implemented tighter monetary policies. They raised interest rates to counteract the escalating inflation, aiming to stabilise the economy while navigating the complexities of a post-pandemic financial landscape. Inflation currently appears to be gradually normalizing, though further crises could potentially disrupt supply chains and thus maintain persistent inflationary pressures (Muckenhaupt et al., 2023a).

Against this background, this paper aims to enhance our understanding of the inflation-hedging properties of listed real estate relative to other asset classes. Such properties are of particular importance to long-term institutional investors (especially pension funds, which typically operate under inflation-linked liability constraints) and retail investors, for whom real capital preservation is a minimum objective. A focus on listed real estate is warranted as many investors choose this exposure type, given the lower unit value and greater liquidity of those assets (Falkenbach and Hoesli, 2017). In the long-term, real estate securities have been shown to behave like the underlying real estate (Hoesli and Oikarinen, 2021). Hence, this paper contributes to the academic literature on the inflation-hedging effectiveness of real estate, as well as provides important practical insights.

Real estate is frequently viewed as a suitable asset class for inflation protection, primarily due to two key mechanisms. First, real estate benefits from rents or lease payments, which often include escalation clauses that adjust for inflation or allow for the passing on of increased costs to tenants. Second, construction costs typically escalate in line with inflation (Bourassa et al., 2011; Ruhmann and Woolston, 2011), and land values should increase at a much faster rate than inflation given its limited supply (Nichols et al., 2013). The empirical evidence, especially for listed real estate, is inconclusive. Research on LRE reveals mixed outcomes regarding their ability to hedge against inflation. Some findings indicate that LRE is effective against expected inflation but not unexpected inflation. Other analyses suggest that LRE may anticipate future inflation changes, while further studies show a negative correlation between equity REIT returns and both expected and unexpected inflation (Gyourko and Linneman, 1988; Titman and Warga, 1989; Park et al., 1990; Glascock et al., 2002; Amenc et al., 2009).

The analyses presented in this paper integrate the various methodological improvements that have been uncovered in the past few years, while using data that include the surge in inflation since 2022. We apply a Panel MS-VECM model and investigate the inflation-hedging ability of various asset classes, including real estate, stocks, and gold based on a sample from 1990 to 2023 for six economies: France, Germany, Sweden, Switzerland, the U.K., and the U.S. The panel setting provides international evidence on the effect of an inflation shock on LRE returns in these countries. Based on impulse response functions and variance decompositions, our paper further confirms the desirable hedging ability of LRE, particularly in the long-term and in stable periods. Three months after the shock, the inflation-hedging ability of LRE to a one standard deviation inflation shock ranges from -8% to 19%. This variation in LRE returns indicates that LRE may react negatively to an inflation shock during turbulent periods. However, in stable periods, even in the short-term, LRE responds significantly positively to an inflation shock. In the long-term, LRE responds positively to inflation shocks, with a 140% return increase in disturbance periods and 280% return increase in stable periods.

Since inflation hedging might be important for investors with long-run horizons, a good understanding of the dynamics of the long-term hedging ability is crucial. For this reason, the paper extends the literature not only by considering non-linear features of inflation hedging in the short-term, but also such features in the long-run. Most of the existing literature combines the Fama and Schwert (1977) framework (which distinguishes between expected and unexpected components of inflation) and the cointegration technique (which distinguishes between long-run equilibrium and short-run dynamics) (Hoesli and Hamelink, 1997, Liu et al., 1997, Hoesli et al., 2008, and many others). Papers that concentrate on short-term fluctuations are limited by their assumption of a stable equilibrium, which may be disrupted by shifts in monetary policy and business cycles. Muckenhaupt et al. (2023a) address this limitation and find that the short-term inflation-hedging properties of listed real estate companies vary with market conditions. In non-crisis periods, LRE provides good protection against inflation, but the ability turns negative in times of turbulence. Similarly, studies that employ cointegration techniques to assess both short-term and long-term relationships face a comparable issue (Bahram et al., 2004; Hoesli et al., 2008; Zhou and Clements, 2010; Lee et al., 2011).

To address this issue, our paper initially demonstrates the time-varying long-term hedging potential of LRE, specifically its reaction to an inflation shock. This is depicted using time-varying impulse response functions through the application of an MS-VECM, which allows for the interpretation and understanding of the non-linear hedging capabilities of LRE over time. Although we also observe a positive response of LRE returns to an inflation shock in the long-term, the magnitude varies with market conditions. More importantly, we also apply the regime-switching process to the long-term equilibrium equation (in the error correction term).

Interestingly, the probability of switching shows a similar pattern across the long- and short-term relationships. Under this framework, we also find that LRE exhibits a better hedging ability in stable periods than during times of turbulence in the long-term equilibrium. After the long-term regime switching process is added, the response of LRE to an inflation shock remains qualitatively robust. In the short-term, we observe a significant positive response only in stable periods. However, in the long-term, a significant positive response occurs in the long-term in both stable and crisis periods.

The remainder of the paper is organised as follows. Section 3.2 discusses the literature. We next discuss the data and methods that we use to test the inflation-hedging ability of the various asset classes (section 3.3), followed by the presentation of our results (section 3.4). The final section concludes.

3.2 Literature Review

Several academic studies have examined the role of listed real estate (LRE) in hedging against inflation. These studies primarily focus on the asset's effectiveness to protect against actual inflation in the short-term, including its expected and unexpected components (e.g., Chen and Tzang, 1988; Titman and Warga, 1989; Chan et al., 1990; Park et al., 1990; Yobaccio et al., 1995; Liu et al., 1997; Gyourko and Linneman, 1988; Hardin et al., 2012; Salisu et al., 2020; Connolly and Stivers, 2022; and Fang et al., 2022), while other studies analyze the long-term relationship (e.g., Glascock et al., 2002; Bahram et al., 2004; Hoesli et al., 2008; Zhou and Clements, 2010; Lee et al., 2011; Lee and Lee, 2012; Magweva and Sibanda, 2020; Fehrle, 2023; Do et al., 2023; and Nguyen, 2023). No clear evidence concerning the short-term effectiveness of LRE emerges from that literature. For example, Liu et al. (1997) conclude that the ability of REITs to protect against expected inflation is inconsistent and inconclusive, while Adrangi et al. (2004) find no support for Fama's proxy hypothesis, which states that the negative relationship between REITs and inflation is symptomatic of a positive relationship between REITs and real economic activity.

By distinguishing between the long- and short-terms, some studies demonstrate that LRE exhibits better long-term inflation hedging abilities than in the short-term (Glascock et al., 2002; Hoesli et al., 2008; Lee and Lee, 2012). However, other studies present mixed results regarding the long-term hedging capabilities of REITs (Bahram et al., 2004; Amenc et al., 2009; Lee et al., 2011). Hoesli et al. (2008) report that LRE returns are positively associated with expected inflation, yet they do not respond to unexpected inflationary shocks. Their findings suggest that the real estate market's adaptation to inflationary changes occurs slowly, indicating that real estate may not consistently provide immediate protection against inflation. In contrast, Bahram et al. (2004) support the conventional view that REITs do not provide inflation hedging (as opposed to direct real estate), while Lee et al. (2011) examine the long-term inflation-hedging characteristics of real estate stocks in developing East Asian countries and report no long-run inflation-hedging capability of LRE.

The diverging results can stem from differences in the regions studied, the methodologies used to assess hedging capabilities, and the diverse ways of measuring inflation shocks. First, most of the literature focuses on the U.S. market (e.g., Chatrath and Liang, 1998; Simpson et al., 2007; Hardin et al., 2012), while less attention has been drawn to the European markets (Matysiak et al., 1996; Obereiner and Kurzrock, 2012; Essafi Zouari and Nasreddine, 2024) or global markets (Ganesan and Chiang, 1998; Le Moigne and La, 2008; Taderera and Akinsomi, 2020; Fehrle, 2023). In this paper, we provide evidence on the hedging ability of real estate assets at an international scale by using a panel model setting.

Regarding the methodology, the most commonly used methods include linear regression (e.g., Anari and Kolari, 2002; Simpson et al., 2007; Demary and Voigtländer, 2009), Vector Autoregressive Modelling, which focuses on the short-term hedging ability (Amenc et al., 2009; Hardin et al., 2012), Vector Error Correction Modelling, which distinguishes between the long- and short-term hedging ability (Glascock et al., 2002; Hoesli et al., 2008; Park and Bang, 2012), and Capital Asset Pricing Modelling (Yobaccio et al., 1995; McCown and Zimmerman, 2007; Rubbaniy et al., 2011; Fang et al., 2022). However, the investigation of the time-varying hedging capabilities has been limited. Our review of the literature suggests that there are only a few studies that explore the dynamic relationship between gold returns and inflation (Beckmann and Czuday, 2013; Conlon et al., 2018).

Our paper expands the literature by integrating short- and long-run analyses with a Markov regime-switching mechanism that allows for changes in monetary policy to be captured across crisis and non-crisis regimes. This innovative approach not only adds to our understanding of asset price dynamics but also refines how assets are perceived as potential hedges against inflation in varying economic climates. MS-VECM has been applied previously in the literature. For instance, Beckmann and Czudaj (2013) apply a MS-VECM model to investigate whether gold has the capability to hedge against inflation, while He et al. (2018) study the role of gold as a safe haven, by applying a Markov-switching CAPM to assess whether two distinct states exist between gold's relationship with the market portfolio. Chiang et al. (2020) apply a Markov-switching vector autoregression model (MS-VAR) to monitor the dynamic links between housing market returns and equities in the U.S. Liu et al. (2023) examine the inflation-hedging ability of commodity futures applying a Markov-switching vector error correction model. The hedging capacity of industrial metal futures exhibits substantial variation over time, with most of the inflation-hedging power emerging under relatively longer and more common regimes covering the Great Moderation and post-subprime crisis. Phoa (2023) also uses a non-linear framework and cautions that conventional simulation models and tools fail to accurately predict the long-term behaviour and impact of inflation. Based on a MS-VECM model, Muckenhaupt et al. (2023a) demonstrate that the short-term hedging ability moves toward being negative during crisis periods. In non-crisis periods, LRE provides good protection against inflation.

When defining inflation shocks, most papers follow the classical definition of Fama and Schwert (1977) (Hoesli et al., 2008), of Fama and Gibbons (1984) (Glascock et al., 2002), or Box–Jenkins/ARIMA approaches (Muckenhaupt et al., 2023a). Recent studies have broken down inflation into several components, such as energy, food, and the core components (Connolly and Stivers, 2022; Fang et al., 2022). In this paper, we employ impulse response functions to illustrate the inflation-hedging capabilities of LRE. These functions show the overall change in asset returns following a one standard deviation idiosyncratic inflation shock, capturing unexpected elements of inflation that are not included in the market's pricing and cost calculations. By utilizing impulse response functions, we provide a more detailed analysis of both the short-term and long-term effects of inflation shocks on asset prices, under different economic climates. Meanwhile, we also decompose inflation into various components using the methods documented in the literature.

3.3 Data and Method

3.3.1 Data Description

Data were compiled for a panel of six economies: France, Germany, Sweden, Switzerland, the U.K., and the U.S. The five European countries have the largest LRE market capitalization in Europe, while the U.S. LRE market is the largest in the world. We use monthly data from 1990 to the end of 2023. LRE returns were obtained from the European Public Real Estate

Association (EPRA). Stock total return indexes were obtained from Refinitiv Datastream. Specifically, these are the CAC40 for France, DAX for Germany, OMX for Sweden, SMI for Switzerland, FTSE 250 for the U.K., and S&P 500 index for the U.S. We also include the price of gold and oil in U.S. Dollars, along with the real three-month Treasury Bill rates, which are a proxy for the risk-free rates, as well as the nominal GDP. Our key variable, namely actual inflation, is derived from the seasonally adjusted consumer price indexes (CPI) obtained from Refinitiv Datastream for the respective countries.

Table 3.1: Summary Statistics

	Mean	*Std*	*Max*	*Min*
France				
LRE	0.638%	5.962%	27.948%	-37.273%
Stocks	0.534%	5.551%	14.485%	-26.487%
Oil	0.348%	12.243%	42.014%	-52.782%
Gold	0.346%	4.269%	13.230%	-23.583%
GDP	0.219%	1.779%	10.639%	-7.377%
Interest rate	3.932%	2.663%	10.475%	-0.339%
CPI	0.141%	0.197%	0.993%	-0.471%
Germany				
LRE	0.314%	7.287%	35.762%	-46.457%
Stocks	0.479%	6.173%	16.298%	-34.468%
Oil	0.348%	12.243%	42.014%	-52.782%
Gold	0.346%	4.269%	13.230%	-23.583%
GDP	0.238%	1.819%	7.425%	-6.544%
Interest rate	3.572%	2.645%	9.105%	-0.649%
CPI	0.171%	0.265%	1.565%	-0.719%
Sweden				
LRE	0.455%	8.501%	38.152%	-44.489%
Stocks	0.796%	6.173%	29.984%	-34.223%
Oil	0.348%	12.243%	42.014%	-52.782%
Gold	0.346%	4.269%	13.230%	-23.583%
GDP	0.212%	2.039%	7.088%	-8.503%

Interest rate	4.366%	3.468%	13.750%	-0.288%
CPI	0.175%	0.358%	2.455%	-1.341%
Switzerland				
LRE	0.483%	4.604%	17.348%	-26.396%
Stocks	0.676%	5.697%	37.355%	-30.075%
Oil	0.348%	12.243%	42.014%	-52.782%
Gold	0.346%	4.269%	13.230%	-23.583%
GDP	0.290%	1.693%	6.717%	-5.661%
Interest rate	2.394%	2.015%	6.977%	-0.975%
CPI	0.086%	0.216%	0.906%	-0.638%
U.K.				
LRE	0.341%	6.045%	21.604%	-37.508%
Stocks	0.585%	4.527%	13.466%	-26.924%
Oil	0.348%	12.243%	42.014%	-52.782%
Gold	0.346%	4.269%	13.230%	-23.583%
GDP	0.238%	1.869%	10.082%	-11.172%
Interest rate	4.555%	2.832%	12.740%	0.209%
CPI	0.219%	0.265%	1.985%	-0.643%
U.S.				
LRE	0.839%	6.046%	27.572%	-54.323%
Stocks	0.741%	4.506%	13.688%	-32.312%
Oil	0.348%	12.243%	42.014%	-52.782%
Gold	0.346%	4.269%	13.230%	-23.583%
GDP	0.359%	0.549%	5.228%	-5.356%
Interest rate	4.245%	2.005%	8.890%	0.620%
CPI	0.217%	0.274%	1.367%	-1.786%

Notes: Descriptive statistics based on our panel including the U.S., U.K., Germany, France, Switzerland, and Sweden. LRE denotes the FTSE/EPRA/NAREIT real estate stock total return index. Stocks denotes for each country the corresponding total return of the stock market index. Oil denotes the oil price in U.S. Dollars. Gold denotes the gold price in U.S. Dollars. GDP stands for the GDP of each country. Interest rate is the 3-month treasury bill rate. CPI stands for Consumer Price Index. I(1) is given for all variables in all countries.

Table 3.1 displays the corresponding summary statistics of our data. The highest average total return is recorded in the U.S. with 10.55% annually, while France, Switzerland, Sweden, the U.K., and Germany follow with annual rates of 7.93%, 5.95%, 5.59%, 4.17%, and 3.84, respectively. The U.K. faces the highest average inflation rate of 2.66% per annum, while Switzerland comes across with the lowest rate at 1.04% per year. In between are the U.S., Sweden, Germany and France with 2.64%, 2.12%, 2.07%, and 1.70%, respectively.

3.3.2 MS-VECM and Impulse Responses

Markov-switching models are key tools for exploring transitions between different states within a dataset, especially time series data with non-stationary traits (Hamilton, 1989). The prevailing literature in this field indicates that single-state models previously employed may not capture effectively the dynamic relationships within the data. Markov-switching models have been used in the context of stocks and bonds (Moore and Wang, 2007; Rey et al., 2014), commodities (Andersen, 2010; Herrera et al., 2017), while the number of studies that apply the time-varying coefficient models to listed real estate is limited (Chiang et al, 2020; Liow and Ye, 2018; Muckenhaupt et al., 2023a).

Additionally, much of the previous literature assesses inflation-hedging ability either by examining the sign of coefficients in a VAR/VECM framework (Glascock et al., 2002; Barkham et al., 1996; Tarbert, 1996; Hoesli et al., 2008), or by investigating the factor loadings of inflation shocks in a CAPM framework (Yobaccio et al., 1995; McCown and Zimmerman, 2007; Rubbaniy et al., 2011; Fang et al., 2022). In contrast to prior studies, we illustrate the hedging ability of assets using impulse response functions. These functions reflect the cumulative change in asset prices in response to a one standard deviation idiosyncratic shock to inflation. The idiosyncratic shock captures the innovative component of inflation that is not factored into individuals' pricing and cost calculations. This identification aligns with the classical definition of an unexpected inflation shock, where such a shock is defined as the difference between actual inflation and the portion of inflation explained by previous inflation, or proxies for macroeconomic conditions such as interest rates. Moreover, employing impulse response functions to quantify inflation-hedging ability can surpass previous methods as it enables us to observe both the long-term and short-term hedging abilities.

We use a Panel MS-VECM to examine the relationship between the return of assets and inflation.[22] By following Beckman and Czudaj (2013), we design the parameters of this model to take a constant value in each regime and to shift discretely from one regime to the other with different switching probabilities. The switches between states are assumed to follow an exogenous stochastic process. Consider an M-regime p^{th} order MS-VECM, which in general, allows for regime shifts in the vector of intercept terms, the autoregressive part, the long-run matrix, and the variance-covariance matrix of the errors:

Equation 3.1: MS-VECM (2)

$$\Delta Y_{i,t} = \Lambda(s_j) + \Gamma(s_j)\Delta Y_{i,t-1} + \Pi(s_j)Y_{i,t-1} + \varepsilon_{t,}$$

where Δ denotes the difference operator, $Y_{i,t}$ represents a K-dimensional vector of time series at period t in country i, $Y_{i,t} = [R_{i,t}, I_{i,t}, X_{i,t}]$ and $R_{i,t}$ is a vector of asset returns, including stocks, LRE, commodities, and gold. $I_{i,t}$ stands for inflation. $X_{i,t}$ are economic control variables such as GDP, real interest rates, and oil prices. $\Gamma(L)(s_j)$ is the $K \times$ K regime-dependent coefficient matrix for short-run dynamics. $\Lambda(s_j)$ denominates a K-dimensional vector of regime-dependent intercept terms. ε_{it} is a vector of error terms with a regime-dependent variance-covariance matrix $\sum(s_j)$, $\varepsilon_{i,t} \sim NIID(0, \sum(s_j))$. The stochastic regime-generating process is assumed to be an ergodic, homogenous, and irreducible first-order Markov chain with a finite number of regimes, $s_j \in \{1, \ldots, M\}$, and constant transition probabilities:

[22] We use the Expectation–Maximization (EM) algorithm to estimate the parameters of the Markov-switching model and to identify the different states or regimes by maximizing the data likelihood function. In our case, the EM algorithm is used to estimate the parameters that govern the probability of switching from one state (or regime) to another, as well as the parameters of each individual state.

Equation 3.2: Transition Probabilities (2)

$$p_{ij} = \Pr(s_{t+1} = j | s_t = v), p_{vj} > 0, \sum_{j=1}^{M} p_{vj} = 1 \ \forall \ v, j \ \in \{1, \dots, M\}$$

The first expression of Equation 3.2 gives the probability of switching from regime *v* to regime *j* at time t + 1, which is independent of the history of the process. p_{ij} is the element in the v^{th} row and the j^{th} column of the M × M matrix of the transition probabilities P. To formalise impulse response functions (IRF), Equation 3.1 can be converted to:

Equation 3.3: Conversion of Equation 3.1

$$Y_{i,t} = \Lambda(s_j) + \left(I + \Pi(s_j) + \Gamma(s_j)\right) Y_{i,t-1} + \varepsilon_{i,t},$$

Thus, the impulse response function can be represented as:[23]

Equation 3.4: Impulse Response Function

$$IRF_H(s_j) = L(s_j) \sum_{h}^{H} \left((I + \Pi(s_j) + \Gamma(s_j)\right)^h e_k$$

where e_k represent a vector of size $K \times 1$, where k indicates the variable that experiences a shock.

Time-varying impulse response functions are calculated by using the transition probabilities of regimes:

[23] A comprehensive derivation of the Impulse Response Function is provided in the Appendix E.

Equation 3.5: Time-Varying Impulse Response Function

$$IRF_{t,h} = IRF_h(s_1) * p_{1,t} + IRF_h(s_2) * (1 - p_{1,t})$$

3.4 Empirical Results

3.4.1 Baseline Results

Using the Maddala-Wu test for stationarity, we show that our panel is I(1), indicating stationarity in first differences. The results are shown in Table 3.2. Considering that the variables are I(1) series, we further perform the Johansen Fisher panel cointegration test using the trace and maximum eigenvalue tests.

Table 3.2: Results of Maddala-Wu Panel Stationarity Test

	Level	Difference	I(d)
lnLRE	6.690	256.920***	1
lnStocks	5.287	242.140***	1
lnOil	14.918	134.980***	1
lnGold	0.426	183.380***	1
lnGDP	1.937	69.125***	1
Interest Rate	5.679	100.440***	1
lnCPI	2.398	174.130***	1

Notes: Results of the Maddala-Wu panel stationarity test based on our panel including the U.S., U.K., Germany, France, Switzerland, and Sweden. LRE denotes the FTSE/EPRA/NAREIT real estate stock total return index. Stocks denotes for each country the corresponding total return of the stock market index. Oil denotes the oil price in U.S. Dollars. Gold denotes the gold price in U.S. Dollars. GDP stands for GDP of each country. Interest rate is the 3-month treasury bill rate. CPI stands for Consumer Price Index. I(1) is given for all variables in all countries.

As reported in Table 3.3, the results by the Johansen Fisher panel cointegration test indicate one cointegration relationship for our panel.

Table 3.3: Results of Johansen Fisher Panel Cointegration Test

Null hypothesis	Alternative	Statistic	Prob.
Stochastic matrix trace			
r = 0	r = 1	74.230	0.000***
r ≤ 1	r = 2	16.290	0.178
r ≤ 2	r = 3	7.223	0.843
r ≤ 3	r = 4	2.938	0.996
r ≤ 4	r = 5	2.920	0.997
Stochastic matrix maximal eigenvalues			
r = 0	r ≥ 1	83.121	0.000***
r ≤ 1	r ≥ 2	16.190	0.183
r ≤ 2	r ≥ 3	10.100	0.607
r ≤ 3	r ≥ 4	2.832	0.996
r ≤ 4	r ≥ 5	2.817	0.997

Notes: Results of the Johansen Fisher Panel Cointegration Test based on our panel including the U.S., U.K., Germany, France, Switzerland, and Sweden. LRE denotes the FTSE/EPRA/NAREIT real estate stock total return index. Stocks denotes for each country the corresponding total return of the stock market index. Oil denotes the oil price in U.S. Dollars. Gold denotes the gold price in U.S. Dollars. GDP stands for GDP of each country. Interest rate is the 3-month treasury bill rate. CPI stands for Consumer Price Index. I(1) is given for all variables in all countries

Table 3.4 reports the constant long-term relationship (β-vector). The first vector is normalised to LRE returns. We find long-term relationships between the performance of listed real estate markets and actual inflation in our panel. In the long-term, LRE can positively hedge against actual inflation. A one percent increase in actual inflation is related to a 1.791 percent increase in the LRE total return of our panel. Concerning other long-term equilibrium relationships, we find negative long-term relationships between LRE returns and gold and oil prices. Furthermore, we find a positive long-term elasticity of GDP and stock performance on LRE returns.

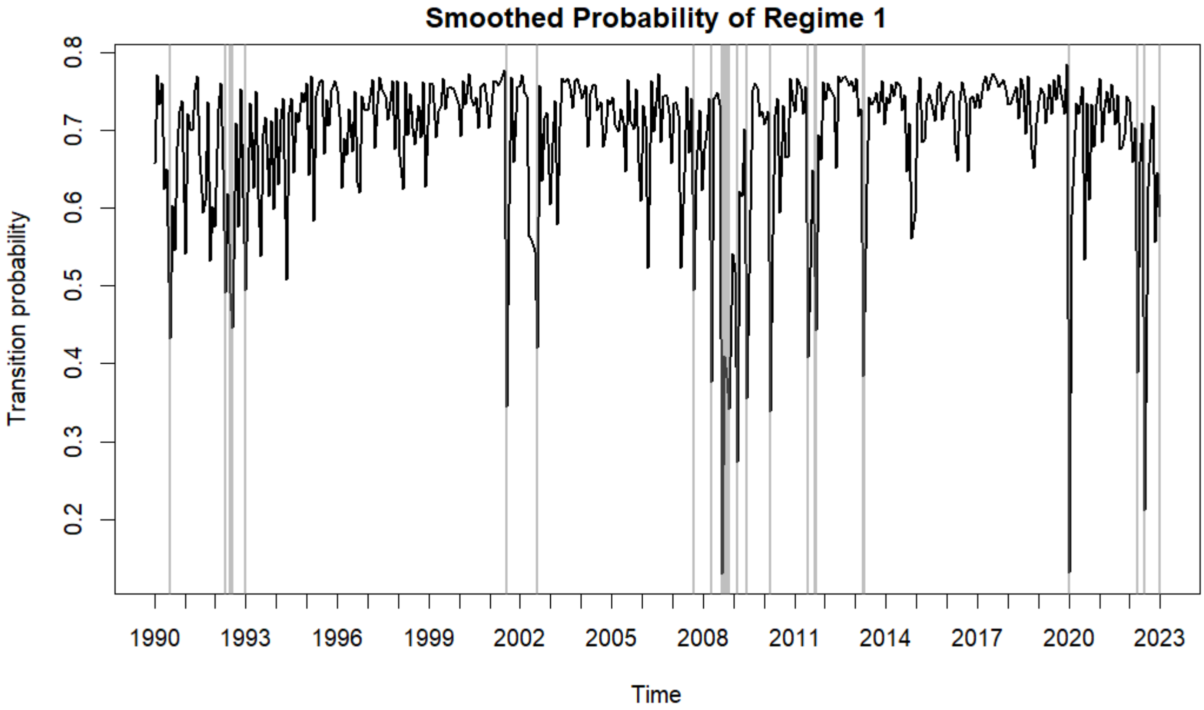
Table 3.4: Long-Term Equilibrium Relationships (beta-vectors)

Variables	Coefficient	Standard Error	Significance
$r_{LRE,t-1}$	1.000	(0.000)	
$r_{stock,t-1}$	-0.450	(0.397)	
$r_{oil,t-1}$	-0.253	(0.050)	***
$r_{gold,t-1}$	-0.832	(0.060)	***
ir_{t-1}	0.036	(0.122)	
GDP_{t-1}	0.938	(0.070)	***
CPI_{t-1}	1.791	(0.089)	***

*Notes: The analysis of the underlying panel is conducted by using an unrestricted constant and includes one rank-based Johansen Fisher Panel Cointegration test. $r_{LRE,t-1}$ denotes the FTSE/EPRA/NAREIT real estate stock total return index. $r_{stock,t-1}$ denotes for each country the corresponding total return of the stock market index. $r_{oil,t-1}$ denotes the oil price in U.S. Dollars. $r_{gold,t-1}$ denotes the gold price in U.S. Dollars. ir_{t-1} are the 3-month treasury bill rates. GDP_{t-1} stands for GDP of each country. CPI_{t-1} stands for consumer price index (inflation) for the corresponding country. Rank denotes the rank of π matrix. Standard errors are included in the parentheses. ***, **,* denotes significance level at 1%, 5% or 10%, respectively. $\zeta_t=Y_t-\beta X_t$, where ζ_t is the error correction term. The coefficient β is the cointegrating coefficient, and it represents the long-term relationship between X_t and Y_t.*

The MS-VECM representation given in Equation 3.1 has been estimated for the observed panel while enabling each parameter to switch between two regimes, including the intercept, the autoregressive elements the residuals variance-covariance matrix, and, most notably, the adjustment parameters to deviations from long-run relationships. The choice of a two-regime model is supported by lower AIC and BIC values, indicating that models with three or more regimes would unnecessarily increase complexity.

Figure 3.1: Smoothed Probabilities

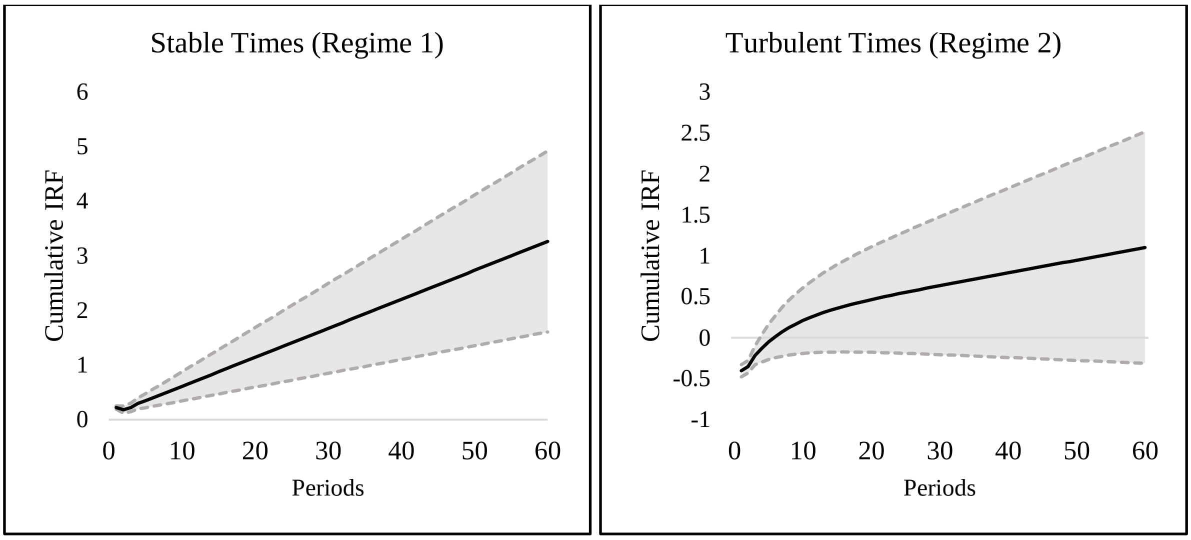


Note: This graph shows the smoothed probabilities of Regime 1 of our MS-VECM.

Figure 3.1 illustrates the switching process. The black line shows the probability of switching to Regime 1. Figure 3.1 effectively demonstrates that Regime 1 represents periods of stability, evidenced by a significant drop in the smoothed probability from around 78% to under 15% during the 2008 Global Financial Crisis (GFC), indicating a transition from stability to instability. On the other hand, Regime 2 is associated with times of economic turmoil. Additional declines in transition probabilities are evident, particularly at the beginning of 2000, during the dot-com bubble, and in 2020, during the Covid-19 pandemic. In this context, the research by Muckenhaupt et al. (2023a) is particularly relevant. They found that during crises such as the COVID-19 pandemic, which brought simultaneous supply and demand shocks, and the GFC, which led to severe disruptions in global financial markets, there was a marked increase in both expected and unexpected inflation volatility. This analysis further emphasises the dynamic shifts between economic regimes in response to changing market conditions.

In the next step, we estimate the impulse response functions based on our Markov Switching Vector Error Correction Model (MS-VECM) characterised by a constant long-run relationship, whereas the short-run dynamics are subject to regime switches (Beckmann and Czudaj, 2013; Muckenhaupt et al., 2023a). The optimal number of lags, determined by the Schwarz Information Criterion (SIC), is set to one. We apply the Cholesky decomposition, and the order is set as stock returns, oil returns, gold returns, GDP, interest rates, inflation, and LRE returns. In Figure 3.2, we show the responses of LRE to a one standard deviation shock in actual inflation. The responses are strongly regime dependent. The upper response of Figure 3.2 corresponds to a stable times regime (Regime 1), whilst the response below refers to a regime of turbulent times (Regime 2). The dashed lines are one standard deviation confidence bands calculated with 1,000 bootstrap replications.

Figure 3.2: Cumulative Impulse Response Functions (Constant Long-Run)



Note: This graph shows the responses of LRE returns to a shock to actual inflation for Regime 1 (stable times) and Regime 2 (turbulent times).

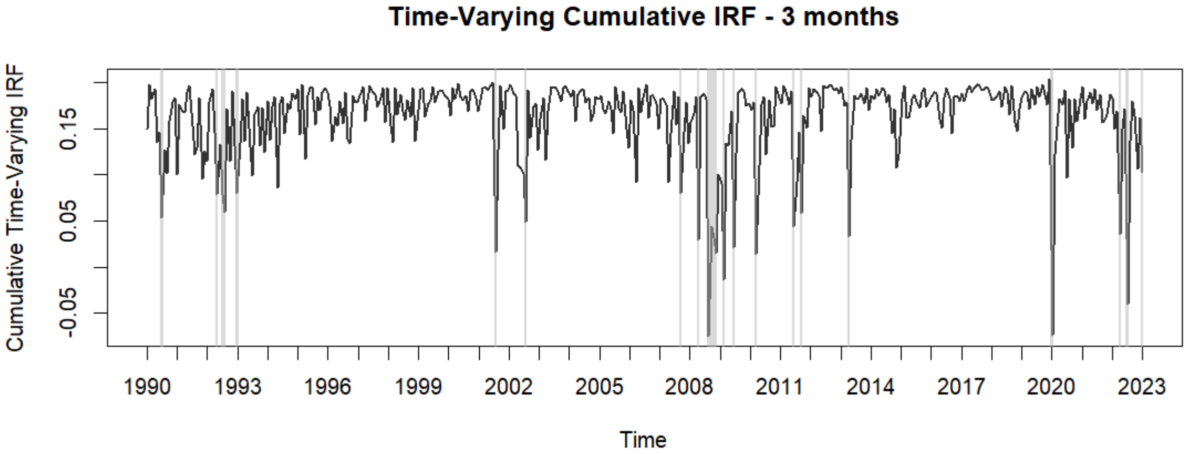
In both regimes, the impulse response shows a significant response of LRE total returns to an inflation shock. In regime one, a one standard deviation shock of inflation leads to a 22% percent increase in the LRE return three months after the shock. The response is statistically significant at a 95% confidence level since the first month. The response is quite persistent and rises to 326% after 60 months. However, for regime two, a significant response only exists in the first five months. A one standard deviation shock to inflation leads to a 35% percent increase in LRE returns five months after the shock.

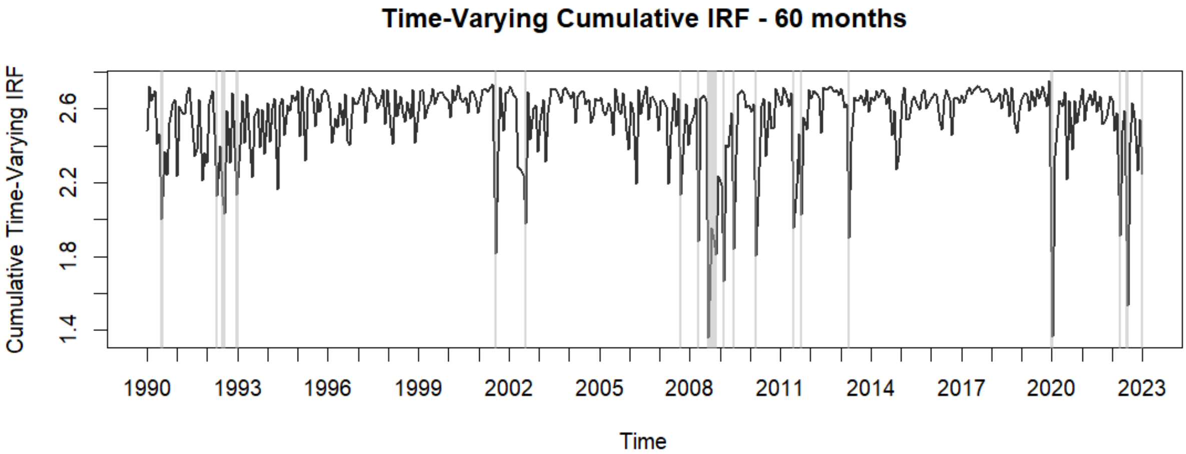
Overall, the responses in the two regimes reveal significant differences in the hedging ability of LRE over different time periods. Second, as shown in Figure 3.2A, during stable periods, the response of LRE to an inflation shock is positive, consistent, and economically remarkable, confirming the desirable inflation hedging ability of LRE during stable times. However, during turbulent times, the response of LRE to an inflation shock is negative, as Figure 3.2B depicts an initial decline. This suggests that in times of economic turmoil, the impact of inflation shocks on LRE returns is less pronounced and possibly less persistent.

This is in line with our expectations. LRE provides good inflation hedging because 1) rental income is adjustable in line with inflation and 2) the gaps between the capitalization rate and the base rate typically decrease as investors recognise a reduced risk in real estate investment, attributed to the common perception that real estate assets offer protection against inflationary pressures. However, during turbulent times, due to the high levels of uncertainty, investors commonly charge a higher risk premium. As a result, the asset value will decrease, and the short-term inflation-hedging ability of LRE will become insignificant or even negative (Muckenhaupt et al., 2023a). This finding also corresponds closely with the results reported by Muckenhaupt et al. (2023a), which identified similar patterns. In this study, 1) we execute a panel regression, aggregating data from several nations, specifically France, Germany, Sweden, Switzerland, the U.K., and the U.S. and 2) our investigation reveals the short-term and long-term effects of inflation shocks on LRE returns.

To provide a better intuitive overview of the response in the short- and long-term, we illustrate the time-varying impulse responses for 3- and 60-month time horizons based on the smoothed probabilities of our MS-VECM. Figure 3.3 shows this graphically. The solid line is the time-varying impulse response, while the gray shadows reflect the turbulent times regime. Figure 3.3A illustrates the short-term response of listed real estate returns to inflation shocks from 1990 to 2023. The responses to a one standard deviation positive shock to inflation fluctuate between 19% and -8%. During stable times, for example, in 2004 or 2019, the response reaches the maximum amount by 19%. However, during economic crisis periods, such as the dot-com bubble in the early 2000s, the landslide effects of the GFC, the COVID-19 pandemic, and the start of the war in Ukraine, we observe a negative response to -8%. However, in the long-term, LRE always provides a positive long-term hedging effect over the whole sample period. As shown in Figure 3.3B, over the long-term, the response remains positive and fluctuates between 140% (during turbulent periods) and 280% (during stable periods). This further confirms the desirable long-term hedging ability of LRE.

Figure 3.3: Time-Varying Cumulative Impulse Response Functions

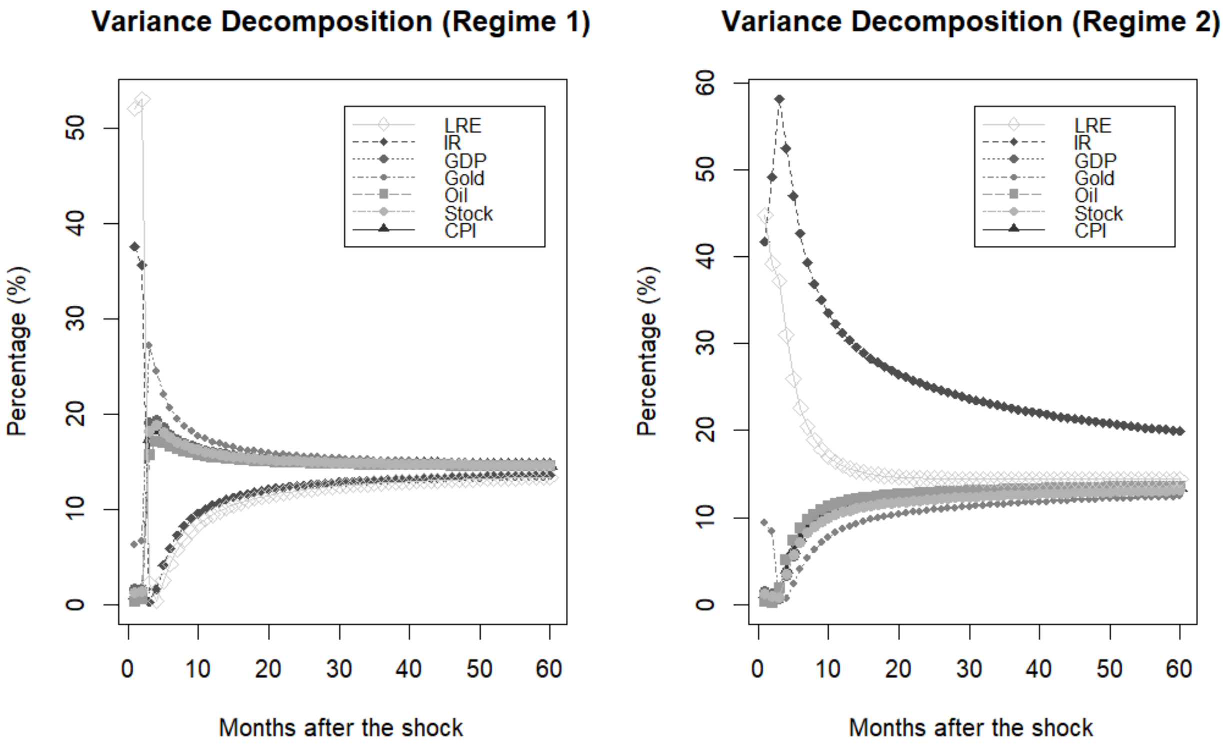




Note: This graph shows the time-varying responses of LRE returns to a shock to actual inflation a short-term horizon (3 months) and a long-term horizon (60 months).

We conduct the variance decomposition to further illustrate how LRE performance is affected by other shocks over 60 months after the shock. Figure 3.4 illustrates the decomposition of LRE returns to shocks to inflation, stocks, oil, gold, GDP, interest rates, and LRE for Regime 1 (stable periods) and Regime 2 (disturbance periods). Initially, for both regimes, the LRE shock predominates in explaining the variance of LRE returns, signifying its immediate impact. The interest rate shock plays a dominant role in both regimes, initially accounting for approximately 40% of the explained variance of LRE returns. Subsequently, the proportion of explained variance of LRE returns by an interest rate shock diminishes, stabilizing at a level between 15% and 20%. In regime one (stable periods), an inflation shock explains up to 20% of the variation in LRE returns, gradually reducing to 15% in the ensuing months. In regime two (disturbance periods), an inflation shock explains a lower proportion of the variations compared to regime one, leading to a 10% variation in LRE returns after a few months. Meanwhile, the variance attributed to other variables such as gold, oil, stocks, and GDP collectively ranges between 10% and 15% in both regimes.[24]

Figure 3.4: Variance Decomposition

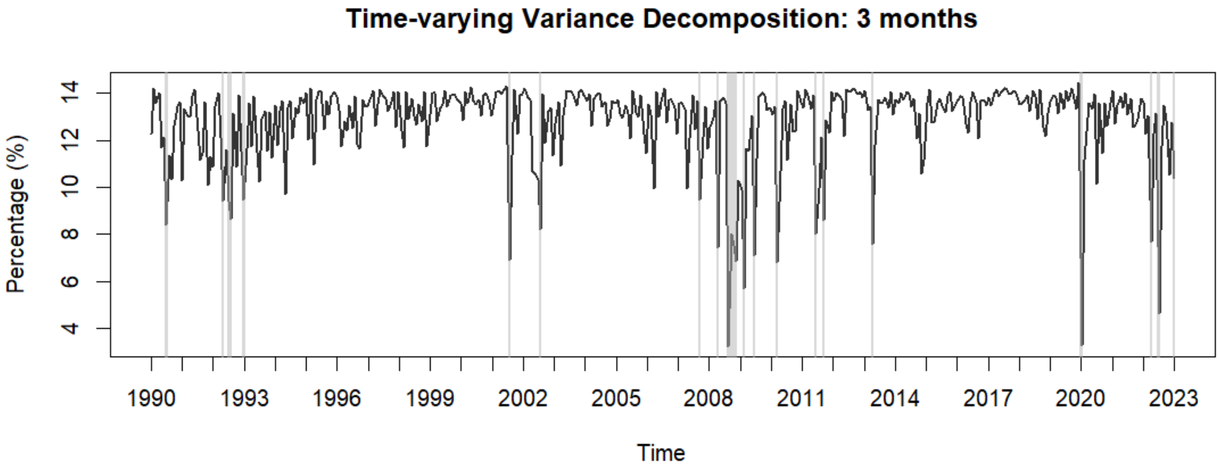


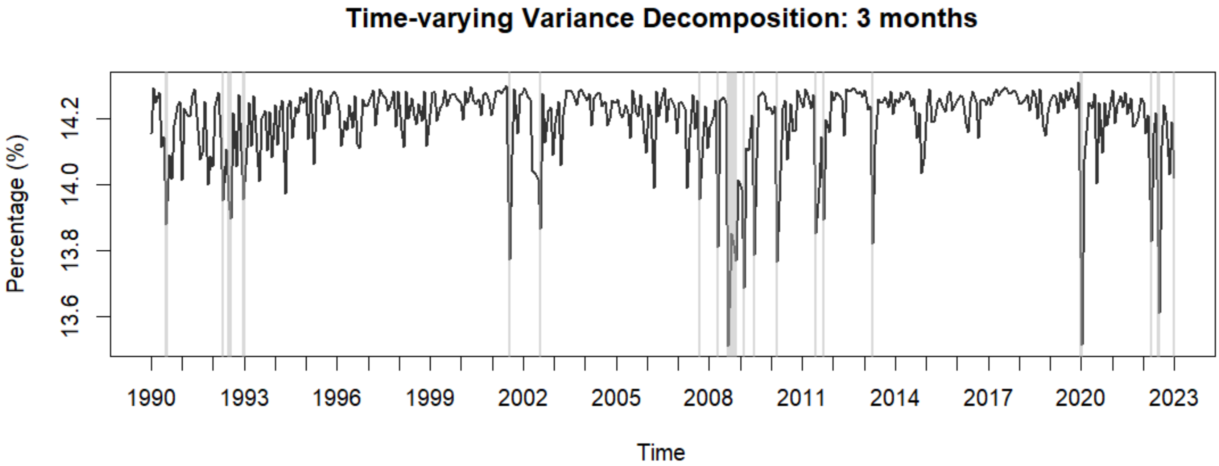
Note: This graph shows the percentage of the variance of LRE returns explained by shocks.

We then combine the variance decomposition approach with the smoothed probabilities of our MS-VECM to further illustrate how the average percentage variance is explained by a shock in the actual inflation over time.

[24] The results are robust with different orders in the Cholesky decomposition process.

Figure 3.5: Time-Varying Variance Decomposition





Note: This graph shows the time-varying percentage of the variance of LRE returns explained by a shock in inflation.

Figure 3.5A shows a range from 4% to 14%, which measures the fraction of variance in LRE returns that can be accounted for by an inflation shock in the short-term. Spanning from 1990 to 2023, the graph's line fluctuates, reflecting the varying effects of inflation shocks on listed real estate returns over time. It is remarkable that the proportion of variation in actual inflation explained by shocks decreases during periods of economic distress. Observations from incidents such as the dot-com bubble, the global financial crisis, Brexit, the COVID-19 pandemic, and the conflict in Ukraine illustrate how these crises influence the behaviour of variance decomposition. Similarly, the lower illustration displays the variance decomposition of returns on LRE over an extended timeframe, 60 months after an inflation shock, from 1990 to 2023. The vertical axis of this chart measures the percentage of forecast error variance in real estate returns that is attributable to inflation changes, with the scale fluctuating from approximately 13.2% to 14.4%. The data indicates a pattern of fluctuation like that observed in the 3-month chart, but with less variation, suggesting a consistent yet variable response to inflation shocks over an extended timeframe.

3.4.2 Additional Results

3.4.2.1 Time-Varying Long Term Relationship

One concern is that our long-term effect is based on time-invariant long-term equilibrium. In other words, the time-varying characteristics are determined by the regime-switching process only in the short-term. To address this concern, we augment our analysis by including regime switches in both the long-run and short-run relationships. Following the methodology outlined in section 3.4.1, the selection of the optimal number of lags, as guided by the Schwarz Information Criterion (SIC), is fixed at one. Since the Johansen Fisher panel cointegration test indicates that there is one cointegration relationship among these variables, we use the Dynamic Ordinary Least Squares Estimator (DOLS) for the long-term equilibrium:

Equation 3.6: Dynamic Ordinary Least Squares

$$y_t = \alpha_{s_j} + \beta_{s_j} x_t + \sum_{j=-p}^{p} \gamma_{j,s_j} \Delta x_{t-j} + \varphi_{t,s_j},$$

Where the regime (s_j) determines the switching of the intercept, the slope coefficients, and the error terms. We then generate a combined series of residuals according to Equation 3.7.

Equation 3.7: Combined Series of Residuals

$$\varphi_t = \varphi_{1,t} * p_{1,t} + \varphi_{2,t} * (1 - p_{1,t}),$$

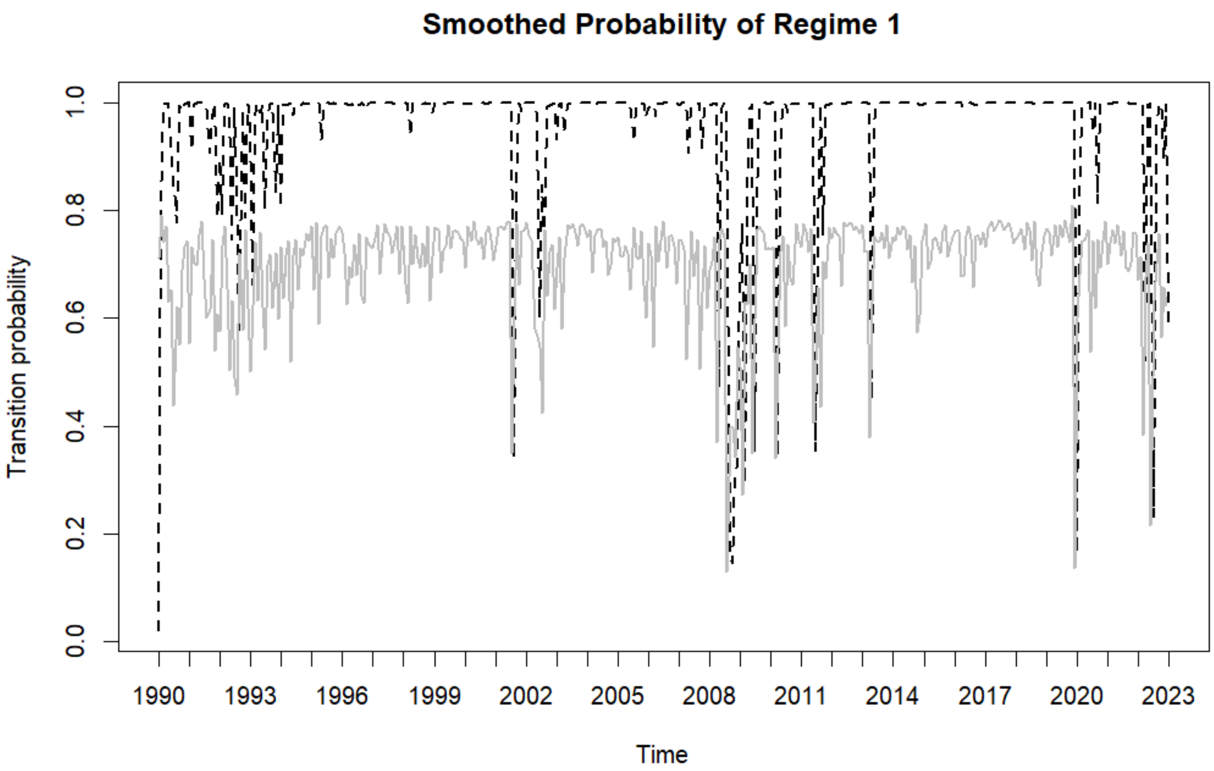
where we calculate the product of residuals from Regime 1 with their smoothed probabilities and adding this to the product of Regime 2 residuals with their smoothed probabilities. Based on the Augmented Dickey-Fuller test, the residual series is confirmed to be stationary, with a test statistic of -8.80 and a p-value of 0.01. This indicates strong evidence against the null hypothesis of a unit root at the 1% significance level. Thus, we can incorporate φ_t into the short-term equations (Equation 3.8), aiming to derive insights into the speed of adjustment.

Equation 3.8: Short-Term Equation

$$\Delta Y_t = \alpha(s_j)\varphi_t + \Phi(s_j)\Delta X_{t-1} + \epsilon_t(s_j)$$

It should be noted that adding a regime-switching process leads to four separate configurations in the long and short dynamics – two regimes for the long-term ($s_j^{Long} = 1,2$) and two regimes for the short-term ($s_j^{Short} = 1,2$), as we do not want to restrict the same regimes in the long- and short-term relationships. Figure 3.6 illustrates the probability of switching for both the long-term (black dashed line) and the short-term (grey solid line). Interestingly, the data indicates a similar switching process between the stable period (Regime 1) and the time of turbulence (Regime 2) in both the long- and short-terms.

Figure 3.6: Smoothed Probabilities in the Long-Term and Short-Term



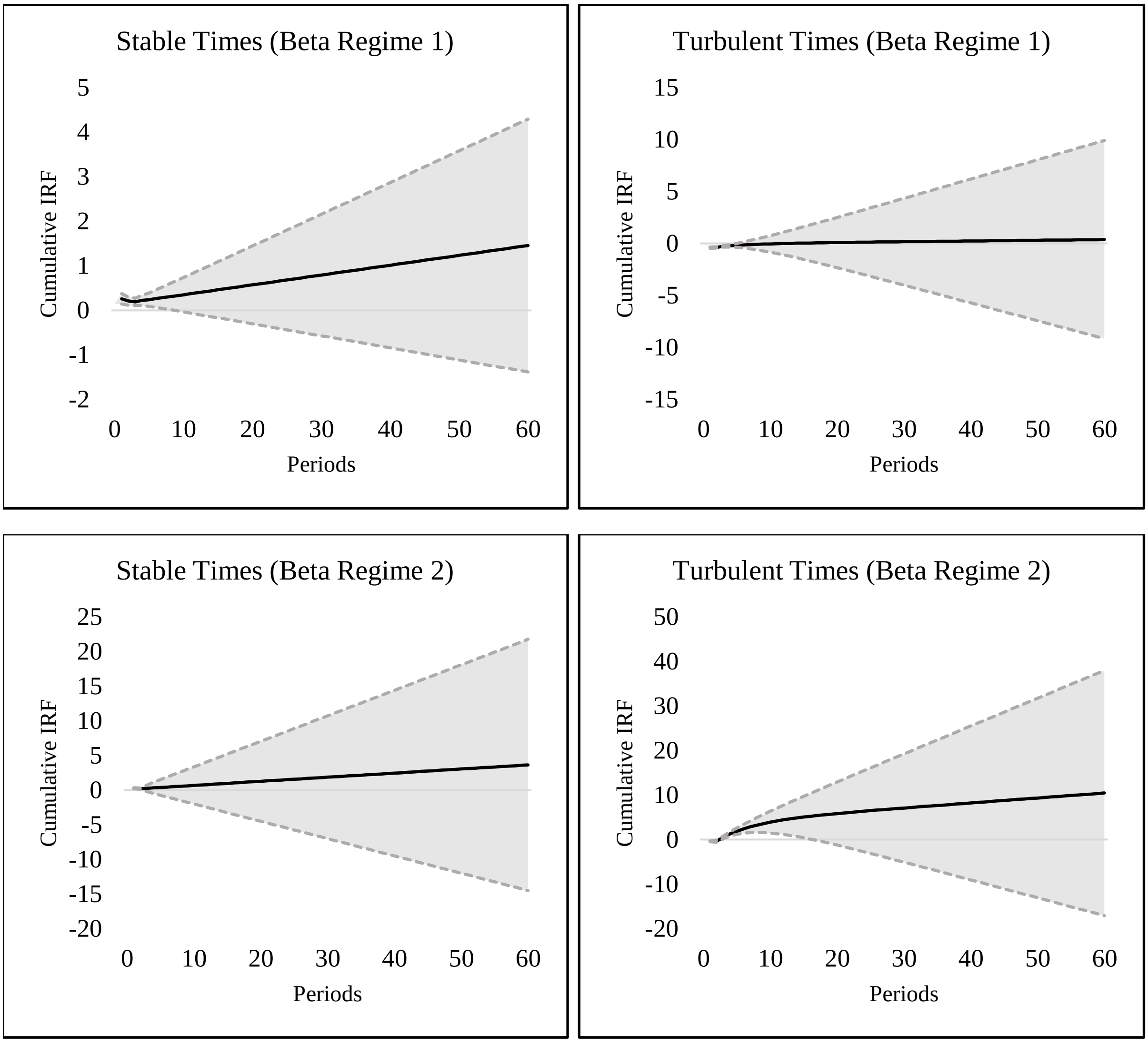
Note: This graph shows the smoothed probabilities of Regime 1 of our MS-VECM in the long-term (black dashed line) and short-term (grey solid line).

Figure 3.7 illustrates the response of LRE to a one standard deviation inflation shock based on the combination of four configurations (Figure 3.7A, $s_j^{Long} = 1, s_j^{Short} = 1$; Figure 3.7B: $s_j^{Long} = 2, s_j^{Short} = 1$; Figure 3.7C $s_j^{Long} = 1, s_j^{Short} = 2$; and Figure 3.7D: $s_j^{Long} = 2, s_j^{Short} = 2$). The impulse response is based on the same order as in our baseline model.[25] The diagrams in Figure 3.7 are characterised by their wide confidence intervals. The large confidence intervals are due to the additional parameters in the regime-switching process in the long-term, leading to a much larger standard error. However, the magnitude of the response is also amplified. In the case of the long- and short-terms, both fall in regime 1 (stable periods), a

[25] The derivation closely follows that presented in the Appendix E, with distinction lying in the matrix $B(s_j) = \begin{bmatrix} 1 & -\beta_{12}(s_j) & \cdots & -\beta_{1,k}(s_j) \\ 1 & -\beta_{22}(s_j) & \cdots & -\beta_{2,k}(s_j) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & -\beta_{k2}(s_j) & \cdots & -\beta_{k,k}(s_j) \end{bmatrix}$, which now incorporates switching as denoted by (s_j).

significant response occurs from one to 10 months after the shock, amounting to 35% in the 10th month. Both the long- and short-term relationships fall in regime 2 (crisis period), while the response to the inflation shock remains significantly negative from the first to the second month, but becomes insignificant three months after the shock. When long-term and short-term relationships fall in different regimes, the response is between the abovementioned two scenarios. Overall, the response of LRE returns to an inflation shock exhibits a similar trend. The hedging ability is more vital during stable periods. During turbulence times, the positive hedging ability disappears or even becomes negative.

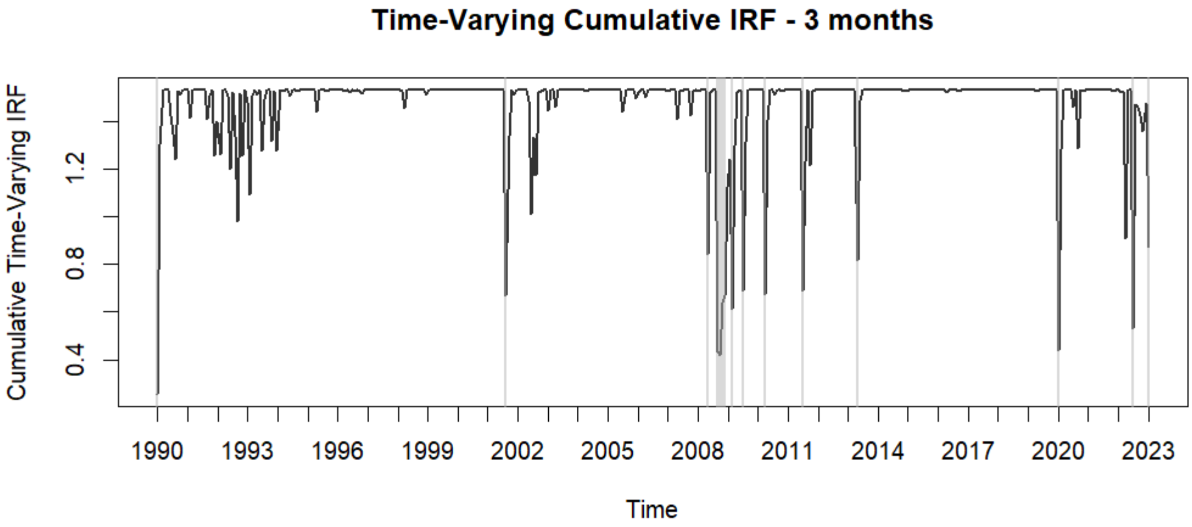
Figure 3.7: Cumulative Impulse Response Functions (Switching Long-Run)

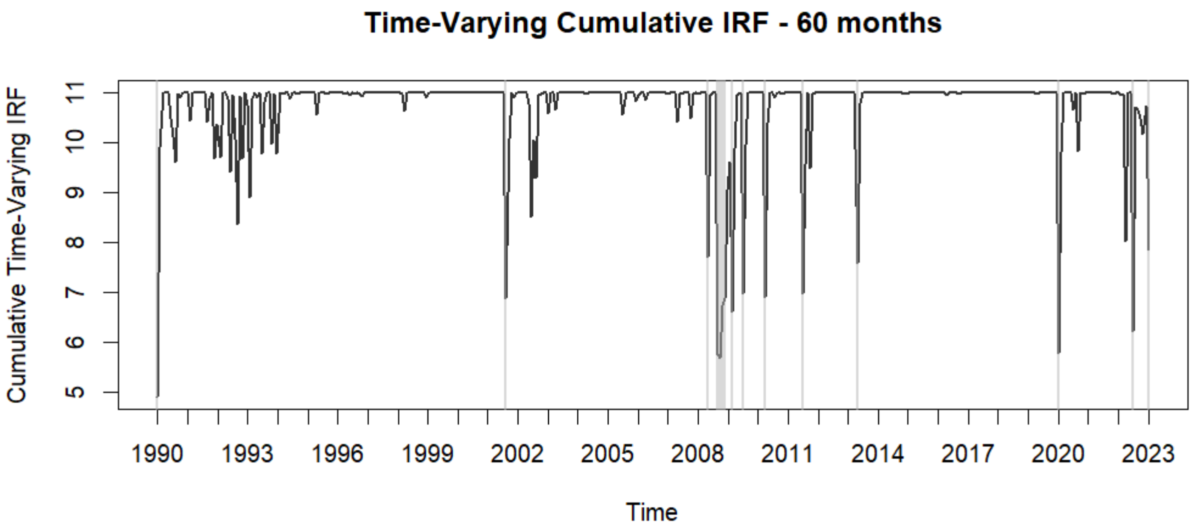


Note: This graph shows the responses of LRE returns to a shock to actual inflation for Regime 1 (stable times) and Regime 2 (turbulent times) with a time-varying short- and long-run.

Similar to the approach described in section 3.4.1, we present the time-varying impulse responses of LRE to actual inflation, analysed separately at three and 60 months post-shock. As shown in Figure 3.8A, the responses of LRE returns to a one standard deviation inflation shock fluctuate between 130% and 40% three months after the shock. The lower part of Figure 3.8 displays a long-term perspective, demonstrating a more pronounced variation in the impulse responses, ranging from 11.00 to 5.00. To give further insights to the time-varying model, we also show the time-varying variance decomposition as in section 3.4.1. Figure 3.9 looks very similar to Figure 3.5, indicating the robustness of our model. However, adding the time-varying long-term equilibrium does not improve the goodness of fit. This is evident from the fact that the AIC for the model with a time-invariant long-term relationship (as specified in section 3.4.1) is -59.605, while the AIC for the model with a regime-switching long-term relationship is -6.821. Similar conclusions can also be drawn using the BIC criterion. Given the substantially lower AIC and BIC values observed in the model with a time-invariant long-run relationship, we adopt the time-invariant model as our baseline model in section 3.4.1. The time-varying model serves to further validate the robustness of our chosen baseline model.

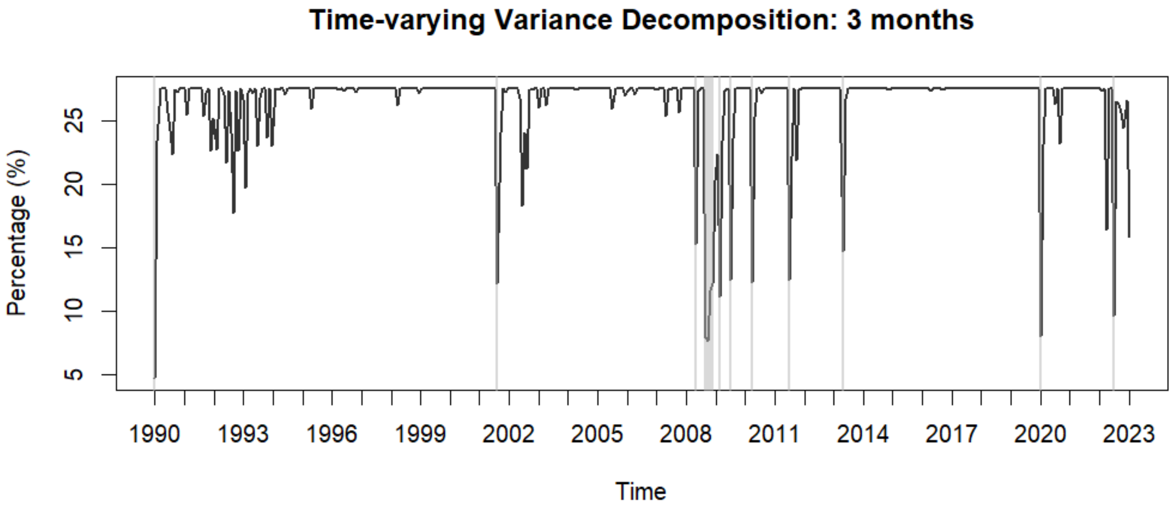
Figure 3.8: Time-Varying Cumulative Impulse Response Functions

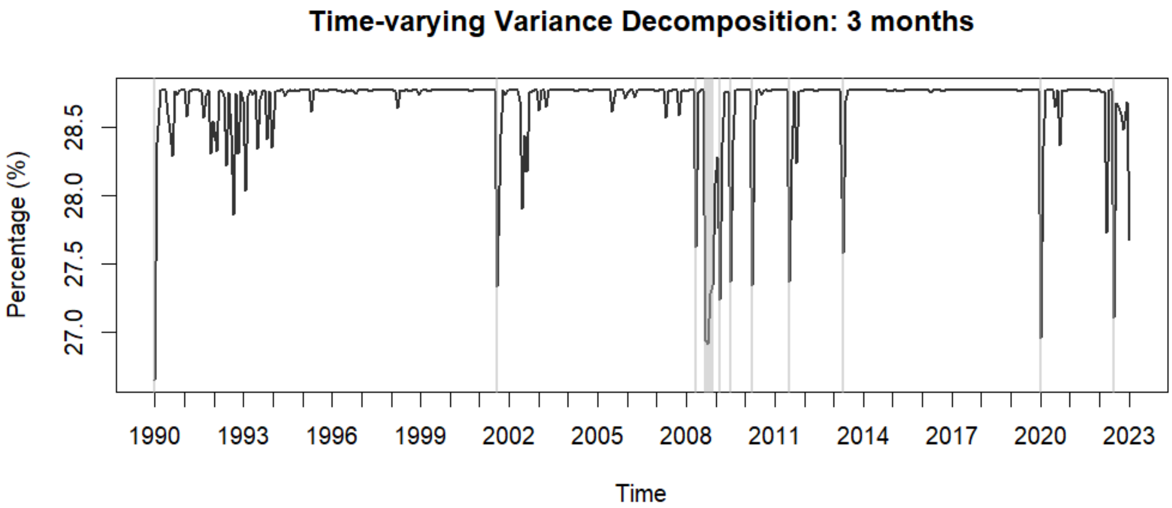




Note: This graph shows the time-varying responses of LRE returns to a shock to actual inflation a short-term horizon (3 months) and a long-term horizon (60 months).

Figure 3.9: Time-Varying Variance Decomposition





Note: This graph shows the time-varying percentage of the variance of LRE returns explained by a shock in inflation.

3.4.2.2 Alternative Inflation Shocks

We further use alternative ways to identify inflation shocks. First, we follow Glascock et al. (2002) and identify an inflation shock as the shock to the unexpected component of inflation based on the decomposition framework established by Fama and Gibbons (1984).[26] We compute expected inflation as the difference between the three-month Treasury Bill rates and the expected real interest rate. The expected real rate is identified as the equally-weighted moving average of the past twelve months' ex post real rates. The ex post real rates are defined

[26] Liu et al. (1997) discovered that this approach outperforms other inflation proxies.

as the difference between the Treasury Bill rates and the rates of change in the CPI (actual inflation). In mathematical terms, the expected inflation at time t (EI_t) can be expressed as:

Equation 3.9: Calculation of Expected Inflation

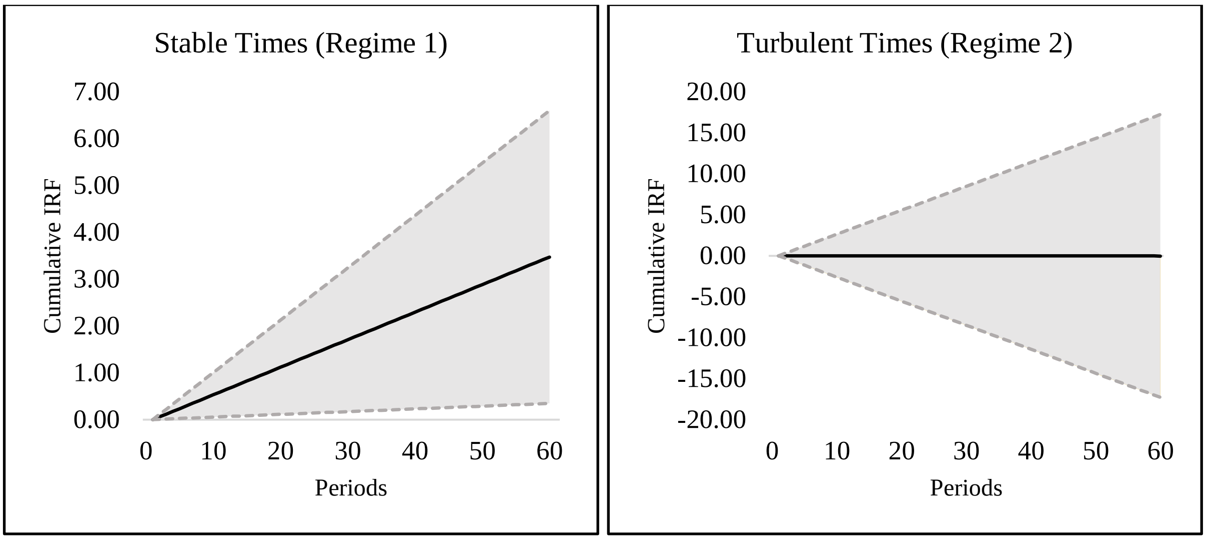
$$EI_t = Treasury\ Bill\ rates_{t-1} - \frac{1}{12}\sum_{s=t-1}^{t-12}[Treasury\ Bill\ rates_{s-1} - Inflation_s]$$

Unexpected inflation (UI_t) is calculated by subtracting expected inflation from actual inflation, yielding the following equation:

Equation 3.10: Calculation of Unexpected Inflation

$$UI_t = Inflation_t - EI_t$$

Figure 3.10: Cumulative Impulse Response of LRE Returns to Unexpected Inflation



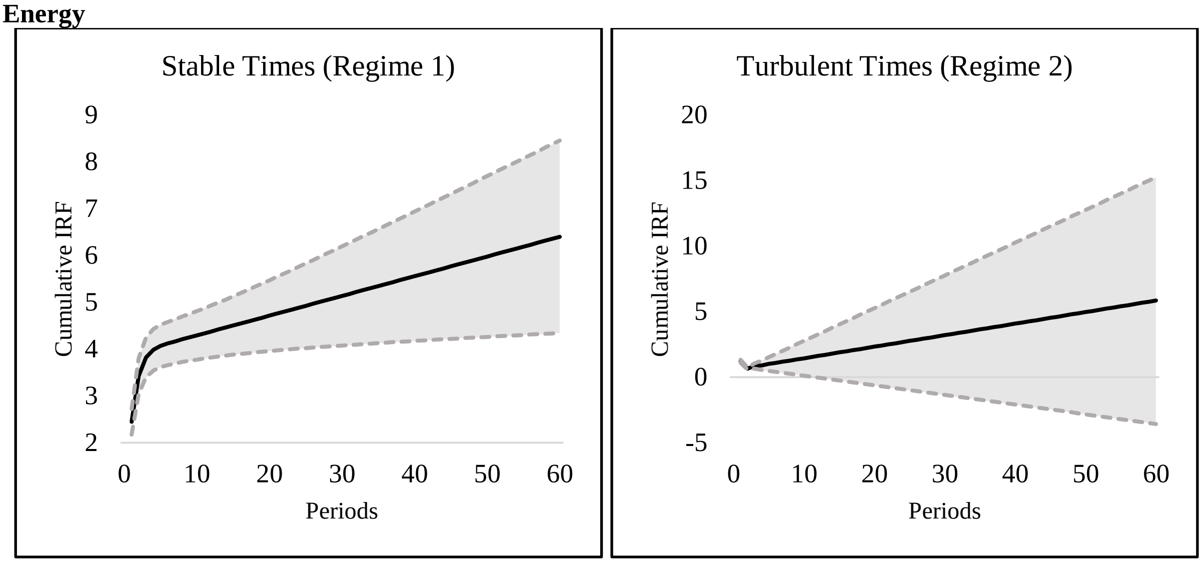
Note: This graph shows the responses of LRE returns to a shock to unexpected inflation for Regime 1 (stable times) and Regime 2 (turbulent times).

Figure 3.10 illustrates the response of LRE to a shock in unexpected inflation. Our analysis reveals that from the first month onward, LRE exhibits strong hedging capabilities against unexpected inflation, highlighting its effective protection against inflation shocks. This is crucial, considering the complex nature of unexpected inflation. Unexpected inflation arises from various factors, including sudden monetary policy changes (Fisher, 1930), supply and demand shocks (Blanchard and Quah, 1989; Hess and Lee, 1999), exchange rate fluctuations and inaccuracies in economic forecasts (Taylor, 2000; Ito and Sato, 2008; Kandil, 2008; Beckmann and Czudaj, 2017), and shifts in fiscal policy (Sargent and Wallace, 1981; Cochrane, 2022). These elements collectively highlight the complexity behind the unforeseen changes in inflation, emphasizing the influence of both domestic policies and global economic conditions.

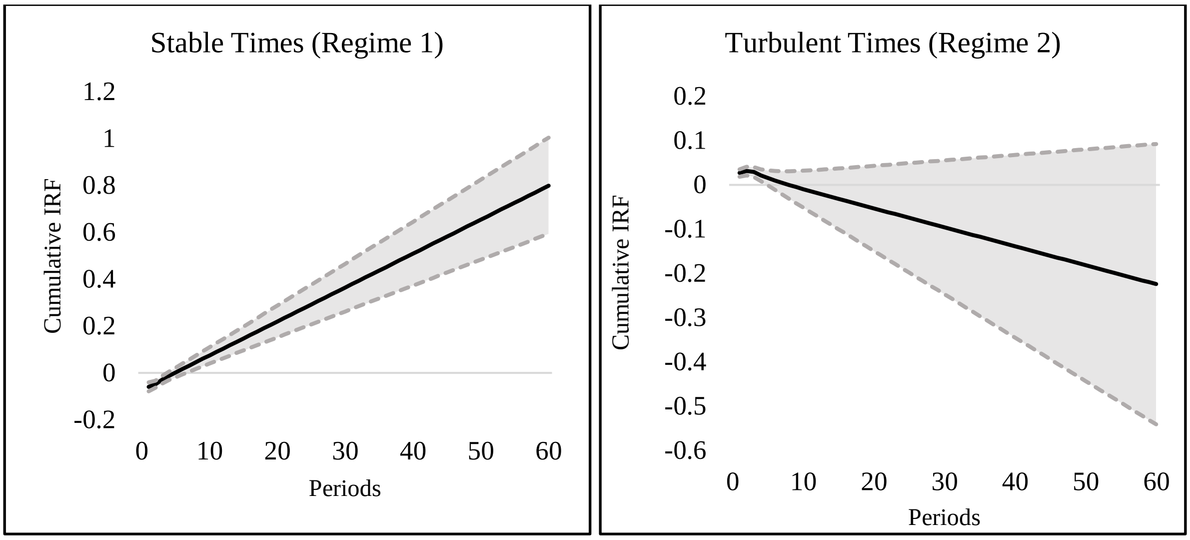
Second, we follow Fang et al. (2022) and break down overall inflation into three distinct categories: Energy, Food, and Core. We then substitute CPI with the respective CPI measurements for analysis. Figure 3.11 illustrates the results. For stable periods, LRE has strong hedging properties against energy inflation from month one onwards. Additionally, a one standard deviation shock to food inflation leads to a 3% increase in LRE returns three months after the shock. During periods of instability, returns from LRE offer protection against inflation, specifically against energy inflation for months 1 to 11, and against food inflation during the first quarter. Regarding core inflation, there is no evidence of significant hedging capabilities for LRE, which is qualitatively in line with Connolly and Stivers (2022) and Fang et al. (2022), who show that the relationship between REIT returns and core-inflation shocks remains unchanged during periods of economic weakness.

Figure 3.11: Cumulative Impulse Response of LRE Returns to Disaggregated Inflation

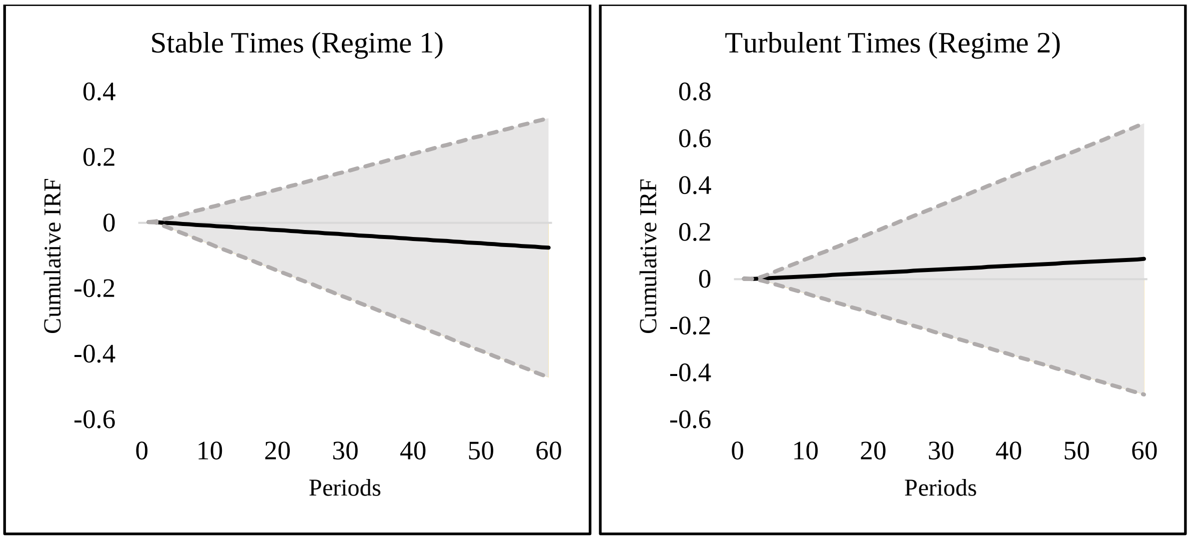
Energy



Food



Core

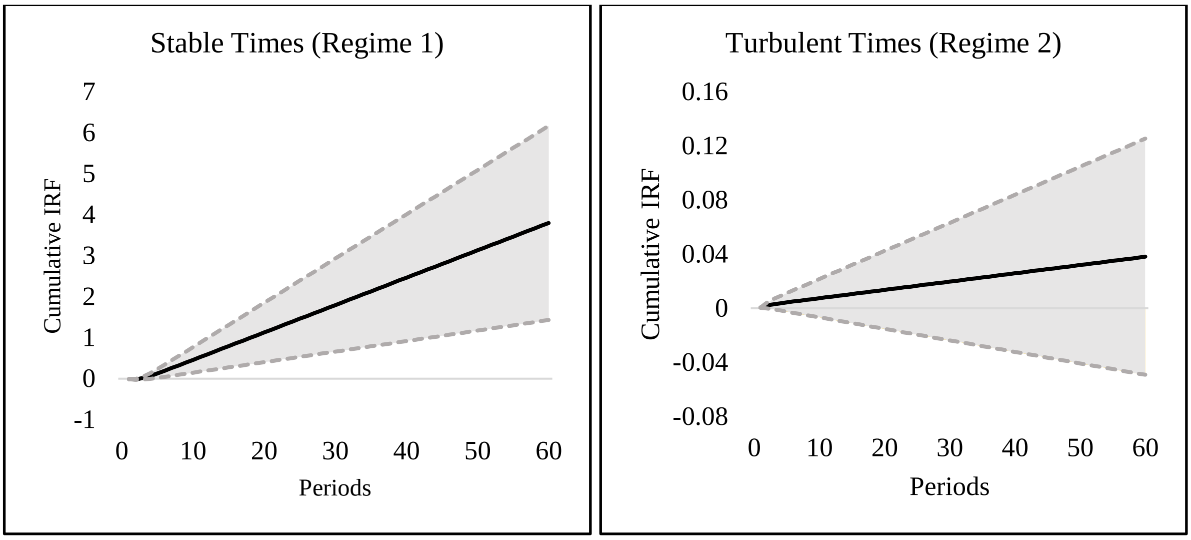


Note: This graph shows the responses of LRE returns to a shock to energy, food, and core inflation for Regime 1 (stable times) and Regime 2 (turbulent times).

3.4.2.3 Hedging Ability of Direct Real Estate

To dig deeper into the relationship between real estate returns and inflation, our analysis now considers the direct real estate market through the inclusion of the net asset value (NAV) of listed real estate firms, sourced from EPRA. This method utilises the NAV as a proxy for the performance of levered private market real estate assets, offering a more focused perspective on how real estate reacts to inflation. The NAV forms the basis of the listed real estate indexes, hence ensuring consistency across private and public markets. This allows us to examine the effects of inflation on the direct real estate market. Our findings suggest a more delayed response of the direct real estate market to inflationary pressures when compared to the listed market. Notably, as illustrated in Figure 3.12, the significance of the direct market's reaction to an inflationary shock becomes apparent after a four-month period in stable conditions and amounts to 45% in month 10. For the turbulent regime, we do not see any significant effect.

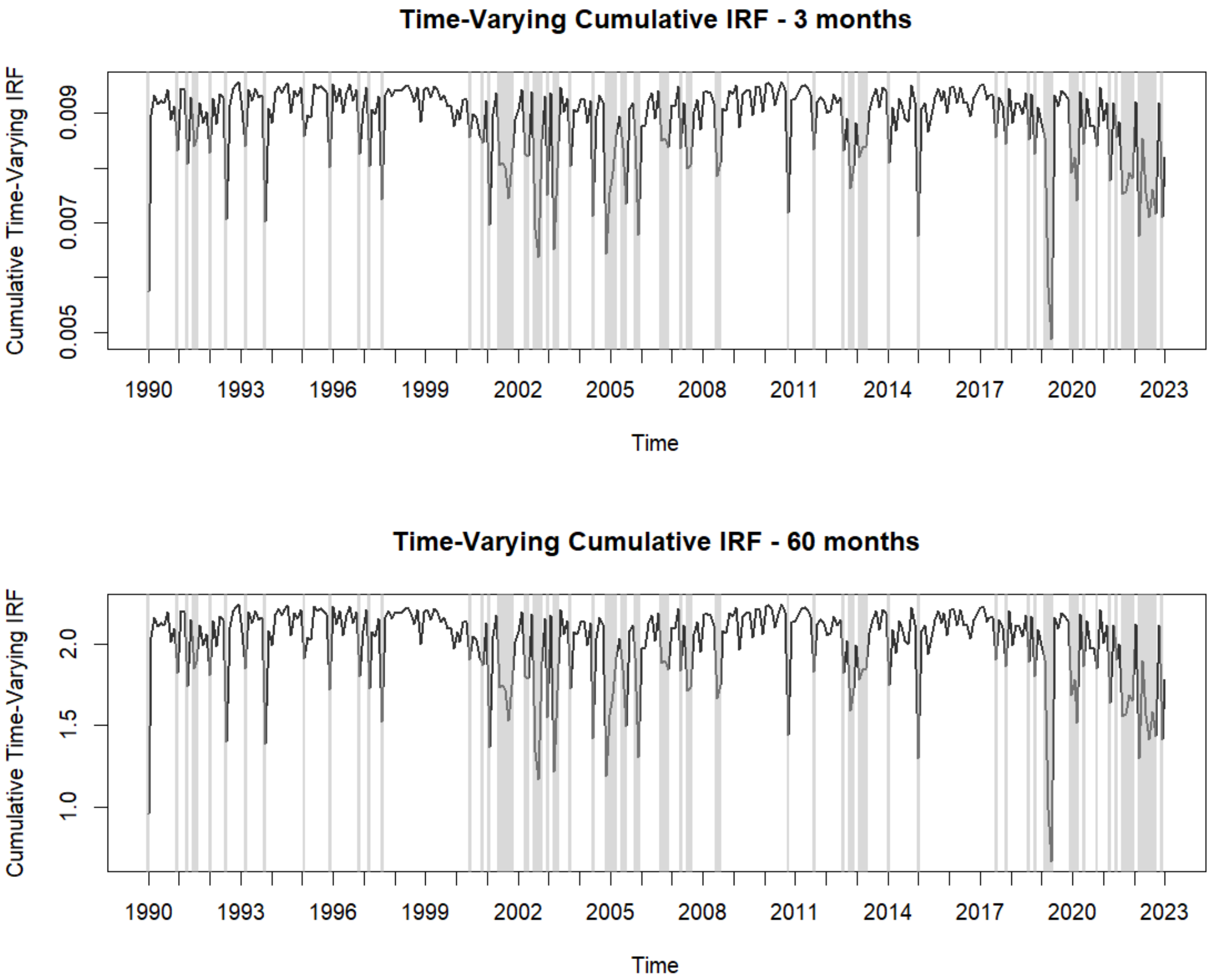
Figure 3.12: Cumulative Impulse Response of Direct Real Estate Returns to Inflation



Note: This graph shows the responses of direct real estate returns to a shock to actual inflation for Regime 1 (stable times) and Regime 2 (turbulent times).

This delayed response is consistent with the understanding that the direct market takes longer to adjust to shocks (Hoesli and Oikarinen, 2012). This can be attributed to two aspects. First, direct real estate investments are not as liquid as stocks or LRE and the process of buying or selling properties is time-consuming. This illiquidity contributes to the slower reaction of property prices and rents to economic changes, including inflation shocks. Second, the direct real estate market is characterised by information asymmetries and varying degrees of market efficiency across different locations and property types. These factors can further delay the transmission of inflation signals into property valuations and rental adjustments.

Figure 3.13: Time-Varying Response of Direct Real Estate Returns to Inflation

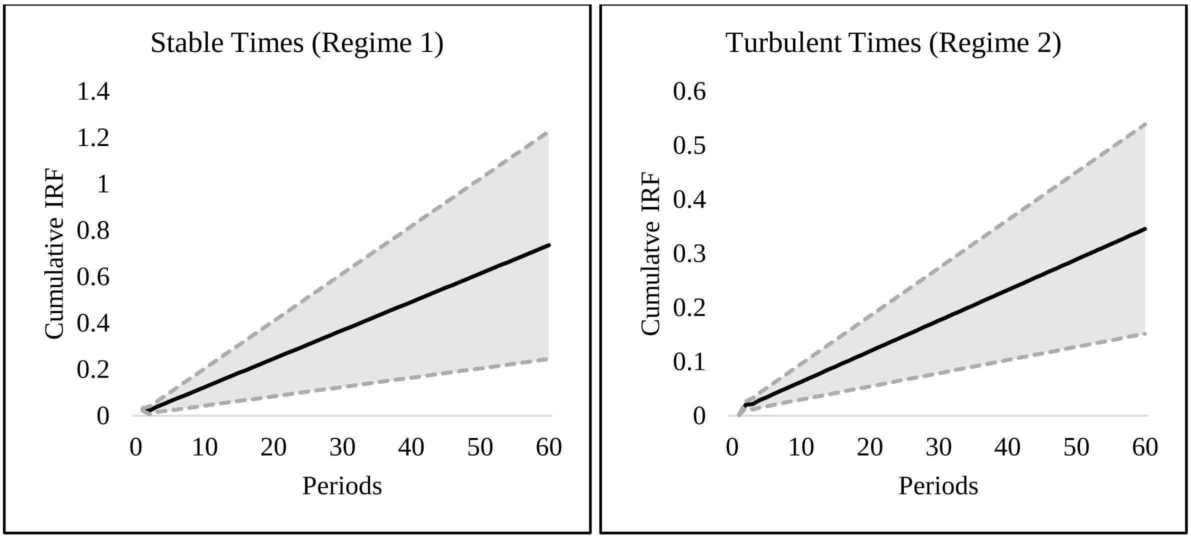


Note: This graph shows the time-varying responses of direct real estate returns to a shock to actual inflation in a short-term horizon (3 months) and a long-term horizon (60 months).

To further illustrate the time-varying nature of direct real estate returns to a shock in inflation, we show the time-varying impulse response functions for the short- and long-terms in Figure

3.13. The figure shows again that, in the short-term, the effect of an inflation shock is relatively small for the direct real estate market. The impact fluctuates between 1.0% and 0.5% over a three-month horizon. In the longer term, the impact is larger and fluctuates between 220% and 90%.

Figure 3.14: Cumulative Impulse Response of Desmoothed Direct Real Estate Returns to Inflation



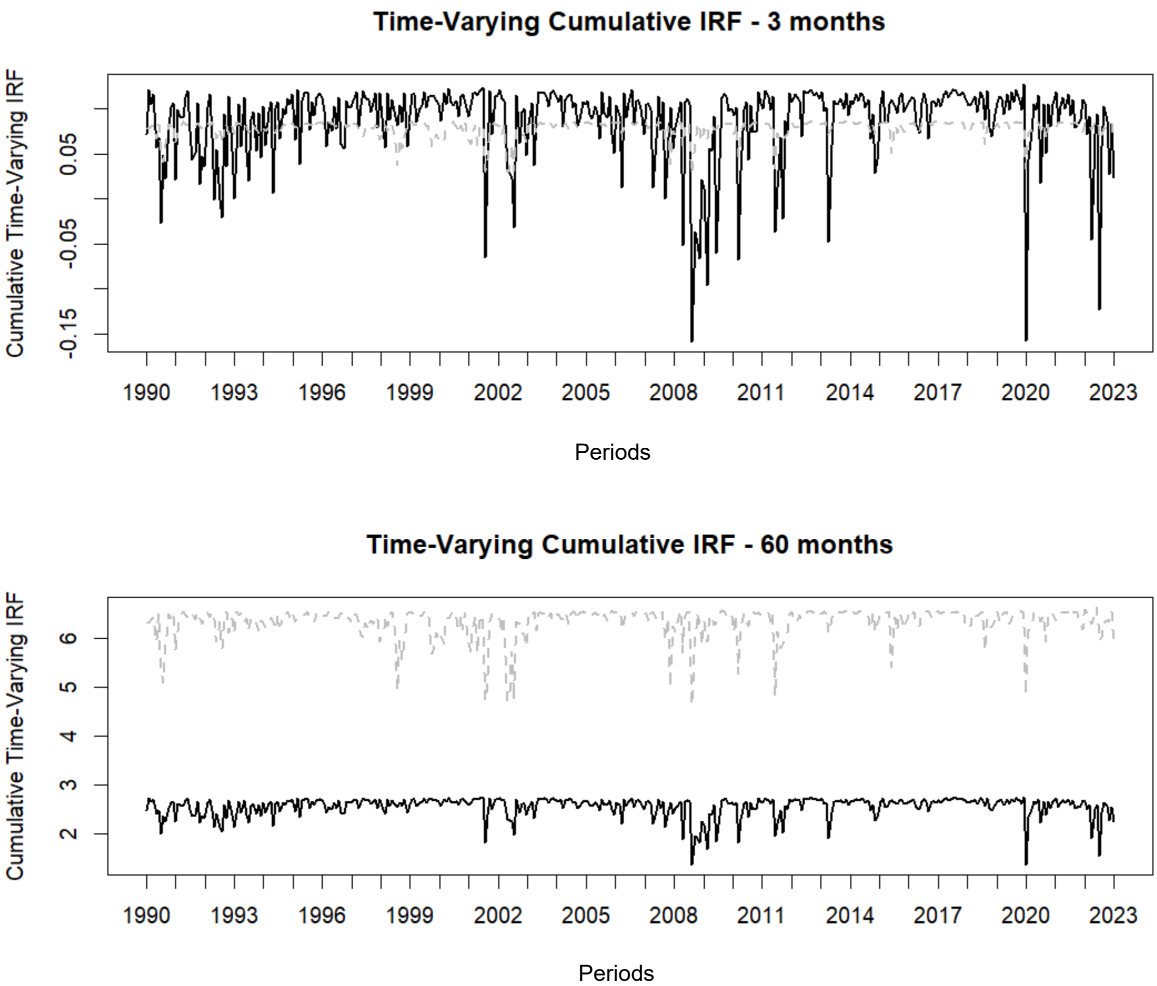
Note: This graph shows the responses of desmoothed direct real estate returns to a shock to actual inflation for Regime 1 (stable times) and Regime 2 (turbulent times).

In traditional appraisal-based valuation of assets, values tend to be smoothed because appraisals are subjective, infrequent, and often lag current market conditions (Clayton et al., 2001). This can mask the true volatility of the asset's market value, leading to potential misinterpretations of risk and value by investors and managers (Lai and Wang, 1998). We correct our NAV returns for appraisal smoothing by applying a reverse filtering desmoothing method (Geltner, 1993), with an alpha value of 0.5, suggesting a balanced weighting between the most recent appraised value and the desmoothed value from the prior period. Figure 3.14 shows the results, demonstrating an immediate and significant effect of an inflation shock on real estate returns. Consequently, the method counteracts the delay traditionally seen due to the appraisal process. The observed effect upon applying this method aligns with our expectations. By reducing the smoothing effect, the adjusted NAVs should more closely track real-time changes in asset values, leading to a more accurate representation of an investment's current value and risk profile. This adjustment can significantly enhance the transparency and responsiveness of NAV reporting, which is beneficial for investors and managers in making informed decisions.

3.4.2.4 Other Asset Classes

The comparative analysis examines the inflation-hedging effectiveness of LRE, in contrast to other asset classes such as stocks and gold. By evaluating the time-varying impulse responses for both stocks and gold, as shown in Figures 3.15 and 3.16, we gain insights into their behaviour under inflationary pressures. Figure 3.15, especially the upper part, shows a similar pattern of stocks compared to LRE, maintaining a similar scale and with only minor differences. However, a notable deviation is observed in the lower part of Figure 3.15, which shows a range of 620% to 490%, in stark contrast to the range of 280% to 140% observed for LRE. A one standard deviation inflation shock leads to a maximum impulse of 10% in the stock returns over a three-month horizon. This suggests that although the trends are largely parallel, stock impulses to a shock in inflation tend to be higher during turbulent periods. Interestingly, we find that stocks show a better hedging ability than LRE in the long-term, but LRE outperforms stocks in hedging inflation in the short-term, especially during stable periods.

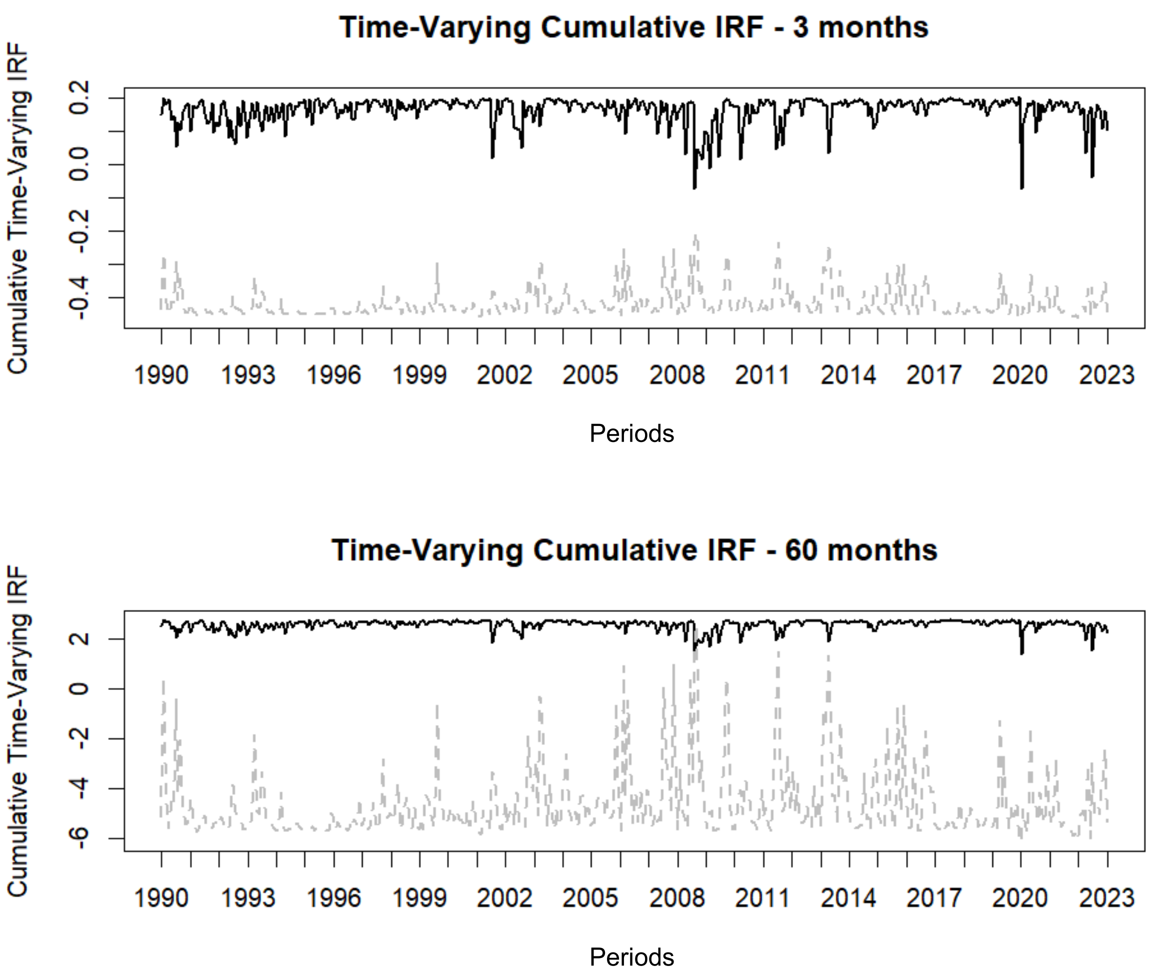
Figure 3.15: Time-Varying Response of Stock Returns to Inflation Shock



Note: This graph shows the time-varying responses of stock returns (grey dashed line) and LRE (black solid line) to a shock to actual inflation a short-term horizon (3 months) and a long-term horizon (60 months).

Gold exhibits strong positive impulses to a shock in inflation during turbulent times, which means that the return of gold changes in response to a sudden increase in inflation. More precisely, a one standard deviation inflation shock leads to a maximum impulse of 200% in the gold return over a 60-month horizon. This aligns with the theory that gold serves as a 'safe haven' asset in times of crises (Figure 3.16). This observation is consistent with existing literature, including studies by Baur and Lucey (2010), Baur and McDermott (2010), or Bredin et al. (2015) which all have explored gold’s role as a safe-haven asset. The reasons why this may be the case are as follows. First, gold is scarce and tangible, with a history of value recognition across cultures and time periods. This scarcity and physicality provide a sense of security that is not as easily undermined by the devaluation of paper money during inflation. Second, gold has a long history as a store of value. When paper currency loses value, gold is often seen as a stable investment that can potentially offer returns that outpace the rate of inflation. Finally, gold often has a low correlation with other financial assets like stocks and bonds. When these assets do poorly, often due to the same economic factors causing inflation, gold's price may rise, making it a useful diversifier in an investment portfolio.

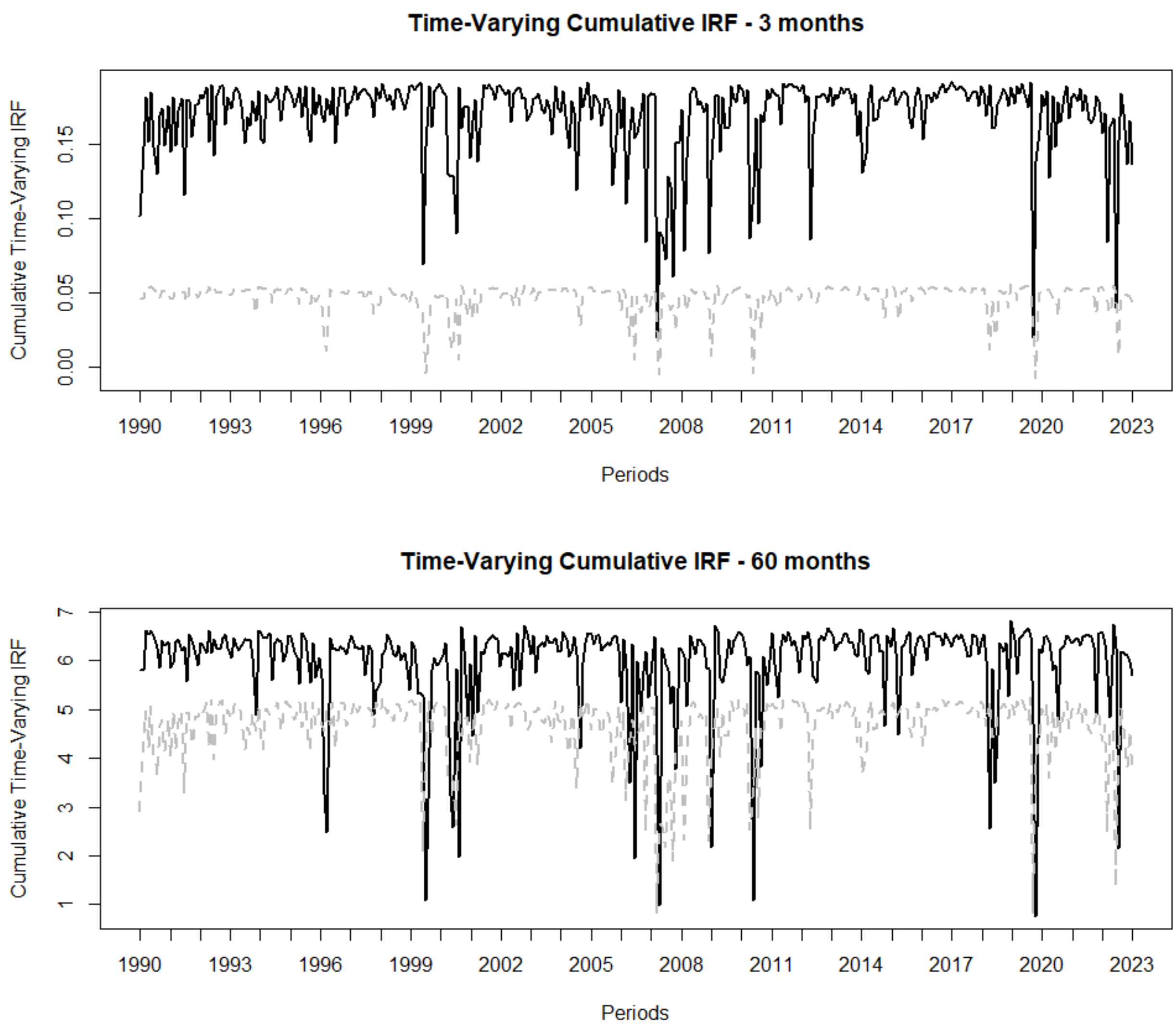
Figure 3.16: Time-Varying Response of Gold Returns to an Inflation Shock



Note: This graph shows the time-varying responses of gold returns (grey dashed line) and LRE (black solid line) to a shock to actual inflation a short-term horizon (3 months) and a long-term horizon (60 months).

Moreover, previous research has consistently demonstrated that gold often functions as an effective long-term inflation hedge (Bampinas and Panagiotidis, 2015; Conlon et al., 2018). Additionally, gold can also serve as an inflation hedge in the short-run, as indicated by studies conducted by Ghosh et al. (2004) and Hoang et al. (2016).

Figure 3.17: Time-Varying Response of Small-Cap Stock Returns to an Inflation Shock



Note: This graph shows the time-varying responses of small-cap stock returns (grey dashed line) and LRE (black solid line) to a shock to actual inflation a short-term horizon (3 months) and a long-term horizon (60 months).

Considering Clayton and MacKinnon's (2003) suggestion that LRE performance is more closely linked with small-cap stocks than with the general stock market, we conduct a robustness test by incorporating small-cap stock indices as an alternative to the benchmark indices previously used (the data are as follows: MSCI France SmallCap for France, SDAX for Germany, MSCI Sweden SmallCap for Sweden, MSCI Switzerland SmallCap for Switzerland, FTSE SmallCap for the U.K., and RUSSELL 2000 for the U.S.).

Figure 3.17 shows the time-varying impulse response functions of small-cap stock returns and LRE returns. The pattern is similar to Figure 3.14, but the responses of the small-cap stocks are more unstable, especially compared to general stock indices and in the long-term. This somewhat more volatile reaction can be explained by the fact that small-cap stocks tend to be more volatile and sensitive to local economic changes than large-cap stocks. Moreover, small-cap stocks often have a different risk-return profile compared to the broader market or to large-cap stocks (Levis, 2002).

3.5 Conclusion

Recently, inflation has again emerged as a worldwide worry, prompting investors to grasp the inflation-buffering capacities across various asset categories. This research investigates the inflation-hedging capabilities of LRE in the context of changing economic regimes, both in the short- and long-term, by utilizing a Panel Markov switching vector error correction model (MS-VECM). The time period under review includes several periods of inflation, including the most recent and recent episode, which started in 2022.

Using a panel of monthly return data for LRE companies for France, Germany, Sweden, Switzerland, the U.K., and the U.S. – from 1990 to 2023, this research reveals that the response of LRE returns to inflation shocks is strongly regime-dependent. In stable economic times, LRE returns exhibit a consistent positive relationship with inflation shocks both in the short- and long-terms. A one standard deviation inflation shock leads to a 19% increase in the LRE returns three months after the shock, and a maximum of 326% up to 60 months after the shock. The response is quite persistent. The inflation shock can explain nearly 20% of variations in the LRE return three months after the shock and the effect slightly decreases to 14% 60 months after the shock. In contrast, during turbulent economic periods, the impact of inflation shocks on LRE returns can be significantly negative in the short-term, as a one standard deviation inflation shock leads to a 8% decrease in the LRE return three months after the shock. But from an economic perspective, only 4% of the variations of LRE are explained by an inflation shock. Thus, inflation shocks do not play a noticeable role in LRE returns in the short-term during crisis periods. However, over a longer period, the proportion explained by an inflation shock rises to around 14%.

Second, LRE exhibits a better hedging capacity during the long-term than in the short-term. In the short-term, we even notice a significant negative inflation-hedging coefficient during times of turbulence. However, in the long-term, there is always a positive relationship between LRE returns and inflation. Moreover, the long-term (60-month) response of LRE to an inflation shock is much more pronounced than the short-term (3-month) response. The results are also confirmed by the variation decomposition, where in the short-term, the relative importance of an inflation shock is less than 4% during crisis periods, but in the long-term, an inflation shock amounts to around 14% of the variations in both crisis and stable periods.

Third, the research effectively captures the changes in the hedging ability of LRE during economic crises, such as the dot-com bubble, the global financial crisis (GFC), the COVID-19 pandemic, and the war in Ukraine. These crises are visible in the regime-switching analysis, demonstrating the importance of considering economic conditions when assessing LRE’s inflation-hedging properties. From an investor’s perspective, the efficiency of LRE as an inflation hedge is highly dependent on the time horizon. Interestingly, the changing nature of the hedging ability during crisis periods is also confirmed in the long-term relationship, when we incorporate a switching process in the long-term equilibrium equation. In other words, the changing nature of the relationship during the crisis is not only via the speed of adjustment, but can also be reflected in the long-term equilibrium.

Fourth, LRE serves as a robust hedge against alternative inflation shocks. LRE protects against unexpected inflation starting from the first month, especially during stable periods. Also, when considering energy, food, and core inflation components, LRE offers hedging properties against energy and food inflation during stable periods, but lacks noticeable protection during unstable times. There is no significant evidence that LRE hedges against core inflation, which aligns with existing literature. Overall, this indicates the multifaceted ability of LRE to hedge against inflation.

Fifth, the direct real estate market shows a delayed but significant response to inflation, with notable effects emerging six months post-shock. This lag is attributed to the market’s illiquidity, long-term leases, and information asymmetries. Over time, the impact of inflation on direct real estate varies, with minimal short-term effects but a more substantial long-term impact.

Overall, this paper contributes to the literature on inflation hedging by providing empirical evidence of the regime-dependent nature of LRE’s response to inflation shocks. These findings can be valuable for investors and policymakers seeking to make informed decisions in times of economic uncertainty and inflationary pressures. Additionally, the study underscores the importance of considering both short- and long-term perspectives when assessing the inflation-hedging effectiveness of asset classes like listed real estate. These results are of importance as investing through the LRE market is often the preferred to investing in real estate given the liquidity of such investments.

4. Tenant Industry Sector and European Listed Real Estate Performance

Abstract

This paper extends the empirical evidence on the relationship between the performance of public real estate companies (PRECs) and the industrial sector of their tenants. By investigating the performance of a large sample of European real estate firms from 2010 to 2019 and information pertaining to the firms' tenants, we find that the systematic risk in the tenants' industry sectors is capitalised in real estate company equity returns. Our results remain robust after correcting for stock beta modifications, tenant sector alpha, tenant anchor effects, and other tenant characteristics. We consider a hypothetical trading strategy that assumes a long position on PRECs whose occupier base is dominated by tenants belonging to riskier sectors, while the trading strategy shortens PRECs whose tenants belong to less risky sectors. The adoption of this strategy yields benchmark-adjusted annual returns of 3.68%.

Keywords: Public Real Estate Companies, Listed Real Estate, Tenants, Industry Sector, Systematic Risk

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4.1 Introduction

Public real estate companies (PRECs) are well known for their hybrid nature. On the one hand, they are listed stocks, and therefore their performance can be influenced by the performance of the general stock market. On the other hand, PRECs are pure real estate players as a significant proportion of cash flows comes from rental revenues and most of the assets are properties (Pagliari et al., 2005; Li et al., 2009; Oikarinen et al., 2011; Hoesli and Oikarinen, 2021; Feng et al., 2022). Much of the literature has focused on the impact of firm-level financial and governance characteristics, such as investment growth (Bond and Yue, 2017; Ling et al., 2019), on corporate performance (Sirmans et al., 2006; Lecomte and Ooi, 2013; Beracha et al., 2019). Recently, more attention has been given to asset level information, such as property location characteristics (Fisher et al., 2022; Ling et al., 2022), the systematic risk and liquidity of local real estate markets (Downs and Zhu, 2020; Zhu and Lizieri, 2020), spatial correlation between the underlying assets (Adams et al., 2015; Zhu and Milcheva, 2020), and the characteristics of properties, such as greenness (Eichholtz et al., 2012; Sah et al., 2013).

In contrast, the source of the cash flows and the engines of property values, the tenants, have received less attention. Liu et al. (2019) find that asset liquidation values, which are measured by tenant quality and the MSA level diversity of industries, can influence REITs' financial choices. Lu-Andrews (2017) shows that tenants with better financial health and higher creditworthiness can reduce the rental income uncertainty and the cash flow volatility of real estate firms. Liquidity management, such as unused credit lines and credit availability, is also influenced by tenant quality. Liu and Liu (2013) observe that a key tenant's departure will lead to a negative abnormal return and increased volatility of the landlord REITs' stocks, implying a landlord-tenant feedback effect on firms' equity performance. Chen et al.'s (2020) study suggests that tenant information – the abnormal return of REITs' publicly traded tenants –

cannot be captured by the classical stock market risk factors, such as Fama-French factors. They attribute this to the investors' limited attention towards tenant information.

Our paper extends the empirical evidence on how the systematic risk of the tenants' industry sector might affect the returns of PRECs. Given the fact that REIT income derives from tenant rent collection, the economic link between tenant and REIT performance is obvious. The tenant-related information may play a critical role in the valuation of real estate companies. For instance, everything else being equal, a retail real estate company's performance could be substantially different, depending on whether tenants tend to be mainly engaged in selling personal and household goods, travel and leisure, or any other type of retailing activity. As stated by Chen et al. (2020), 'changes in the market value of REIT tenants may well provide value relevant information regarding their long-run growth, profitability, and/or viability. In turn, this information is potentially useful to REIT investors who wish to assess each tenant's ability to consistently satisfy long-run lease obligations.'

To reflect the changes in the market valuation of REITs' tenants, we use the systematic risk of the tenant industry sector, which is different from previous literature that focuses on the abnormal return of core tenants (Chen et al., 2020) or the diversification of tenants (Chacon, 2021; Zheng and Zhu, 2021). Our risk measurement has two advantages. First, REITs, in general, own a big property portfolio; as a result, they tend to have mixed tenants. Based on the diversification theory, the idiosyncratic risk may be diversified away and, therefore, will not be priced in the stock return. Therefore, we investigate the systematic risk (beta) of the industry sector where the tenants operate. Although individual tenants' idiosyncratic risks may be diversified away by tenant mix strategy, the sector's systematic risk may remain. Second, the fundamental performance of each tenant, especially when the tenant is a private firm, is not always observable (Chen et al., 2020). In this case, the volatility of the industry sector can provide some information on the changes in the market valuation of individual tenants, especially when the detailed market valuation information is not observable.

Based on the performance of 133 European PRECs from 2010 to 2019, our study suggests a positive relationship between public real estate equity returns and the systematic risk in the tenants' industry sector. A one-standard-deviation increase in the sector beta of tenants is associated with a 6.18% increase in the equity return of PRECs. Investors may perceive a higher industry sector risk and therefore require compensation for taking that risk. This finding is robust after controlling for stock beta modifications, tenant sector alpha, tenant anchor effects, and alternative tenant rating measures.

In this way, this paper extends the literature on the risk-return relationship of PRECs by showing that the tenant sector risk is capitalised in REIT stock returns. The tenant sector risk even plays a more critical role than stock market risk. An investment strategy that buys the stocks of firms with high tenant sector risks and sells the stocks of firms with low tenant sector risks can earn an average benchmark-adjusted return of about 3.68% per year. Previous literature tends to focus on the connection between PRECs and the general stock market, either through correlation analysis or stock market beta (Ling and Naranjo, 1999; Glascock et al., 2000; Chiang et al., 2005; Fei et al., 2010; Liow and Addae-Dapaah, 2010). However, given the hybrid nature of PRECs, a consideration of risk streaming solely from stock market dynamics may not be sufficient. Thus, the risk from the underlying property markets where the assets are located has also received attention (Gao and Topuz, 2020; Fisher et al., 2022; Ling et al., 2022; Zhu and Lizieri, 2022). However, to the best of our knowledge, the risks arising from the tenant sector have not received much attention.

This study also extends the limited empirical evidence on tenant sector structure of European PRECs. Compared with the U.S. market, the European market is relatively new and more fragmented (Brounen and De Koning, 2012; Ghosh and Petrova, 2021; Morri et al., 2021). Unlike U.S. PRECs, their European counterparts more often hold different types of properties within the same region. For instance, based on the data of PRECs in S&P Global Market Intelligence, 85% of U.S. PRECs specialise in one property sector, but over 40% of European PRECs own and manage a mix of property types. To the best of our knowledge, there are no studies on the empirical relationship between tenant structure and firm performance for European PRECs. Moreover, while previous literature focuses on tenant diversification, we focus on tenant sector diversification. Many PRECs show remarkable differences in the level of diversification between individual tenants and the sector in which tenants operate. For instance, in our sample, healthcare, industrial, and retail PRECs exhibit a much higher level (over two times) of individual tenant diversification than tenant sector diversification. This indicates that although these PRECs have quite diversified tenants, these tenants concentrate on one sector. Therefore, the previous finding based on U.S. firms which shows that tenant concentration has a significant impact on firms' performance (Chacon, 2021; Zheng and Zhu, 2021) may not be applicable to the tenant sector diversification for European real estate firms.

The rest of the paper is structured as follows. Section 4.2 briefly reviews the relevant literature. Section 4.3 describes the sample selection, variable construction, and methodology. Section 4.4 discusses the empirical results, followed by the discussion of a series of robustness tests. The final section concludes.

4.2 Literature Review

Our paper builds upon two strands of literature: asset quality and the risk-return relation of PRECs. First, our paper is related to the impact of underlying asset quality on the performance of real estate firms. Firms with high-quality tenants tend to have lower collection costs and are less likely to pay additional costs for searching and re-contracting. Therefore, better tenant quality can mitigate the lease counterparty risk and thus enhance asset quality (Liu et al., 2019). For instance, Liu and Liu (2013) analyse the linkages between tenant quality and the performance of commercial real estate. They find that tenant quality plays a significant role in explaining the cross-sectional variations of REIT returns and market exposure. Liu et al. (2019) show that tenant credit quality, as measured by the Altman Z-score, and location quality, as measured by the degree of industry diversification of the local MSAs, can affect the liquidation value of REITs. They argue that tenant creditworthiness is the main driver and justify this with the fact that there are also costs associated with long-term leases. Lu-Andrews (2017) shows that tenant quality, which is measured by credit rating and Altman Z-scores, affects REIT firm liquidity, such as total corporate liquidity and unused credit lines. This incentives REITs to hold less liquid assets, resulting in an inverse relationship between tenant quality and asset liquidity. Chacon (2021) investigates the impact of tenant concentration on property portfolio performance, risk, and the cost of debt. Utilizing the disclosure of major tenants by 152 Equity Real Estate Investment Trusts (REITs) from 2000 to 2017, he documents a positive relation between tenant concentration and profitability. Zheng and Zhu (2021) study the impact of the tenant mix on REIT performance. They find that REITs that adopt a focused strategy for their underlying tenants present higher cash flows and lower expenses. Moreover, they show that a focused tenant strategy is associated with higher liquidity risk, and as a result a higher required rate of return, and lower dividend growth.

Liu and Liu (2013) explicitly examine the channels through which tenant quality impacts the performance of its landlord's REIT company. Using a sample of 157 major tenant bankruptcy announcements of retail real estate firms, over the period 2000–2010, they find that in an upside phase of the economic cycle, a tenant's bankruptcy has a less negative or could even have a more positive effect on a landlord's stock return. Furthermore, they show that landlords who have properties located in markets with a highly diversified economic base are more likely to exercise the growth option from a tenant vacating the premises and thus realise higher stock returns. However, in case of a recession, the rental revenue of the landlord REITs will be adversely affected, especially in case of properties designed for specific purpose, such as healthcare or shopping centres. Therefore, it is important to investigate how the industry sectoral risk influences the performance of real estate firms.

Indeed, the impact of tenant quality or tenant structure has been more intensively studied in the retail real estate literature. According to Neil and Webb (1994), the existence of overage rents in the commercial real estate retail sector should connect the financial success of landlords and tenants within this market sector. By comparing returns from retail stocks to retail REITs, over the period 1983-1991, they find a positive, contemporaneous relationship between the two asset types. Gatzlaff et al. (1994) observe the impact that the omission of a shopping centre anchor tenant has on the rental rates of the remaining tenants. They find that rental rates of non-anchor tenants decrease by approximately 25% after the loss of an anchor tenant. Gerbich (1998) examine the economic significance of retail tenant mix within shopping centres, and shows how the tenant type affects base rentals. The type of retail tenant is found to be an important determinant of shopping centre base rents for some generic types of tenants. Furthermore, base rents can decrease in size with centre turnover. In Wheaton (2000), rental contracts are set relative to percentages of the retail tenant sales and act as a guarantee that the tenant mix will, in general, remain unchanged. In addition, Wheaton (2000) proposes a model under which the percentage rents agreement prevents landlords from behaving opportunistically by utilizing sales externalities. Therefore, landlords effectively have a ‘duty of care’ obligation to protect the interests of existing tenants in terms of altering the shopping centres’ set ups. Schlauch and Laposa (2001) detect the differences in the corporate real estate strategies of traditional retailers and those of e-tailers. By quantifying the real estate related expenses (e.g., rental expenses to sales ratio), they show the importance of rental expenses or rental income to the retailers’ success.

Ambrose et al. (2018) investigate a sample of retail commercial properties and evaluate the effect of tenant diversification on mortgage spreads within each property. They find that mortgages on properties with a highly diversified tenant base have spreads that are up to 7.1 basis points higher than spreads on mortgages for single-tenant properties. On the other hand, mortgages on properties with moderate levels of tenant diversification have spreads that are up to 5.2 basis points lower than mortgages for single-tenant properties. Zhang et al. (2020) investigate the relationship between tenant mix and retail rents in Dutch high street shopping districts. Rents are found to be higher in shopping districts with a greater tenant mix than in districts with a lower tenant mix. This result remains relatively constant even as the macro-market of rents changes.

Moreover, our paper is also related to the literature on the risk-return relation of PRECs. Most of the literature studies the systematic risk from the general stock market and finds mixed results. This can be explained by the varying characteristics of PRECs, such as property type and location (Gao and Topuz, 2020; Zhu and Lizeri, 2022), firm value, size, leverage (Lang and Scholz, 2015; Alcock and Steiner, 2018), and holding period (Feng et al., 2022), as well as management and agency costs (Delcoure and Dickens, 2004; Ghosh and Sun, 2014). According to Schulte et al. (2011), systematic risk factors can explain returns in conditional models but have no explanatory power in unconditional cross-sectional regressions. Delcoure and Dickens (2004) find that REITs and REOCs have different levels of systematic risk, despite both investing almost exclusively in real estate-related assets. According to their findings, business risk is negatively correlated with systematic risk, as measured by beta, for REITs, while betas are positively correlated with agency costs for REOCs. Additionally, the betas of the two groups differ in their sensitivity to property type and location. A REIT's systematic risk is also affected by its financial leverage and financing structure. Moreover, Lang and Scholz (2015) demonstrate that European real estate equity returns are significantly related to size, value, and liquidity factors, while the influence of the market factor is similar compared to general equity returns. Furthermore, the authors find a significant underperformance of European real estate equities, after adjusting for diverging roles of systematic risk factors driving real estate equity returns. As Fuerst and Marcato (2009) show, both alpha and systematic risk levels depend on the performance characteristics of a portfolio, as well as the probability of achieving alpha. Similarly, Alcock and Steiner (2018) report that REITs with low systematic risk are usually small and have low short-term momentum, low turnover, and high growth opportunities. Holding systematic risk constant, the main driving forces of asymmetric risk are leverage and, to some extent, short-term momentum. DeLisle et al. (2013) find that systematic volatility is not priced in REIT returns, but idiosyncratic volatility is negatively priced in the cross-section of equity REIT returns and largely independent of non-REIT idiosyncratic volatility. Within the total volatility risk profile for REITs, idiosyncratic volatility dominates aggregate volatility. Chaudhry et al. (2004) investigate several determinants of idiosyncratic risk from the perspective of undiversified REIT investors, managers holding options, other option holders, and arbitrageurs. Results indicate that efficiency, liquidity, and earnings variability are the important determinants of idiosyncratic risk, while size and capital are less influential.

Recent academic literature increasingly attempts to quantify risks related to underlying assets. Since real estate assets are fixed in location, location risk has received extensive attention by researchers. The location risk is reflected by the various characteristics of the local market, such as density, liquidity, and industry diversity (Gao and Topuz, 2020; Downs and Zhu, 2022; Fisher et al., 2022; Ling et al., 2022; Zhu and Lizeri, 2022), which can influence future cash flows and the liquidation value of the assets. Thereby, location risks can influence the REIT stock return. However, very limited literature investigates the capitalizing of tenant risks.

One exception is Chen et al. (2020), who propose a 'tenant momentum' strategy yielding an abnormal return of around 5% per year. They attribute this to the investors' limited attention to tenants' information. In addition to examining European listed real estate companies rather than their U.S. counterparts, which is interesting given the unique features of such companies, our paper differs from their paper in two ways. First, although both papers propose a trading strategy based on tenant information, the source of the abnormal return yielded by each strategy is different. Chen et al. (2020) sort the REITs according to the abnormal returns of publicly traded tenants. Our paper investigates the systematic risk of the tenants' sector, and therefore, we sort REITs using sector beta. In our robustness tests, we also include the alpha of the tenant sector and the performance of individual tenants as an additional control variable. The coefficient for tenant sector beta remains significantly positive, indicating that the riskiness of the tenant sector could also predict the REIT return even after tenants' profitability has been controlled.

Second, by studying the systematic risk of the tenant industry sector, we focus on the tenant risk that cannot be easily diversified away by a simple tenant mixing strategy, or at least, the strategy that mixes tenants from the same industry sector. Therefore, the risk of tenants' industry sector may be capitalised in REIT stock returns in addition to risks from individual tenants. According to the 'limited attention hypothesis', investor capability to capture information regarding the fundamental capability of companies to generate cash flows is limited. This particularly applies to private companies (Chen et al., 2020). Therefore, in this paper, we focus on the industry sector of tenants, which can more easily be observed by investors.

4.3 Data and Methodology

We collect data for 205 European PRECs between 2010 and 2019 in 12 countries, including Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. The list of firms is taken from the S&P Global Market Intelligence Database, formerly known as SNL Financials. We follow existing papers in the literature (Lu-Andrews, 2017; Chen et al., 2020; Chacon, 2021) and exclude property companies that specialise in non-disclosure property types from our analysis. Since not all firms report tenants, we acknowledge that our findings on the relation between tenant sector risk and firm equity returns are not applicable to property companies that specialise in non-disclosure property types. The data on company characteristics, including the name of the thirty largest tenants of each PREC and the percentage of the total revenue attributed to each tenant, are from the same database and complemented by manual analysis of annual reports from various companies. Since only the tenant names were available, the industry sector information was gathered and sorted manually.[30] For publicly traded tenant companies, we used the International Securities Identification Number (ISIN) to allocate tenants to the appropriate industry sector. In the case of non-publicly traded tenant companies, we investigated internet webpages, company websites, company reports, and the database Orbis by Bureau van Dijk.

[30] It should be noted that the tenant information has not been collected for Multi-family, Hotel, Speciality, and Self-Storage PRECs. Multifamily property firms, for example, do not disclose tenants due to the fact that they usually do not have any major tenants. Instead, the occupancy structure for these assets is typically characterised by smaller and therefore unreported tenants.

There are 133 PRECs with tenant sector information, representing around 75% of the total market capitalization of the reported companies in the S&P Global Market Intelligence Database. Based on these 133 PRECs, we further collect data regarding tenant and firm characteristics. After excluding firms with missing data, we are left with 73 distinct firms. Our sample is composed of 1,320 distinct tenants, of which approximately 45% are publicly traded companies.[31] Around 40% of PRECs have at least one tenant reporting the credit rating. As we employed a manual processing of data, we were able to identify the appropriate industrial sector for nearly all of the tenants. In Table 4.1 we report the share of tenants in each sector. The most prominently represented sector is the retail sector, while basic resources displays the lowest share of tenants.

Table 4.1: Sector Betas

Sector	Beta	Average of rolling betas	Share of tenants in each sector
Basic Resources	1.525	1.442	0.419%
Banks	1.362	1.371	4.662%
Insurance	1.258	1.276	3.300%
Construction & Materials	1.187	1.198	2.148%
Financial Services	1.153	1.129	7.438%
Automobiles & Parts	1.105	1.479	1.414%
Industrial Goods and Services	1.095	1.137	13.882%
Oil & Gas	1.041	1.058	1.205%
Technology	1.024	0.959	5.186%
Chemicals	0.989	1.092	0.786%
Travel & Leisure	0.938	0.861	7.700%
Real Estate	0.909	0.995	3.091%
Media	0.864	0.864	4.034%

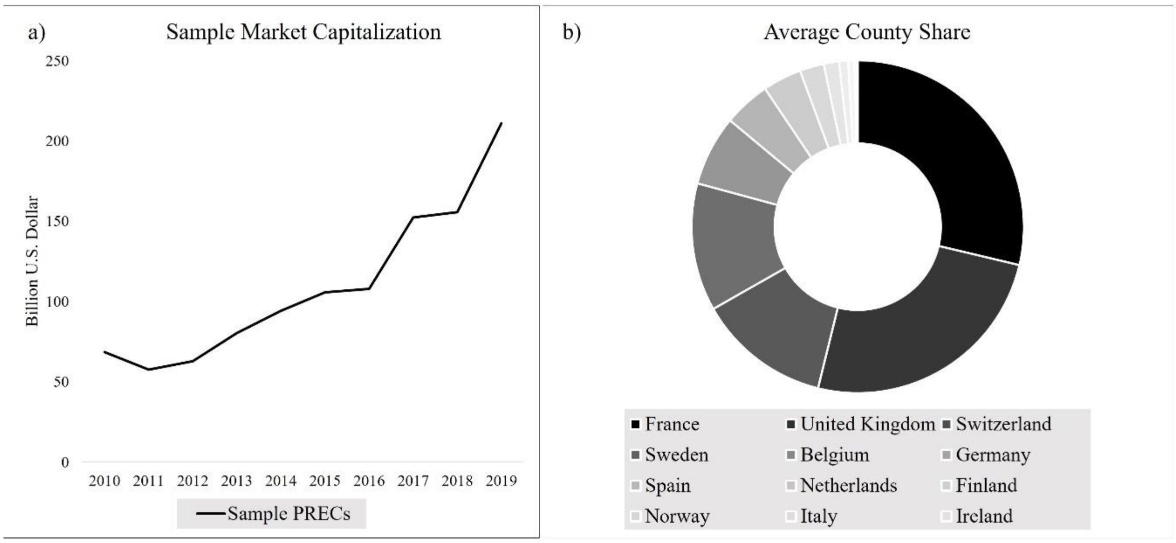
[31] A survivor bias should be negligible. Since we only need the tenants' industry sector, rather than detailed performance data, the information for firms that are not operating today can still be obtained, because we can find such information on the internet. The database Orbis by Bureau van Dijk also provides information on the non-operating firms.

Personal & Household Goods	0.849	0.850	5.605%
Utilities	0.843	0.800	1.310%
Retail	0.842	0.845	21.687%
Telecommunications	0.829	0.741	2.514%
Food & Beverage	0.628	0.623	1.572%
Health Care	0.615	0.597	5.710%
Public	0.000	0.000	6.338%

Description: This table reports the value of sector betas and the share of tenant in each sector. The table includes 19 sectors of the ICB classification. ICB considers 19 supersectors: Oil & Gas, Chemicals, Basic Resources, Construction & Materials, Industrial Goods and Services, Automobiles & Parts, Food & Beverage, Personal & Household Goods, Health Care, Retail, Media, Travel & Leisure, Telecommunications, Utilities, Banks, Insurance, Real Estate, Financial Services, and Technology.

As shown in Figure 4.1a, the market capitalization of the PRECs increased from approximately 69 billion U.S. Dollars in 2010 to 215 billion U.S. Dollars in 2019 based on the sample of our baseline model.[32] As shown in Figure 4.1b, French PRECs have the largest average market capitalization share with around 28%, followed by the U.K. with 26% in our sample.

Figure 4.1: Sample Market Capitalization



Description: Part a) of Figure 4.1 illustrates the sample market capitalization over time. The black solid line is based on the sample of our baseline model. Part b) of Figure 4.1 shows the average country shares of the baseline model.

[32] Our analysis is based on local currency; however, in order to ease the comparison of PREC market sizes internationally, we denominate market caps in U.S. Dollars.

Tenant Sector Beta

The Tenant Sector Beta ($\beta_{i,t}^{sector}$) is the key explanatory variable. In the first stage of our analysis, we breakdown the industrial sector of the firms' tenants into 19 sectors according to the Industry Classification Benchmark (ICB).[33] The real estate firm is then linked to the industrial sectors by the tenants in their buildings:

Equation 4.1: Tenant Sector Beta

$$\beta_{i,t}^{sector} = \sum_{=1}^{S} \omega_{s.i,t-1} \beta_{s,t}^{sector},$$

where β_{s}^{sector} is the sector beta, and $\omega_{s.i,t-1}$ represents the share of revenues of firm *i* in sector *s* at period *t-1*. It should be noted that since firm may release data about their tenants in an annual filing at the end of the year, we use the information on tenant base one year before.

For instance, if firm A has 30% of tenants in the health care sector, 60% of tenants in financial services and technology, and 10% of tenants in the public sector in the previous year, the tenant sector beta $\beta_{i,t}^{sector}$ for firm A will be calculated as:

Equation 4.2: Calculation of Tenant Sector Beta

$$\beta_{A,t}^{sector} = \sum_{s=1}^{3} \omega_{s.i,t-1} \beta_{s,t} = 30\% * \beta_{health,t} + 60\% * \beta_{bank,t} + 10\% * \beta_{publicsector,t}$$ [34]

[33] ICB includes 19 supersectors: Oil & Gas, Chemicals, Basic Resources, Construction & Materials, Industrial Goods and Services, Automobiles & Parts, Food & Beverage, Personal & Household Goods, Health Care, Retail, Media, Travel & Leisure, Telecommunications, Utilities, Banks, Insurance, Real Estate, Financial Services, and Technology.

[34] Because of the low risk of the public sector, its beta is set to 0. However, in the robustness test, we also drop the tenants from the public sector and the results remain robust.

The sector beta (β_s^{sector}) measures the riskiness of each industrial sector in which tenants of the companies were allocated. A beta larger than one indicates that the equity returns of firms in this sector are more cyclical than the market. Sector betas are derived according to the sensitivities of the aggregated sectoral stock indices of European countries relative to the aggregated European STOXX600 index:

Equation 4.3: Sector Beta

$$r_{s,d}^{sector} - r_{f,d} = \alpha_s^{sector} + \beta_s^{sector}\left(MKT_d^{STOXX600} - r_{f,d}\right) + \epsilon_d$$

where $r_{s,d}^{sector}$ is the daily return of the aggregated index for sector *s* in day *d* and $r_{f,d}$ is the risk-free return in day *d*. α_s^{sector} stands for the alpha for sector *s*. β_s^{sector} represents the market beta for sector *s*. We consider two methods to calculate the beta. First, we use a fixed beta. We run a standard CAPM model based on daily returns over the entire sample period. However, a fixed beta may be subject to a significant peak-ahead bias, therefore we consider a time-varying beta using a 3-year rolling window (Lantushenko and Nelling, 2020). For example, the sector beta in year 2010, is estimated by a regression that is run over the 2007-2009 period. The 2011 sector beta estimations use the period 2008-2010, etc. This method ensures that returns are priced using information observed at the time of the regression.[35]

Table 4.1 illustrates the results for the average of rolling sector betas and fixed sector betas for each sector based on the ICB classification. As can be seen, the differences are not very remarkable. Among these sectors, the health care sector and food & beverage sector have the lowest betas, below 0.65. The sectors of basic resources, banks, and insurance have the highest betas.

[35] We thank an anonymous reviewer for suggesting this.

Stock Betas

As PRECs are listed on the stock market, it is necessary to contemplate the equity market risk exposure. We follow Kallberg et al. (2000) and Chiang et al. (2005) and use both single- and multi-factor models. In the baseline model, we show the results based on the single-factor model. In the robustness tests section, we also indicate results based on three and five-factors as well as other benchmark indices.

The equity market risk exposure is determined by a one-factor model, with the sensitivity of a firm return to stock market returns measured as the conditional factor loading ($\beta_{i,t}^{stock}$) for stock *i* and year *t*:

Equation 4.4: Stock Betas

$$r_{i,t,d}^{Stock} - r_{f,t,d} = \alpha + \beta_{i,t}^{Stock}\left(MKT_{t,d}^{STOXX600} - r_{t,d}\right) + \epsilon_{i,t,d}$$

where $r_{i,t,d}^{firm}$ is the daily return in day *d* in year *t* for firm *i* and $r_{f,t}$ is the corresponding risk-free return. Appendix F plots the distribution of the stock betas. The majority of betas are in the scope of 0.5 to 1.0, but there are also outliers in the negative range and the strongly positive field.

Firm Characteristics

To account for market power or concentration, we include tenant sector and property type diversification, which are constructed using the Herfindahl-Hirschman Index (HHI). The Tenant sector HHI is calculated using the percentage revenues of the tenants in each sector. HHI_{Sector} ranges from 0 to 1, with 1 representing only one tenants' sector for a PREC and hence an absolute concentration. The lower the HHI value, the less focused is the underlying tenant sector base of a PREC. Specifically, it is estimated by squaring the revenue share of each tenant sector with respect to the total revenues of all tenant sectors for the given sector *i* in a given year *t*, and then summing the squared shares across the tenant sectors, as presented in Equation 4.5.

Equation 4.5: HHI Sector

$$HHI_{i,t}^{Sector} = \sum_{l=1}^{L}(H_{i,l,t})^2$$

where $H_{i,l,y}$ is the revenue share of each tenant sector *l* for PREC *i* with *l* = 1,2,...,*L* in year *t*. *L* is the total number of tenant sectors of PREC *i*. In addition to the tenant sector focus, we also account for the property type diversification. Property type concentration is calculated as Equation 4.6:

Equation 4.6: HHI Type

$$HHI_{i,t}^{Type} = \sum_{l=1}^{L}(\frac{Q_{i,l,t}}{S_{i,t}})^2$$

where $Q_{i,l,t}$ is the size of properties of public real estate company *i* that belongs to type *l* with *l* = 1, 2, ..., *L* in year *t*; $S_{i,t}$ is the total size of properties held by PREC *i* in year *t*. *L* is the total number of asset types that firm *i* holds.

As shown by previous literature, the creditworthiness of tenants can also reflect asset quality. So we control for tenant quality at the firm level. Following Lu-Andrews (2017), we obtain annual S&P credit ratings of tenants if available. The credit ratings from our sample range from AAA to C, with 20 various ratings. To quantify these ratings, we assign the value of 0 to ’C’, 1 to ’CC’, 2 to ’CCC-’, up to 20 assigned to a ’AAA’ rating. We weight the various ratings in each firm by using the percentage of revenue provided by tenants in the respective real estate firm. The higher the tenant credit rating, the better is the assumed quality of the tenant firm.

Previous literature shows that the performance of PRECs can also be influenced by other characteristics, such as size, leverage, asset quality, and growth opportunities. We follow Liu and Liu (2013), Lu-Andrews (2017), Liu et al. (2019), Riddiough and Steiner (2020), and control for the following firm characteristics: Firm size defined as the log of market capitalization (SIZE), financial leverage as the total liabilities divided by the total assets (L/A), the market-to-book value (MB), which is used as a proxy for growth opportunities, the annual change in NOI (NOI), the real estate investment growth (GROWTH), the volatility of return (VOLAT), and REIT status (REIT). The volatility of return (VOLAT) is calculated for each year by using daily return data. To get the annual volatility of returns, we multiply the daily volatility of a year by the squared root of the number of working days in a year. The annual change in NOI is calculated as the log-difference of the annual net operating income (NOI), which reflects the growth of property level cash flows.

To control for country specific characteristics, such as different specifications of monetary policies or the freedom to move, two reasonable options exist. The traditional way is using country fixed effects. However, those effects are based on the company's headquarters, according to S&P Global Market Intelligence.[36] As a result, the international investment

[36] As an alternative to our base model, we ran a model with different geographic parameters including a geographic diversification measure ($HHI_{Country}$), a country specific risk variable, and country fixed effects instead of country shares of portfolios. Country specific risk variable is defined as:

$$\beta_{i,t}^{country} = \sum_{c=1}^{C} \omega_{c.i,t}\beta_c$$

Based on the property portfolio of each firm, we calculate the average systematic risk of all countries where the firms' properties are located. β_c is the country beta, and $\omega_{c.i,t}$ represents the share of properties of firm *i* in each country at period *t*. $\omega_{c.i,t}$ is calculated as the size of properties located in country c to the total size of properties.

activities of companies are underestimated, as companies may have international property portfolios. We avoid this problem by considering country shares of portfolios. Country shares of portfolios are defined as the share of properties of firm *i* in each country at period *t* and are calculated as the size of properties located in country *c* relative to the total size of properties. The country shares of portfolios have an average sum of 98.5% among the 20 different European countries.

Table 4.2 presents the descriptive statistics of our base model. The average annual return across all companies is 16.30%[37], and the average volatility is 21.35%. The average tenant sector beta in our sample is 0.861, the average stock beta is 0.480. Regarding the tenant quality, the average rating is 13.312, ranging from 20 (equivalent to 'AAA') to 0 (equivalent to 'C'). On average, the tenant sector concentration (HHI_{Sector}) is 0.405, and the standard deviation is 0.259. The property type concentration has a higher mean of 0.605, while the tenant concentration has a lower mean of 0.181. Regarding the firm characteristics, our sample shows an average size of 2.484 billion U.S. Dollars, an average liabilities-to-assets ratio of 0.494, and an average market-to-book ratio of 1.059. The average growth rate of net operating income in our sample is 6.00%, and the average growth rate of real estate investment is 10.12%.

Table 4.2: Descriptive Statistics

	Mean	SD	Min	Max
Return data				
r_t	16.30%	29.98%	-68.29%	288.20%
VOLAT	21.35%	9.35%	4.71%	98.93%
$\beta_{i,t}^{Stock}$	0.480	0.301	0.234	1.399
Tenant characteristics				
$\beta_{i,t}^{Sector}$	0.861	0.185	0.177	1.187

The results are similar to the base model and the coefficient for the variable of interest is significantly positive. Detailed results are available upon request.

[37] We winsorise the annual return of our sample at the 0.5% level. Nevertheless, our results stay robust without winsorising. Detailed results are available upon request.

RATING SCORE	13.305	2.369	4.000	20.000
HHI_{SECTOR}	0.399	0.253	0.106	1.000
HHI_{TENANT}	0.181	0.173	0.033	1.000
ANCHOR	0.255	0.190	0.033	1.000
SINGLE TENANT	0.255	0.190	0.000	1.000
Firm characteristics				
SIZE (Billion USD)	2.518	3.103	0.006	24.115
L/A	0.496	0.131	0.064	0.791
MB	1.061	0.427	0.295	5.784
NOI GROWTH	5.39%	22.90%	-114.64%	122.94%
RE GROWTH	9.25%	20.45%	-100.00%	125.73%
HHI_{TYPE}	0.602	0.262	0.210	1.000
REIT DUMMY	0.631	0.483	0.000	1.000

Description: This table presents the descriptive statistics return data, tenant characteristics, and firm characteristics for the full sample of European PRECs during the 2010-2019 sample period for PRECs that report tenants. The return data includes the return of PRECs, the volatility of returns (VOLAT), and the stock beta ($\beta_{i,t}^{Stock}$). The tenant characteristics are explained by the tenant sector beta ($\beta_{i,t}^{Sector}$), the S&P credit ratings of tenants, the HHI_{SECTOR}, HHI_{TENANT}, ANCHOR, and SINGLE TENANT. The firm characteristics consist of the market capitalization, the liabilities-to-assets ratio, market-to-book ratio, the net operating income, the real estate investment growth, the HHI_{TYPE}, and the REIT dummy. The property type concentration is also measured by the Herfindahl index (HHI_{TYPE}) based on the shares of assets across property types.

4.4 Empirical Analysis

4.4.1 Regression Results

An unbalanced panel regression is conducted to identify whether the sector risk is capitalised in PREC returns:

Equation 4.7: Panel Regression

$$r_{i,t} - r_{f,t} = \alpha + \gamma\beta_{i,t}^{sector} + \sum_{k=1}^{K} c_k X_{k,i,t} + e_{i,t},$$

where $r_{i,t}$ is the firm's annual excess return with respect to the risk-free return. $\beta_{i,t}^{sector}$ stands for the tenant sector beta and γ^{Sector} is the corresponding coefficient. A positive γ^{Sector} coefficient indicates that the tenant sector risk is capitalised in PREC returns.

The $X_{k,i,t}$ characteristics represent a set of control variables, including the liabilities-to-assets ratio, size, net operating income growth, the market-to-book ratio, the tenant S&P long-term credit rating, real estate investment growth, the volatility of returns, and a REIT dummy. The property type diversification and tenant's industrial sector diversification are also controlled in $X_{k,i,t}$. c_k are the respective coefficients. We also control for property type, firm, and year fixed effects. Last, we control for country shares of portfolios as described in section 4.3.

Table 4.3 presents the main results. Model 1 represents the results based on time-fixed sector betas, and Model 2 is based on time-varying sector betas. Model 1 assumes that the betas of the industry sector will remain constant throughout the analysis and are known beforehand. A peek-ahead bias can occur if tenants are assumed to know their sector in advance. This issue is therefore addressed in Model 2 by utilizing a time-varying sector beta, which serves as our baseline setting.

As shown in Model 2, as the sector risks increase, PREC returns increase significantly as well. Investors require a higher return to compensate for a higher exposure to tenants from riskier industrial sectors. Economically, a one-standard-deviation change in the sector beta will result in a 6.18% increase in PREC returns per annum, which is calculated as the coefficient multiplied by the standard deviation of the tenant sector beta.

Table 4.3: Tenant Sector Beta Models

	(1)	(2)
$\beta_{i,t}^{Sector}$	0.193***	0.334***
	(0.045)	(0.087)
$\beta_{i,t}^{Stock}$	0.062	0.080
	(0.177)	(0.169)
r_{t-1}	-0.103*	-0.201**
	(0.052)	(0.099)
REIT	0.688	0.785
	(1.197)	(1.337)
GROWTH	-0.275***	-0.277***
	(0.063)	(0.060)
RATING SCORE	-0.021***	-0.023***
	(0.007)	(0.008)
L/A	-0.415	-0.165
	(0.425)	(0.300)
VOLAT	0.133	-0.018
	(0.463)	(0.490)
NOI	0.138***	0.103***
	(0.032)	(0.029)
MB	0.070	0.010
	(0.235)	(0.253)
SIZE	0.044	0.111
	(0.075)	(0.097)
HHI_{TYPE}	-0.014	0.133
	(0.104)	(0.105)
HHI_{SECTOR}	0.043	-0.052
	(0.138)	(0.156)
Country Shares	Yes	Yes
Time FE	Yes	Yes
Type FE	Yes	Yes
Company FE	Yes	Yes
Observations	443	420
R^2	0.662	0.678

*Description: This table reports the results of the panel regression based on a panel of European PRECs across 2010 and 2019. The dependent variable is the return to measure the performance of the PRECs. The variable of interest is the tenant sector beta $\beta_{i,t}^{Sector}$. We control for stock beta, the lagged return, REIT dummy, real estate investment growth, the credit rating score of tenants, the liabilities-to-assets ratio, the volatility of returns, the annual change in NOI, the market-to-book ratio, SIZE, property type and tenant sector concentration. We also include fixed effects of time, company, and type. Furthermore, we control for country shares of portfolios. Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

With respect to the coefficients for control variables, we find that firms with a lower tenant S&P long-term credit rating have higher returns. This indicates that an appropriate risk premium for the credit rating of tenants appears to be required, given the fact that lower-rated tenants represent a higher risk for real estate companies. While the credit rating of a company obviously reflects information associated with the industry in which a company operates, it is a broader measure since it additionally reflects business conditions which a company faces. This may explain the reasons why after controlling for the tenant rating, the systematic risk of the tenants' industry sectors is furthermore capitalised in PREC returns.

Real estate investment growth has a negative coefficient; this can be explained by the fact that high investment growth may result in higher management costs and therefore reduce PREC returns. A positive relationship between the net operating income and firm returns confirms that asset level profitability can influence firm's stock performance. Interestingly, we do not find any significant impact from the stock market beta. This can be explained by the relatively small size of European PRECs. As shown by Alcock and Steiner (2018), smaller REITs tend to exhibit lower systematic risk.

We follow Ling et al. (2022) and conduct Fama-MacBeth cross-sectional regressions with corrected standard errors. Because the number of observations in each of the years 2010 to 2014 is less than 40, we run cross-sectional regressions grouped every two years. This approach helps to avoid problems caused by a low number of observations.

Model (3) of Table 4.4 displays the results. The coefficient of the tenant sector beta is positive and significant, indicating that the tenant sector risk is capitalised in REIT stock returns. The coefficient of tenant sector beta is lower than that in the panel regression, but remains statistically significant. This robustness test underlines our baseline results in an important way.

Table 4.4: Fama-MacBeth Model

	(3)
$\beta_{i,t}^{Sector}$	0.111***
	(0.042)
$\beta_{i,t}^{Stock}$	0.030
	(0.138)
r_{t-1}	-0.130
	(0.131)
REIT	-0.029
	(0.044)
GROWTH	-0.157*
	(0.080)
RATING SCORE	-0.005
	(0.003)
L/A	-0.011
	(0.136)
VOLAT	0.391**
	(0.159)
NOI	0.202***
	(0.032)
MB	0.060
	(0.034)
SIZE	0.009
	(0.025)
HHI_{TYPE}	0.009
	(0.050)
HHI_{SECTOR}	-0.040
	(0.028)
Type	Yes
Observations	420
R^2	0.319

*Description: This table reports the results of the Fama-MacBeth cross sectional regressions based on a panel of European PRECs across 2010 and 2019. Fama-MacBeth cross sectional regressions use two year rollings due to the limited number of observations in years before 2015. The dependent variable is the return to measure the performance of the PRECs. The variable of interest is the tenant sector beta ($\beta_{i,t}^{Sector}$). The control variables are the same as in Table 4.3. We also control for type dummy. Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

4.4.2 Excess Return and Portfolio Construction

We further show how to generate benchmark-adjusted returns (also known as alphas) on PREC portfolios according to the tenant sector risk. We construct 12-month buy-and-hold portfolios using the market capitalization as the weights. We sort stocks according to their tenant sector risk ($\beta_{i,t}^{sector}$). In total, we construct four portfolios. The breakpoints for each grouping are the

25th, 50th, and 75th percentiles. As shown in Panel A, Table 4.5, with the increase in the tenant sector risks (from portfolio 4 to 1), the average daily return increases from 0.023% per day (Portfolio 4) to 0.031% per day (Portfolio 1), which is equivalent to an annual return of 6.003% (Portfolio 4) and 8.091% (Portfolio 1). We then use the time series of the returns of each of those four composite portfolios to estimate the composite portfolio alphas:

Equation 4.8: Estimation of Composite Portfolio Alphas

$$r_{p,d} - r_{f,d} = \alpha_p + \beta_{p,1}MKT + \beta_{p,2}SMB + \beta_{p,3}HML + \beta_{p,4}MOM + \beta_{p,5}EPRA + \epsilon_{p,d},$$

where $r_{p,d}$ is the market capitalization-weighted daily return on a given portfolio and $r_{f,d}$ is the corresponding risk-free rate as measured by the yield on the one-month Treasury bill. We use Fama-French factors to be consistent with prior research. The data is obtained from Ken French's website. In particular, the factors comprise a market return index (MKT), the difference between the returns on diversified portfolios of small stocks and big stocks (SMB), the difference between the returns on diversified portfolios of high book-to-market (value) stocks, low book-to-market (growth) stocks (HML), and the momentum factor, described as the tendency of a stock price to maintain movement dynamics recorded in the immediately previous period (MOM). To control for the influence of aggregated European real estate markets, we include European public real estate returns by using the EPRA NAREIT Developed Europe Index.

Table 4.5: Calendar Time Portfolio Regressions by Tenant Sector Risk

Panel A: Portfolio returns				
	Mean	SD	Min	Max
Portfolio 1 (Highest 25^{th})	0.00031	0.00331	-0.02162	0.02130
Portfolio 2 (50^{th} to 75^{th})	0.00028	0.00437	-0.02876	0.02579
Portfolio 3 (25^{th} to 50^{th})	0.00025	0.00489	-0.02908	0.02776
Portfolio 4 (Lowest 25^{th})	0.00023	0.00472	-0.04252	0.04458
MKT	0.00027	0.01074	-0.08800	0.06850
SMB	0.00005	0.00435	-0.02250	0.03210
HML	-0.00011	0.00440	-0.02130	0.03760
MOM	0.00041	0.00601	-0.04130	0.04510
EPRA	0.00040	0.00976	-0.09378	0.06372

Panel B: Calendar time portfolio regressions by tenant sector risk							
	alpha	MKT	SMB	HML	MOM	EPRA	R^2
HIGH	0.0001889***	0.047***	0.085***	0.073***	0.052***	0.227***	0.547
	(0.00004)	(0.007)	(0.013)	(0.012)	(0.008)	(0.006)	
	0.0001216**	0.040***	0.075***	0.067***	0.026***	0.349***	0.678
	(0.00005)	(0.008)	(0.015)	(0.013)	(0.009)	(0.007)	
	0.00008942	0.077***	0.100***	0.043***	-0.001	0.355***	0.635
	(0.0001)	(0.009)	(0.018)	(0.016)	(0.011)	(0.008)	
LOW	0.00004782	0.090***	0.132***	-0.017	0.031***	0.333***	0.593
	(0.0001)	(0.009)	(0.018)	(0.016)	(0.011)	(0.008)	
HIGH-LOW	0.00014110**	-0.043***	-0.047**	0.090***	0.020	-0.106***	0.114
	(0.0001)	(0.011)	0.021)	(0.019)	(0.013)	(0.010)	

*Description: This table reports results from calendar time portfolio regressions. Portfolios are sorted into four groups from the bottom to the top 25th percentile based on the tenant sector beta ($\beta_{i,t}^{Sector}$). Alpha stands for benchmark adjusted return. MKT stands for the return factor, SMB stands for the size factor, HML stands for book to market value factor, and MOM stands for the monthly premium on winners minus losers. EPRA stands for the returns of EPRA NAREIT Developed Europe Index. The portfolios are constructed based on daily data. Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

As shown in Table 4.5, firms with the 25th quantile highest tenant sector risk exhibit a significant average benchmark adjusted return (alpha) of 4.93% per year (0.019% per day, as shown in Panel B, Table 4.5). Firms with the 25th quantile lowest tenant sector risk show an average annual benchmark adjusted return of 1.25%, which is not significantly different to zero. Therefore, we propose a hypothetical "long-short" trading strategy that exploits the information in the tenant sector risk. This strategy buys the composite portfolio with the 25th quantile highest tenant sector risk and sells the composite portfolio with 25th quantile lowest tenant sector risk. It yields a significantly positive alpha of approximately 0.014% per day. We can use this long-short hedge strategy to exacerbate excess returns stemming from the tenant sector risk, which can earn an average benchmark adjusted return of 3.68% per year. This is slightly lower than a strategy based on the geographic dispersion of the underlying assets (4.56% per year) (Milcheva et al., 2021) and a 'tenant momentum' strategy (4.73% to 5.33%) (Chen et al., 2020), but similar to the strategy based on the market timing ability (3.6% per year) (Ling et al., 2019).

4.4.3 Robustness Tests

4.4.3.1 Dropping the Public Sector

As shown in Table 4.1, the most prominent industry sector is the retail sector, while the sector of basic resources displays the lowest share of tenants. The share of public sector is 6%, which encourages us to conduct a robustness test excluding the public sector in the construction of our tenant sector beta.

Model 4 in Table 4.6 depicts the results of the robustness test. The coefficient of the tenant sector beta is 0.304 and remains robust.

4.4.3.2 Stock Beta Modifications

Another robustness test is the modification of the stock beta from Model 2 by considering various asset pricing models and market indexes. First, we use the EPRA NAREIT Developed Europe Index, which is designed to represent general trends in eligible real estate equities in developed countries in Europe. We estimate the following equation:

Equation 4.9: Stock Beta Modification - EPRA

$$r_{i,t,d} - r_{f,t,d} = \alpha + \beta_{i,t}^{EPRA}\left(MKT_{t,d}^{EPRA} - r_{f,t,d}\right) + \epsilon_{i,t,d},$$

where $r_{i,t,d}$ is the daily return in day *d* in year *t* for firm *i* and $r_{f,t}$ is the corresponding risk-free return.

Second, we show results for stock betas based on a standard CAPM model using Fama-French market factor as the return market portfolio. The estimation equation is given by:

Equation 4.10: Stock Beta Modification – One Factor

$$r_{i,t,d} - r_{f,t,d} = \alpha + \beta_{i,t}^{MKT} MKT_{t,d} + \epsilon_{i,t,d},$$

Third, we provide results for stock betas based on the Fama-French Three Factor Model. Our model is denoted by:

Equation 4.11: Stock Beta Modification – Three Factors

$$r_{i,t,d} - r_{f,t,d} = \alpha + \beta_{i,t}^{MKT} MKT_{t,d} + \beta_{i,t}^{SMB} SMB_{t,d} + \beta_{i,t}^{HML} HML_{t,d} + \epsilon_{i,t,d},$$

Fourth, we provide results for stock betas based on the Carhart Four Factor Model. Our model is denoted by:

Equation 4.12: Stock Beta Modification - Four Factors

$$r_{i,t,d} - r_{f,t,d} = \alpha + \beta_{i,t}^{MKT} MKT_{t,d} + \beta_{i,t}^{SMB} SMB_{t,d} + \beta_{i,t}^{HML} HML_{t,d} + \beta_{i,t}^{MOM} MOM_{t,d} + \epsilon_{i,t,d},$$

Last, we display a Fama-French Five Factor Model. The equation then has the following form:

Equation 4.13: Stock Beta Modification - Five Factors

$$r_{i,t,d} - r_{f,t,d} = \alpha + \beta_{i,t}^{MKT} MKT_{t,d} + \beta_{i,t}^{SMB} SMB_{t,d} + \beta_{i,t}^{HML} HML_{t,d} + \beta_{i,t}^{CMA} CMA_{t,d} + \beta_{i,t}^{RMW} RMW_{t,d} + \epsilon_{i,t,d},$$

Appendix F b-f displays the distribution of the modified stock betas. A relatively high percentage can be found in the range 0.5 to 1.0, but we observed the presence of outliers in the negative range and the strongly positive zone. For example, “Norwegian Property ASA” has the highest value of 1.400, while “Immobiliare Grande Distribuzione SIIQ SpA” has the lowest beta of -0.234. Appendix G displays an unconditional correlation matrix of the above modified stock betas and our variable of interest, the tenant sector beta. As can be seen in the table, the base tenant sector beta and the stock beta modifications are not correlated while the variety of stock betas have correlation coefficients among themselves of at least 0.663.

For one-factor, three-factor, four-factor, and five-factor models, we adjust our tenant sector beta. As shown in Table 4.6, the coefficients of the tenant sector betas are 0.332, 0.330, 0.316, 0.301, and 0.334, and thus robust and significant. It should be noted that the results are also robust if we use Fama-Macbeth regression to estimate the coefficients.

Table 4.6: Stock Beta Modifications and Tenant Sector Alpha

	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\beta_{i,t}^{Sector}$	0.304***	0.332***	0.330***	0.316***	0.301**	0.334***	0.347***
	(0.107)	(0.092)	(0.080)	(0.103)	(0.150)	(0.096)	(0.073)
$\alpha_{i,t}^{Sector}$							0.551
							(0.868)
$\beta_{i,t}^{EPRA}$		0.054					
		(0.161)					
$\beta_{i,t}^{MKT}$			0.054	0.085	0.028	0.074	
			(0.193)	(0.161)	(0.079)	(0.162)	
$\beta_{i,t}^{SMB}$				-0.150	-0.010	-0.131	
				(0.105)	(0.078)	(0.097)	
$\beta_{i,t}^{HML}$				-0.071***	-0.041*	-0.092***	
				(0.014)	(0.022)	(0.013)	
$\beta_{i,t}^{MOM}$					0.221***		
					(0.023)		
$\beta_{i,t}^{RMW}$						0.086*	
						(0.046)	
$\beta_{i,t}^{CMA}$						0.006	
						(0.005)	
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	420	420	420	420	420	420	420
R^2	0.676	0.676	0.677	0.696	0.719	0.707	0.679

*Description: This table reports the results of the panel regression based on a panel of European PRECs across 2010 and 2019. The results are robust by conducting Fama-MacBeth cross sectional regressions with corrected standard errors. The dependent variable is the return to measure the performance of the PRECs. The variable of interest is the tenant sector beta $\beta_{i,t}^{Sector}$. Stock betas vary in the models (5) to (9). Model (10) includes tenant sector alpha ($\alpha_{i,t}^{Sector}$). Other control variables are the same as in Table 3. We also control for fixed effects of time, company, and type. Furthermore, we control for country shares of portfolios. Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

4.4.3.3 Tenant Sector Alpha

In addition to the systematic risk, previous literature also studies the benchmark-adjusted return (alpha). For instance, Chen et al. (2020) sort REITs according to the abnormal returns of individual publicly traded tenants. Ling et al. (2022) use the geographically weighted risk-adjusted return (alpha) as a proxy for the excess return of REITs' property portfolio (αPPR) and find that αPPR predicts the cross-section of returns in the public REIT market. In our robustness tests, we also test whether it is the benchmark-adjusted return (alpha), rather than the systematic risk (beta) of the tenants' industry sector, that influences the public real estate returns. Therefore, we follow Ling et al. (2022) and construct a tenant sector alpha in addition to the tenant sector beta, based on Equation 4.14:

Equation 4.14: Tenant Sector Alpha

$$\alpha_{i,t}^{sector} = \sum_{s=1}^{S} \omega_{s.i,t-1} \alpha_{s,t}^{sector},$$

where $\alpha_{s,t}^{sector}$ is the sector alpha, and $w_{s.i,t}$ represents the share of revenues of firm *i* in sector *s* at period *t*. The sector alpha is the intercept calculated from the sensitivity of the aggregated sectoral stock indices of European countries to the European STOXX600 index, using a 3-year rolling window CAPM approach, as in Equation 4.3. In Table 4.6 we report that the tenant sector alpha does not significantly influence listed real estate returns. The coefficient for tenant sector beta remains statistically significant. Therefore, we conclude that the PREC returns are influenced by the systematic risk of tenants' industry sector rather than by the risk-adjusted return.

4.4.3.4 Anchor Tenant and Tenant Diversification

To test the role of the tenants, we follow Zheng and Zhu (2021) and create a variable (ANCHOR), which is defined as the revenue share of the largest tenant to the overall revenues of a given PREC, to control for the potential anchor tenant effect. In Model 11, we replace the variable for tenant sector diversification with the ANCHOR variable. Our variable of interest remains robust, while the anchor tenant or dominant tenant does not have a significant relationship with returns.

In our baseline model, we included tenant sector concentration as the control variable. In the robustness test, we construct the Herfindahl index based on individual tenants, rather than the industry sector of tenants (Patatoukas, 2011; Campello and Gao, 2017). It shows the concentration of properties of a PREC among its tenants. Accordingly, it is calculated by squaring each tenant's revenue share with respect to the total revenues of all tenants in a given year *t*, and then summing the squared share across tenants, as presented in Equation 4.15. HHI_{TENANT} has a range from 0 to 1, where 1 represents an absolute concentration of tenants for a PREC. If the HHI value of a PREC is lower, it will have a less focused tenant base.

Equation 4.15: HHI Tenant

$$HHI_{i,t}^{TENANT} = \sum_{l=1}^{L} (H_{i,l,y})^2,$$

where $H_{i,l,y}$ is the revenue share of each tenant *l* for PREC *i* with *l* = 1,2,...,*L* in year *y*. *L* is the total number of tenants of PREC *i*. Appendix H shows a comparison between the HHI_{SECTOR} and HHI_{TENANT}. As expected, the tenant concentration in each property type is lower relative to the tenant sector concentration. The average retail tenant sector concentration is 0.707, while the average tenant concentration for the analogous property type is 0.262. For healthcare, industrial, and retail PRECs, the average HHI_{TENANT} is less than 0.300, while the average HHI_{SECTOR} is over 0.700. This indicates that although these PRECs have quite diversified tenants, these tenants concentrate on one sector.

In Model 12, we replace the variable for tenant sector diversification with HHI_{TENANT}, i.e., the tenant focus. While we see a very significant variable of interest, the tenant focus does not appear to have a significant influence.

Furthermore, in Model 13 we control for the case where there is only one tenant in the portfolio of the PREC. For this, we create a dummy variable called SINGLE TENANT. The results in Table 4.7 show that the tenant sector beta remains significantly positive[38]

4.4.3.5 Rating Dummy Construction

To further our robustness tests, we consider an alternative measure for the tenant credit rating. Model (14) in Table 4.7 includes a variable labelled RATING DUMMY, which is defined as the share of tenants who have a credit rating. Each tenant with a credit rating is assigned the value of one and otherwise zero. We then calculate the average credit rating of all tenants of the firm in that year. In Model (15) we combine the variable RATING SCORE and the variable RATING DUMMY. When we only use the rating dummy, the number of observations increases to 559 (33%). For both models, the variable of interest and the tenant rating variables remains highly significant.

[38] Our findings are further strengthened by a series of other robustness tests. As an alternative to HHI_{SECTOR}, we construct a single tenant sector dummy and an anchor tenant sector variable, similar to the variables SINGLE TENANT and ANCHOR. The significance of our variable of interest remains strongly positive. Detailed results are available upon request.

Table 4.7: Tenant Diversification, Anchor Tenant Effect, and Tenant Share

	(11)	(12)	(13)	(14)	(15)	(16)
$\beta_{i,t}^{Sector}$	0.334***	0.329***	0.341***	0.117***	0.379**	0.351***
	(0.103)	(0.101)	(0.093)	(0.065)	(0.065)	(0.086)
ANCHOR	-0.088					
	(0.333)					
HHI_{TENANT}		-0.500				
		(0.185)				
SINGLE TENANT			-0.080			
			(0.155)			
RATING SCORE	-0.022**	-0.021**	-0.023**		-0.022**	-0.022***
	(0.009)	(0.010)	(0.010)		(0.008)	(0.008)
RATING DUMMY				-0.220***	-0.240***	
				(0.064)	(0.033)	
TENANT PEROFRMANCE						0.031
						(0.033)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country Shares	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	420	420	420	420	420	420
R^2	0.678	0.680	0.678	0.604	0.684	0.678

*Description: This table reports the results of the panel regression based on a panel of European PRECs across 2010 and 2019. The dependent variable is the return to measure the performance of the PRECs. The variable of interest is the tenant sector beta $\beta_{i,t}^{Sector}$. Model (11) includes an anchor tenant variable (ANCHOR). Model (12) includes a tenant concentration measure (HHI_{TENANT}), and model (13) a single tenant dummy (SINGLE TENANT). Model (14) includes a RATING DUMMY and excludes the RATING SCORE, while model (15) combines the RATING SCORE and RATING DUMMY. Model (16) includes the variable TENANT PERFORMANCE. Other control variables are the same as in Table 3. We also control for fixed effects of time, company, and type. Furthermore, we control for country shares of portfolios. Furthermore, we control for country shares of portfolios. Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

4.4.3.6 Individual Tenant Performance

We introduce an additional robustness test after we comprehended the individual performance of publicly traded tenants. We therefore extend our model by inclusion of a new, 'TENANT PERFORMANCE' labelled variable, which is defined as the average of tenants' annual return.

We illustrate the result in Table 4.7 Model (16). Our sample size decreases by 16 observations. The impact of tenant sector beta appears to remain robust, while the coefficient displays a value of 0.351. This indicates that the tenant sector beta can improve the prediction of PREC stock return even after the performance of individual tenants has been included. We however report that while the impact of tenant sector beta remains statistically robust, the coefficient on tenant performance is insignificant which might be attributable to the fact that tenant credit rating has already been controlled.

4.5 Conclusion

In our research, we examined the impact of the tenant's industrial sector risks upon the performance of PRECs. The previous academic literature attempted to measure asset quality of real estate firms using either tenant credit worthiness or the location of the assets. We propose an extension to these measurements, by inclusion of the systematic risk of the industry in which the tenants operate, hence proposing consideration of a new risk factor for PRECs' risk assessment.

Our findings suggest that the systematic risk of tenant's industry sectors appears to be capitalised, hence implying that it is being a component of the realised equity returns of PRECs. Our research suggests that firms exposed to tenants from more volatile industries exhibit significantly higher returns. Furthermore, a one-standard-deviation increase in the sector beta of tenants is associated with a 6.18% increase in the equity return.

We therefore considered a hypothetical long and short trading strategy which is driven by the tenant sector risk in order to test implications of our results. The results of such trading strategy indicates that investors can earn a benchmark-adjusted return of 3.68% per year by holding or buying stocks of companies with high tenant sector risk, and selling stocks with low tenant sector risk.

Overall, our results demonstrate the importance of tenants, beyond the attributes that have been investigated previously, such as tenant quality, on real estate firms' stock performance. As a consequence, the systematic risk in the tenants' industries can serve as an additional risk factor for PRECs. Investors' exploration of the tenants' industry sectors can act as a useful indicator of PRECs' stock riskiness. Therefore, the risks associated with tenants should not be ignored by property managers and investors.

5. Only a Halo Effect? Exploring the Impact of E, S, and G on Real Estate Equities

Abstract

This paper examines the impact of ESG ratings on the market valuation and intrinsic value of Public Real Estate Companies (PRECs) across 38 countries from 2015 to 2021. Utilizing instrumental variable analysis to address endogeneity, the findings indicate a positive correlation between ESG metrics and market valuation, particularly through the Environmental and Social components. The results reveal that a high Social component score is inversely related to systematic risks, suggesting it can enhance a firm's intrinsic value by reducing the volatility of its equity through the valuation channel. Conversely, although the Environmental component boosts market valuation, it lacks clear correlation with either the idiosyncratic risk or valuation channels, highlighting the critical role of social factors in improving both the intrinsic and market valuation of PRECs.

Keywords: ESG, Performance, Public Real Estate Companies, Listed Real Estate

Authors: Badr Hayar, Jan Muckenhaupt, Bing Zhu[39]

Status: Working Paper[40]

[39] Author contributions based on CRediT roles: Validation, visualization, and writing – both the original draft and review & editing – were conducted by Jan Muckenhaupt. Conceptualization, data curation, software, formal analysis, and methodology – were conducted by Badr Hayar. Supervision was provided by Bing Zhu.
[40] Full paper presentation at the 29th ERES Conference in London.

5.1 Introduction

In the present landscape, companies hold a substantial obligation regarding their impact on society and the environment. Under these circumstances, investors, lenders, and other stakeholders are advocating for a greater integration of environmental, social, and governance (ESG) factors into their strategic business choices. This is further strengthened by governments who are implementing various regulations to steer investors toward this goal. These regulations act as a catalyst for the broader shift in investor preferences toward more sustainability and societal well-being, seeking both financial returns and positive impact (Chen et al., 2020). The reason for the focus on these ESG criteria is based on the environmental and social dimensions. The ecological dimension is characterised by vital climate change, as demonstrated by the signing of a treaty by 174 nations at a United Nations meeting in 2015 in Paris, which aims to limit global warming to below 2 degrees. The social dimension is based on the growing prevalence of corporate social responsibility (CSR), which has spurred the implementation of sustainable initiatives across diverse sectors. Supporters of CSR maintain that acting as a responsible corporate citizen can potentially influence financial performance (Bénabou and Tirole, 2010).

There are extensive studies on the link between ESG metrics and listed real estate in the existing literature (Feng and Wu, 2021; Aroul et al., 2022; Chacon et al., 2024). Much of the literature has focused on the disclosure of ESG information, such as the ESG disclosure relation between REIT debt financing and firm value (Feng and Wu, 2021) or fund performance (Devine et al., 2022). Other work investigated the inclusion of ESG in a real estate portfolio and studied the impact of ESG commitment on the firm's financial performance (Cajias et al., 2011). However, there is still an ongoing debate on whether ESG investment is a value-enhancing activity or just corporate window-dressing (Barka et al., 2023). While Giese et al. (2019) conclude that companies' ESG information was transmitted to their fundamental value, both through their systematic risk profile (lower costs of capital) and their idiosyncratic risk profile (higher profitability and lower exposures to tail risk), Korinth and Lueg (2022) find no overall impact of ESG on the idiosyncratic risk in the German stock market. Similarly, Izcan and Bektas (2022) could not find any significant relationship between the social dimension and the idiosyncratic risk of European banks. Additionally, some studies show that there is not necessarily a significant relationship between ESG and cash flow indicators (Gregory, 2022; Humphrey et al., 2012). There are still no consistent conclusions regarding this question, especially for real estate firms. This discrepancy raises questions about a possible mis-valuation of PRECs in this context, prompting us to seek answers to these questions.

To address this question, we investigate whether the impact of ESG on real estate firm performance is driven by mis-valuation or, alternatively, if improved ESG performance enhances the fundamental value of the firm's stock. We consider both market valuation and stock intrinsic value. Market valuation is quantified using the classical mis-valuation indicator, Tobin's Q. To measure intrinsic value, we follow Giese et al. (2019) and investigate cash flow, systematic, and idiosyncratic risks. Unlike previous literature, which focuses mainly on the U.S. market, we conduct an international analysis, with our sample including 342 PRECs in 38 economies. Additionally, our paper attempts to address the issues of endogeneity and selection bias by using a 2SLS approach and Heckmann two-stage regression with country policies and ESG awareness as an instrumental variable. Very limited literature carefully addressed the potential endogeneity issue. One exception is the study by Eichholtz et al. (2019), which investigated the greenness of REITs and used two instrumental variables: local greenness and local environmental policies. They admonished that endogeneity is not controlled in a lot of studies. We follow their strategy. Furthermore, we conduct a Heckman two-stage correction to control for possible selection bias. By using this approach, we integrate a further instrument called the Google index, which reflects the countries' sustainability awareness.

Using the firm-level data from 2015 to 2021, our paper confirms a positive impact of ESG on Tobin's Q of PRECs, indicating that improved corporate sustainability increases a firm's market valuation relative to its true value. Further, we find evidence of an impact on the fundamental value. After examining the cash flow, idiosyncratic risk, and valuation channels, our analysis reveals a notable impact of ESG factors on systematic risk, especially when applying methods to minimise endogeneity. The subcomponent analysis shows consistent findings, with the Social and Governance elements of ESG amplifying its overall effect on systematic risk, suggesting that ESG scores contribute more to fundamental value than to stock price misvaluation. While ESG significantly affects profitability and earnings, its influence on other risk and valuation channels appears marginal or non-existent. Notably, the Social (S) component enhances firms' intrinsic value by reducing systematic risks and improving market valuation. In contrast, the Governance (G) component lacks a significant impact on market valuation, and the positive effect of the Environmental (E) component on valuation does not correspond with any identified channel.

The rest of the paper is structured as follows. Section 5.2 briefly reviews the relevant literature. Section 5.3 describes the data and variables. Section 5.4 explains the different channels and the methodology. Section 5 discusses the empirical results. The final section concludes.

5.2 Literature Review

In recent years, the role of ESG has increased in the world of real estate. We investigate two different strands of research based on ESG and the performance of PRECs. One strand explores the relationship between ESG (and its sub-components) and cash flows, systematic and idiosyncratic risk, and Tobin's Q. A second strand is based on the equity market mis-valuation of ESG.

While certain studies indicate that ESG may not have a substantial correlation with cash flow indicators (Gregory, 2022; Humphrey et al., 2012), Brounen et al. (2021) examine the interaction of the performance of PRECs and the application of environmental, social, and governance ratings across European markets and show, that investors are willing to pay to access companies with higher sustainable ratings. An analysis by Aroul et al. (2022) examines the relationship between the ESG performance of Real Estate Investment Trusts (REITs) and their operational efficiency and performance. In their study, the authors report that REITs that perform well on the ESG scale have higher operational efficiency and performance. Feng and Wu (2021) show how ESG disclosure is related to REIT debt financing and firm value. They conclude that REITs with higher levels of ESG disclosure have lower costs of debt, higher credit ratings, and higher unsecured debt to total debt ratio. Eichholtz et al. (2019) discovered that REITs with a greater proportion of environmentally certified buildings experience reduced bond spreads in the secondary market. These findings remain consistent across various estimation approaches, suggesting that environmental risk is accurately incorporated into pricing within the real estate debt market. Newell and Lee (2012) investigate the influence of CSR and financial factors (market capitalisation, book-to-market value, gearing, and beta value) on REIT performance in Australia. They show that the environmental, social, and corporate governance dimension of CSR is not separately priced by REIT investors. Lecomte and Ooi (2013) examine the relationship between corporate performance and the makeup of corporate governance among externally managed Singaporean REITs. The results support a positive link between corporate governance and stock performance.

Examining how ESG factors affect the valuation of PRECs, Chacon et al. (2024) explore how a company's valuation, cash flow, and risk are influenced by its ESG performance. By using GRESB ESG performance data from 2019 to 2021 for international REITs, they show that REITs with better ESG performance scores have lower firm value (firm Q and market-to-book ratios) and operating cash flow. In addition, they show that strong ESG-performing REITs exhibit higher firm risk, which could be caused by an overinvestment in ESG activities by the management. Fuerst and McAllister (2011) measure the effects of environmental certification on office values. They identify three drivers of price differences between non certified and certified buildings, namely additional occupier benefits, lower holding costs of investors, and lower risk premiums. The results suggest that, compared to buildings in the same submarkets, eco-certified buildings have both a rental and sale price premium. In contrast, Velte (2017) found no significant impact of ESG on Tobin's Q.

Assessing the influence of ESG on the risk associated with PRECs, Erol et al. (2023), the environmental component of ESG is negatively correlated with REITs' excess return and positively related to systematic risk, whereas social and governance components do not significantly affect REITs' financial performance. In addition, the authors found that S-investing has generated significant financial benefits as the S-score is positively related to excess return and the Sharpe ratio, while the S-score is negatively related to systematic firm risk. As demonstrated by Chacon et al. (2024), REITs that perform strongly in terms of ESG factors exhibit a higher level of firm risk. Based on these results, they conclude that REIT management may overinvest in ESG activities at the expense of shareholder value, particularly during periods of market stress. By dissecting firm value into cash flow and risk components, they observe that firms with higher ESG scores have lower cash flows and higher risk. Devine et al. (2022) investigate the performance of private equity real estate funds and voluntary disclosures regarding ESG factors. To bolster the robustness of their analyses, they substitute the raw returns with Fama-French-Carhart Alphas. This substitution aims to remove systematic capital markets risk from their model, isolating signals associated with idiosyncratic risk. They observe a positive association between GRESB reporting and risk-adjusted returns for private equity real estate funds in a cross-sectional analysis. Conversely, the studies by Korinth and

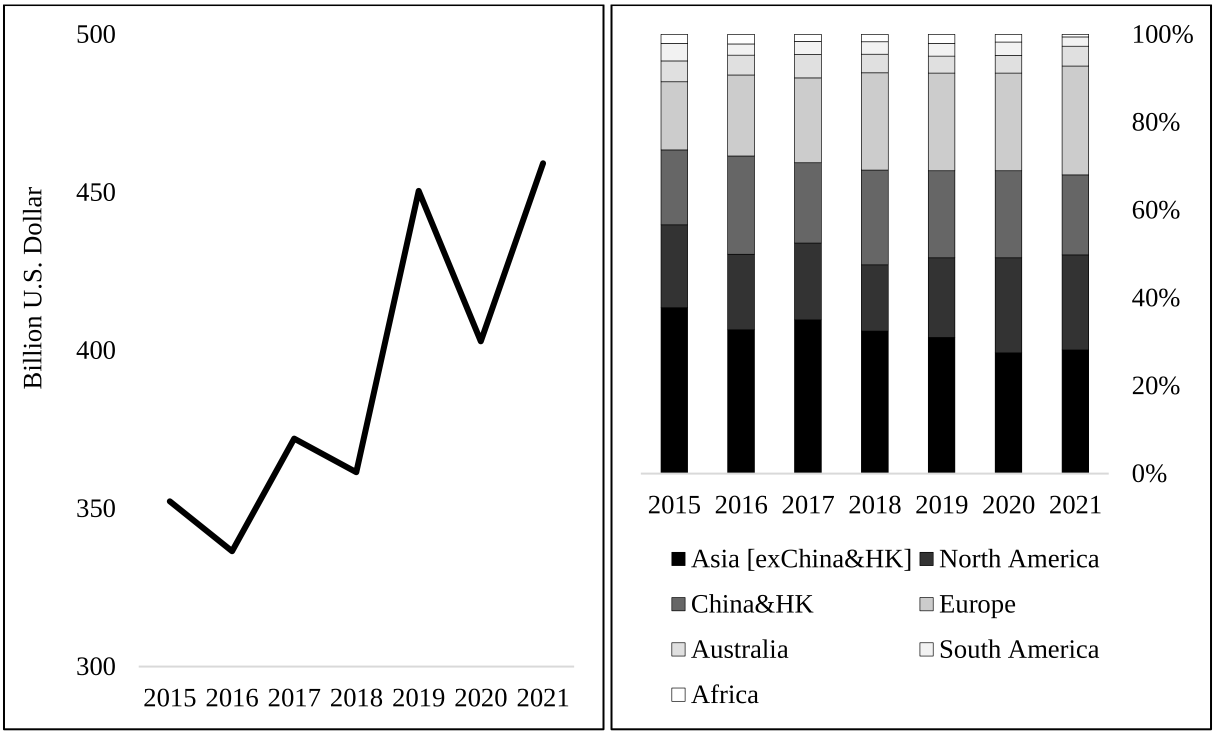
Lueg (2022) or Izcan and Bektas (2022) reveal that ESG factors do not have a significant overall effect on idiosyncratic risk.

The second strand of our research is related to the mis-valuation of PRECs. Giese et al. (2019) examined three transmission channels within a standard discounted cash flow model to demonstrate the link between ESG information and company valuation and performance, namely the cash-flow channel, the idiosyncratic risk channel, and the valuation channel, to establish a link between ESG information and company valuation and performance. As a result, they found that companies' ESG information affects their valuation and performance both through their systematic risk profile (lower costs of capital and higher valuations) and their idiosyncratic risk profile (higher profitability and lower exposure to tail risk). The primary findings by Barka et al. (2023) indicate that ESG scores contribute to equity mis-valuation by strengthening the degree of equity overvaluation or mitigating equity undervaluation. Furthermore, their research reveals that companies with moderate ESG scores demonstrate positive abnormal returns. Bofinger et al. (2022) demonstrated that sustainable investing leads to higher levels of equity market mis-valuation and a reduction in market efficiency. Limited empirical studies have provided corroborating evidence that the stock market inefficiently values ESG commitment due to the substantial demand for firms' compliance with sustainability criteria and institutional investors' preference for high-ESG-rated companies (Riedl and Smeets, 2017; Hartzmark and Sussman, 2019).

5.3 Data

We collect data for 342 PRECs between 2015 and 2021 in 38 countries. Data on ESG is obtained from Bloomberg Professional. The data on company characteristics are from the S&P Global Market Intelligence Database, formerly known as SNL Financials. Further data on control variables such as firm size, firm age, financial leverage, and asset growth are compiled from Refinitiv Datastream. Figure 5.1a shows the market capitalization of PRECS based on our sample. The market capitalization increased from approximately 350 billion U.S. Dollars in 2015 to 460 billion U.S. Dollars in 2021. As shown in Figure 5.1b, Asian PRECs have the largest average market capitalization share with around 30%, followed by North America and Europe with 20%, respectively.

Figure 5.1: Market Capitalisation International Sample



Description: Part a) of Figure 5.1 illustrates the sample market capitalization over time. The black solid line is based on the sample of our baseline model. Part b) of Figure 5.1 shows the regional distribution of our sample.

We follow the existing literature and use a variety of measures for the performance of PRECs. The market valuation is measured by Tobin's Q (Cannon and Vogt, 1995; Zheng and Zhu, 2021; etc.). To investigate the three channels, including the cash flow channel, the idiosyncratic risk channel, and the valuation channel, we further consider operating performance, financial performance, and risk measurement. The firm's operational performance is measured by the net operating income (NOI/TA), and earnings before interest and taxes as a percentage of the total assets (EBIT/TA). The financial performance is measured by general & administrative expenses (G&A/TA), and interest expenses scaled by total assets (IE/TA). The systematic risk of a firm is measured by its stock market beta (Kallberg et al., 2000; Muckenhaupt et al., 2023b), and the idiosyncratic risk, is measured by the variations that cannot be explained by systematic risk (Chaudhry et al., 2004; Chiang et al., 2009; etc.). Both are computed by a single-factor model, where we measure the responsiveness of a firm's returns to fluctuations in stock market returns as the conditional factor loading ($\beta_{i,t}^{stock}$) for stock *i* and year *t*:

Equation 5.1: Single-Factor Model

$$r_{i,t,d}^{stock} - r_{f,t,d} = \alpha + \beta_{i,t}^{stock}\left(MKT_{t,d} - r_{t,d}\right) + \epsilon_{t,t,d},$$

where $r_{i,t,d}^{stock}$ is the daily return in day d in year *t* for firm *i* and $r_{f,t,d}$ is the corresponding risk-free return. $\hat{\beta}_{i,t}^{stock}$ captures the systematic risk and the standard deviation of $\hat{\epsilon}_{t,t,d}$.

As ESG scores are multidimensional indexes derived from environmental, social, and governance disclosures, the possibility exists that one dimension can eliminate opposing effects of another dimension. To avoid this problem, we create an overall ESG performance score derived from the three corresponding subcomponents (*E, S,* and *G*) retrieved from Bloomberg Professional. *E* measures the environment score of a firm *i* in the period *t*. *S* measures the social score of a firm *i* in period *t*, and *G* is the average of *G1* and *G2*, where *G1* measures the governance score related to the board structure of a firm *i* in period *t*, while *G2* measures the governance score related to executive compensation of firm *i* in a period *t*. The overall ESG performance score is calculated by the average of *E, S,* and *G*. Furthermore, we consider the effect of each subcomponent separately. As a result of this classification, it is possible to determine which dimension of the ESG score has the strongest impact on the valuation and performance of PRECs.

Previous literature has shown that the performance of PRECs can be influenced by characteristics such as firm size, firm age, financial leverage, and asset growth. We are guided by the studies of Feng and Wu (2021), Aroul et al. (2022), and Chacon (2024), and control for the following firm characteristics: Firm age defined as the age of a PREC since its IPO date, firm size defined by the total assets of a company, financial leverage defined as the total liabilities divided by the equity (L/E). The asset growth is calculated by the annual change in total assets.

Table 5.1: Descriptive Statistics

	Mean	SD	Max	Min
ESG data				
ESG Score	52.720	19.430	99.380	6.200
E Score	54.570	28.430	100.000	2.900
S Score	52.910	28.490	100.000	3.800
G Score	51.990	24.170	100.000	0.000
Performance data				
NOI/TA	0.039	0.022	0.157	-0.213
EBIT/TA	0.047	0.064	2.495	-1.082
G&A/TA	0.017	0.048	0.465	0.001
IE/TA	0.013	0.010	0.089	-0.001
Tobin's Q	1.065	0.553	4.920	-0.260
Systematic Risk	0.544	0.518	2.976	-0.388
Idiosyncratic Risk	0.014	0.008	0.075	0.000
Firm characteristics				
FS (Mio $) (Total Assets)	63.640	194.740	2,301.160	0.060
Age (IPO established)	18.000	10.060	70.00	3.000
Leverage	1.320	1.810	48.350	-5.450
Asset Growth (%)	10.580	18.460	157.910	-49.830

Description: This table presents the descriptive statistics ESG data, performance data, and firm characteristics for the full sample of PRECs during the 2015-2021 sample period for PRECs that report ESG indicators. The ESG data includes the ESG score and its subcomponents, the E score, S score, and G score. The performance data are explained by the NOI/TA, FFO/TA, G&A/TA, IE/TA, and Tobin's Q. The firm characteristics consist of the firm size (Total Assets), the firm age (IPO established), the financial leverage (Total Liabilities/Total equity), and the asset growth.

Table 5.1 presents the descriptive statistics of our model. The average ESG performance score is 52.72. The G score measures an average score of 51.990, which is slightly lower than the scores of E (54.570) and S (52.910). Turning to the performance indicators, we see averages of 0.039 and 0.047 for NOI/TA and EBIT/TA, respectively. G&A/TA shows a mean of 0.017, while the interest expenses as a percentage of total assets are characterised by an average of 0.013. Tobin's Q has a mean of 1.065 and a standard deviation of 0.553. The systematic risk, measured by PREC's stock market beta, shows an average value of 0.544. The idiosyncratic risk reveals an average value of 0.014.

5.4 Method

5.4.1 Impact on Market Valuation

An unbalanced panel regression is conducted to identify whether ESG has a significant impact on the market value of listed real estate firms, where the market valuation is measured by Tobin's Q:

Equation 5.2: ESG - OLS Model

$$y_{i,t} = \beta_0 + \beta_{ESG} ESG_{it} + \sum_{k=1}^{K} c_k X_{k,i,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ represents one of the dependent variables Tobin's Q. ESG_{it} is the ESG performance score. The $X_{k,i,t}$ represent a set of control variables, including the firm size, firm age, financial leverage, and asset growth. c_k is the respective coefficient vector. We also control for time and company-fixed effects.

To further bolster our results, we are taking the potential endogeneity of our ESG performance variable into account, because the firm with higher financial performance or higher market valuation may pay more attention to the sustainability issues. We use the country's sustainability policy development as the instrument. More specifically, it is defined as the SDG rating score provided by Cambridge University. Country policies force PRECs to disclose ESG information, which in turn urges PRECs to adopt ESG strategies. This will be considered by investors, who will prefer an ESG-oriented company over another. On the other hand, the country's sustainability policy will not be influenced by the performance of individual firms. The model is characterised by the following equations:

Equation 5.3: First-Stage Equation

$$ESG_{it} = \beta_0 + \beta_{\mathrm{CP}}\, CP_{i,t} + \sum_{k=1}^{K} c_k X_{k,i,t} + \varepsilon_{i,t}$$

Equation 5.4: Second-Stage Equation

$$y_{i,t} = \beta_0 + \beta_{\widehat{ESG}} \widehat{ESG} + \sum_{k=1}^{K} c_k X_{k,i,t} + \varepsilon_{i,t}$$

where $CP_{i,t}$ stands for the country's policy defined as our instrumental variable. All other components of equation 5.3 and 5.4 are equal to the components of equation 5.2.

Furthermore, we acknowledge that only 30% of PRECs have an ESG score, which may raise concerns that our sample is not randomly distributed, i.e., larger PRECs are more likely to focus on more developed ESG-conscious real estate markets. To account for the potential selection bias, we conduct a Heckman correction based on a two-stage model:

Equation 5.5: Probit-Model

$$P(Z_{it}) = \beta_0 + \beta_{\mathrm{GI}}\, GI_{i,t} + \sum_{k=1}^{K} c_k X_{k,i,t} + \varepsilon_{i,t}$$

Equation 5.6: Corrected Model

$$y_{i,t} = \beta_0 + \beta_{IM} IM_{i,t} + \beta_{\mathrm{ESG}} ESG_{it} + \sum_{k=1}^{K} c_k X_{k,i,t} + \varepsilon_{i,t}$$

where Z_{it} is a binary variable equal to 1 if the ESG performance score exists and 0 if not. $GI_{i,t}$ stands for Google Index defined as our instrumental variable. $IM_{i,t}$ is the inverse Mills ratio to correct the potential selection bias. In the first stage, we estimate the probability for a company to have an ESG score and use the country-level ESG awareness ($GI_{i,t}$) as the instrumental variable. ESG awareness is defined as a Google index, which measures the extent to which the term ESG is used or searched in each country. Thus, we consider the extent of sustainable investments in a country to be positively correlated with the level of ESG awareness. The integration of ESG will be implicit if companies, institutional investors, and stakeholders recognise the importance of integrating ESG strategies into their daily operations. On the other hand, it will not directly correlate with the shocks to individual real estate firm performance.

5.4.2 Impact on Intrinsic Value

To investigate the impact of ESG on the fundamental value, we follow Giese et al. (2019) and consider three transmission channels based on the discounted cash flow formula. The first channel is a systematic risk transmission channel, described as the valuation channel. Additionally, we delve into two idiosyncratic transmission channels, namely, the cash-flow channel and the idiosyncratic risk channel. Through a detailed analysis of these channels, we aim to shed light on the relationship between ESG factors and the fundamental value of PRECs.

According to Gregory et al. (2014), the cash-flow channel focuses on the profitability of the firm. It indicates that companies with a high ESG rating can be more competitive than their competitors due to more efficient use of resources, better human capital development, or better innovation management. Additionally, they state that companies with a high ESG score may perform better in developing long-term business plans and long-term incentive plans for senior management. In this paper, we consider several operating and financial cash flows, including net operating income, operating expenses, interest payments, and EBIT.

The idiosyncratic risk channel is founded on the works of Jo and Na (2012) and Oikonomou et al. (2012). Companies exhibiting robust ESG attributes typically maintain superior risk control and compliance standards both throughout the organization and within their management of the supply chain. Additionally, due to their enhanced risk control measures, companies with high ESG ratings experience fewer occurrences of significant incidents like fraud, embezzlement, corruption, or litigation cases. These incidents have the potential to significantly affect the company's value and, consequently, its stock price. Moreover, reduced occurrences of risk incidents ultimately result in diminished stock-specific downside or tail risk concerning the company's stock price.

The valuation channel has been discussed in studies by Eccles et al. (2014) and Gregory et al. (2014). They argue that a robust ESG profile contributes to elevated valuations through the following mechanism: Companies possessing a strong ESG profile demonstrate reduced vulnerability to systematic market shocks, resulting in lower systematic risk. A lower systematic risk leads to a lower cost of capital and thereby improves a firm's value. Thus, in this paper, we investigate the systematic risk of the firm's equity return, the stock beta, to test the valuation channel. To quantify the different effects of the above-explained channels, we apply Equations 5.2 to 5.6 but substitute the dependent variable y with various performance indicators.

5.5 Empirical Results

5.5.1 Impact on Market Valuation

Table 5.2 displays the relationship between ESG scores and the valuation of PRECs measured by Tobin's Q. Our findings consistently indicate a positive and statistically significant association between Tobin's Q and ESG, irrespective of the method used. To provide specific figures, a one percent increase in the ESG score results in valuation increases of 0.283%, 0.311%, or 0.266%, depending on whether OLS, 2SLS, or Heckman correction is applied. The positive impact is in line with other studies (Feng and Wu, 2021; Devine et al., 2022; etc.). Exceptions were identified by Buchanan et al. (2018) and Chacon et al. (2024). They documented a negative link between ESG performance scores and firm value during times of turbulence, i.e., the global financial crisis and the COVID-19 pandemic. The strong impact on a firm's valuation might be explained by the fact that the stock market appreciates any decent investment in ESG, by overvaluing the corresponding companies (Bofinger et al., 2022).

With respect to the coefficients of our control variables, we find that PRECs with smaller size, older age, and higher leverage ratio have a higher Tobin's Q. Table 5.2 also reports the results for the first stage regression for the 2SLS regression and Heckmann Regression. As shown in Table 5.2, the ESG score positively relates to the sustainability policy. The coefficient for the instrumental variable is significantly positive. The F statistic is significant and above 10, confirming the instrument's relevance. We also follow Acemoglu et al. (2001) 's easy-to-interpret version of the overidentification test (J-Test) to test the exogeneity. As reported in Table 5.2, the test statistic is insignificant, confirming the exogeneity of the instrument. For the

Heckmann correction model, the instrument of the google search index is also significantly positively related to the ESG performance and the F statistics also confirm the relevance of the instrument.

Table 5.2: Impact of ESG Score on Valuation

	Tobin's Q				
	OLS	TSLS		Heckman	
		Stage 1	Stage 2	Stage 1	Stage 2
I.M. Ratio					-0.183**
					(0.084)
IV (Policy)		0.007***			
		(0.001)			
IV (GIndex)				0.016***	
				(0.080)	
ESG Score	0.283***		0.311***		0.266***
	(0.070)		(0.078)		(0.071)
Size	-0.225***	0.025***	-0.226***	0.606***	-0.304***
	(0.013)	(0.004)	(0.014)	(0.028)	(0.032)
Age	0.212***	-0.009	0.212***	0.137**	0.190***
	(0.024)	(0.011)	(0.024)	(0.053)	(0.027)
Leverage	0.009*	-0.016***	0.010*	-0.058***	0.022***
	(0.005)	(0.005)	(0.005)	(0.011)	(0.007)
Asset growth	0.001	-0.000	0.001	-0.000	0.001*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes
F-Statistic		52.29***		44.700***	
J-Test		0.000			
Observations	1258	1257	1257	1227	1227
R^2	0.423	0.107	0.422	0.138	0.417

*Description: This table reports the results based on a panel of international PRECs across 2015 and 2021 by using OLS, 2SLS, and Heckman two-stage correction. The dependent variable is Tobin's Q to measure the valuation of the PRECs. The variable of interest is the ESG Score. We control for size, age, leverage, and asset growth. We also include fixed effects of time and company. IV stands for the instrumental variable. Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

5.5.2 Impact on Intrinsic Value

Although it is quite evident that ESG performance can positively affect the market valuation of PREC equities, it is still a question whether the intrinsic value is also influenced. Tables 5.3, 5.4, and 5.5 investigate the three channels but use different identification strategies. Table 5.3 presents the results based on OLS estimation. As shown in Table 5.3, a rising ESG score leads to decreasing NOI and IE. The results are in line with the existing literature. For instance, Feng and Wu (2021) found a negative impact of ESG on the cost of capital, while Chacon et al. (2024) documented a negative relationship between ESG and NOI. Moving to our G&A/TA and EBIT/TA models, we find no significant impact, which is also consistent with Devine and Yönder (2021). Since EBIT/TA and idiosyncratic risk are not significantly influenced by the ESG score, we argue that neither the cash flow channel nor the idiosyncratic risk channel indicates a higher intrinsic value. Additionally, within the OLS framework, it appears that companies with a higher ESG score do not demonstrate a reduced level of systematic risk. This indicates that the intrinsic value of these firms may not be positively impacted, or could even be negatively affected, by their ESG score through the valuation channel.

As mentioned before, OLS estimates may suffer from the problem that firms with better performance or a higher valuation are more likely to participate in the ESG disclosure program and achieve better ESG scores. Therefore, we perform 2SLS regression. After employing the county-level sustainability index as the instrument, we obtained slightly different results from the OLS regression.[41]

First, with regard to the cash flow channel, in addition to observing a negative influence of ESG on NOI and IE, we also detect a positive effect of ESG on G&A. However, the coefficient for

[41] F-statistic for each model is significant at 5% level (Stock and Yogo, 2002), confirming the relevance of the instrument. The J-test is statistically insignificant, confirming the exogeneity of the instrument.

EBIT to total assets remains statistically insignificant, indicating that ESG does not influence the intrinsic value via the cash flow channel. Second, for the idiosyncratic risk channel, the 2SLS method yields consistent results with the OLS method. Third, with regard to the valuation channel, the influence on the systematic risk of PRECs becomes noticeable. Our analysis reveals a significantly positive coefficient for the ESG score. Thus, after addressing the endogeneity issue, the ESG performance is significantly related to the intrinsic value via the valuation channel.

Table 5.3: Impact of ESG Score on Intrinsic Value: OLS Results

	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
ESG Score	-0.022***	-0.101	-0.003***	-0.005	-0.159	0.003
	(0.006)	(0.206)	(0.001)	(0.009)	(0.111)	(0.002)
Size	-0.006***	-0.169***	-0.002***	-0.003	0.099**	-0.000
	(0.002)	(0.058)	(0.001)	(0.002)	(0.038)	(0.001)
Age	0.008**	0.426***	-0.017***	-0.006	0.123*	0.000
	(0.003)	(0.121)	(0.003)	(0.004)	(0.064)	(0.000)
Leverage	0.002*	0.139***	0.000	0.000	0.094***	0.000
	(0.001)	(0.025)	(0.000)	(0.000)	(0.023)	(0.000)
Asset growth	-0.000	0.004	-0.000***	0.000	-0.001	0.000
	(0.000)	(0.003)	(0.000)	(0.000)	(0.001)	(0.000)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	518	382	859	972	573	573
R^2	0.090	0.409	0.225	0.042	0.226	0.109

*Description: This table reports the results based on a panel of international PRECs across 2015 and 2021 by using OLS. The dependent variable are NOI/TA, G&A/TA, IE/TA, EBIT/TA, systematic risk, and idiosyncratic risk. The variable of interest is the ESG Score. We control for size, age, leverage, and asset growth. We also include fixed effects of time and company. Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

Table 5.4: Impact of ESG Score on Intrinsic Value: 2SLS Results

	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
ESG Score	-0.027***	0.180***	-0.009***	0.005	-0.272**	0.005
	(0.005)	(0.005)	(0.002)	(0.005)	(0.119)	(0.003)
Size	0.001**	-0.002***	-0.001***	0.003***	0.118***	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.039)	(0.001)
Age	0.001	-0.007***	-0.001**	-0.003*	0.113*	0.001
	(0.002)	(0.000)	(0.001)	(0.002)	(0.065)	(0.002)
Leverage	-0.001	0.003***	-0.001***	-0.001***	0.087***	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.023)	(0.000)
Asset growth	-0.000	0.000	-0.000	-0.000	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
IV	0.008***	0.009***	0.009***	0.006***	0.005**	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
J-test	-0.002	-0.002	-0.002	-0.010	0.041	0.002
F-Statistic	31.19***	15.52***	15.15***	25.02***	16.86***	14.99***
Observations	519	383	860	972	573	573
R^2	0.090	0.409	0.225	0.040	0.255	0.165

*Description: This table reports the results based on a panel of international PRECs across 2015 and 2021 by using 2SLS. The dependent variable are NOI/TA, G&A/TA, IE/TA, EBIT/TA, systematic risk, and idiosyncratic risk. The variable of interest is the ESG Score. We control for size, age, leverage, and asset growth. We also include fixed effects of time and company. IV stands for Instrumental Variable (Country Policy). Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

Table 5.5 presents the results of the Heckman two-stage correction. The results are quite in line with results based on the 2SLS estimation. The correction term, I.M. Ratio, is mostly insignificant in Table 5.5, except for the models of NOI/TA, G&A/TA, and systematic risk, indicating a low likelihood of a selection bias[42]. While most of the results are similar, there are a few reversed results, which are likely a result of selection bias. The previously significant relationship between the ESG score and the *G&A/TA* becomes insignificant. Overall, the Heckman two-stage regression analysis indicates that ESG performance lacks a significant

[42] The F-statistic is similar to Table 4. Each model shows a value over 3.5, indicating the relevance of the instrument at a 5% significance level (Stock and Yogo, 2002).

connection to the fundamental valuation of PREC securities, consistent with the results obtained using the OLS model.

Table 5.5: Impact of ESG Score on Intrinsic Value: Heckman Results

	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
I.M. Ratio	0.017*	0.020**	-0.005	-0.014*	-0.283***	-0.002
	(0.010)	(0.009)	(0.004)	(0.007)	(0.105)	(0.002)
ESG Score	-0.019***	0.012	-0.008***	0.009*	-0.109	0.002
	(0.005)	(0.004)	(0.002)	(0.005)	(0.107)	(0.002)
Size	0.004**	-0.000	-0.002***	0.005**	-0.061	-0.001
	(0.002)	(0.001)	(0.000)	(0.002)	(0.054)	(0.001)
Age	0.001	-0.001	-0.003***	-0.001	-0.0	-0.000
	(0.002)	(0.003)	(0.001)	(0.002)	(0.068)	(0.001)
Leverage	-0.000	0.004***	-0.000	-0.001***	0.169***	0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.028)	(0.001)
Asset growth	-0.000	-0.000	-0.000***	-0.000	0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
IV	0.006**	0.012***	0.009***	0.016***	0.032***	0.032***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
F-Statistic	5.599**	8.798***	3.555**	6.088**	12.19***	5.433**
Observations	519	383	860	972	573	573
R^2	0.092	0.417	0.225	0.043	0.400	0.125

*Description: This table reports the results based on a panel of international PRECs across 2015 and 2021 by using a Heckman two-stage correction. The dependent variable are NOI/TA, G&A/TA, IE/TA, EBIT/TA, systematic risk, and idiosyncratic risk. The variable of interest is the ESG Score. We control for size, age, leverage, and asset growth. We also include fixed effects of time and company. IV stands for Instrumental Variable (Google Index). Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

5.5.3 Subcomponent Analysis

Although we did not find a significant effect of aggregated ESG performance on the intrinsic value of LRE firms, it is not necessary to assume that the finding will remain the same if we analyse each factor separately. Table 5.6 presents the findings pertaining to the environmental subcomponent E. In Panel A, we display the outcomes derived from an OLS analysis. Similar to the analyses conducted for the overall ESG score, a noteworthy and statistically significant positive relationship exists between the E Score and Tobin's Q. However, we do not observe any significant influence of the E Score on EBIT or risk. Instead, we identify a significant negative impact on the ratios of NOI/TA and IE/TA. A higher E score negatively correlates with net operating income, which may be explained by the additional costs associated with this practice. However, the negative effect is offset by reduced interest payments, indicating that the ESG premium largely arises from reduced financial costs, particularly given the relatively low interest rates in various green loans. Consequently, we do not find clear evidence that ESG significantly improves profitability. Panel B displays the outcomes from the 2SLS analysis, while Panel C portrays the findings resulting from the Heckman two-stage correction. In both scenarios, the findings support the conclusions made in Panel A. However, a positive and significant relationship is observed for G&A/TA in Panels B and C, which was not the case in Panel A. Additionally, although EBIT/TA showed no significant relationship in Panel A and B, it exhibits a positive and significant relationship in the selection bias corrected model represented in Panel C. Nonetheless, the coefficient's significance at only the 10% level suggests a limited support for the impact that the E score has on the firm's intrinsic value.

Table 5.6: Impact of E Score on Intrinsic Value

Panel A: OLS Model

	Market Valuation	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	Tobin's Q	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
E Score	0.167*** (0.048)	-0.027*** (0.006)	-0.108 (0.218)	-0.002** (0.001)	-0.011 (0.009)	-0.089 (0.117)	-0.001 (0.005)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1258	518	382	859	1006	573	573
R^2	0.423	0.085	0.408	0.242	0.011	0.247	0.121

Panel B: 2SLS Model

	Market Valuation	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	Tobin's Q	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
E Score	0.193*** (0.054)	-0.018*** (0.000)	0.007** (0.003)	- 0.010*** (0.001)	0.004 (0.003)	-0.205 (0.128)	0.164 (0.118)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV	0.008*** (0.001)	0.012*** (0.001)	0.014*** (0.001)	0.013*** (0.001)	0.008*** (0.001)	0.007*** (0.002)	0.007*** (0.002)
J-Test	0.007	-0.000	-0.000	-0.000	-0.000	0.043	-0.000
F-Statistic	58.66***	22.54***	14.46***	14.27***	24.74***	11.28***	10.58***
Observations	1257	519	383	860	972	573	573
R^2	0.423	0.085	0.408	0.242	0.040	0.247	0.121

Panel C: Heckman Correction

	Market Valuation	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	Tobin's Q	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
I.M. Ratio	-0.180** (0.084)	0.016 (0.010)	0.021** (0.009)	-0.006 (0.004)	0.013* (0.007)	-0.287*** (0.107)	-0.002 (0.002)
E Score	0.157*** (0.048)	-0.012*** (0.003)	0.005* (0.003)	-0.007*** (0.001)	0.005* (0.003)	-0.048 (0.113)	0.003 (0.002)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV	0.016*** (0.002)	0.006** (0.003)	0.011*** (0.002)	0.008*** (0.002)	0.015*** (0.002)	0.031*** (0.002)	0.032*** (0.002)
F-Statistic	77.11***	5.444**	7.932***	6.638**	6.038**	11.95***	3.089*
Observations	1257	519	383	860	972	573	573
R^2	0.419	0.088	0.415	0.244	0.043	0.401	0.125

*Description: This table reports the results based on a panel of international PRECs across 2015 and 2021 by using an OLS (Panel A), a 2SLS (Panel B), and a Heckman two-stage correction (Panel C). The dependent variables are NOI/TA, G&A/TA, IE/TA, EBIT/TA, systematic risk, and idiosyncratic risk. The variable of interest is the E Score. We control for size, age, leverage, and asset growth. We also include fixed effects of time and company. IV stands for Instrumental Variable (Country Policy or Google Index). Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

Table 5.7 presents the findings related to the social subcomponent S, with Panel A containing the results obtained through OLS analysis. Once more, we discern a favourable influence of the social component on Tobin's Q. Simultaneously, we note a substantial adverse effect on the systematic risk of PRECs. Panel B and Panel C largely validate the outcomes observed in Panel A. In Panel B, there is evidence of an impact of the S score on G&A/TA and EBIT/TA, while in Panel C, we do not observe a negative impact on the net operating income. The impact of the S component on the systematic risk remains statistically significant even after the Heckmann correction. In sum, we find that the improved market valuation by good performance of social factors is explained by the valuation channel – reduced systematic risk. The foundational elements of Corporate Social Responsibility (CSR), which include environmental sustainability, community engagement, and ethical governance, hold significant relevance within the real estate sector (Newell and Lee 2012; Newell et al. 2011). The core function of the real estate industry is to supply spaces that support commercial activities, residential life, and recreational pursuits. The connection between the real estate domain and the environmental landscape is deeply intertwined, direct, and frequently manifests in a tangible integration (Chiang et al., 2019). Engaging in activities to enhance social responsibility helps strengthen relationships with stakeholders, reducing the business risk for firms. For instance, improving the performance of social components sometimes requires participating in social initiatives, which can provide organizations with access to human resources, social resources, and capital at a low cost, thereby significantly decreasing the risk of failure and improving organizational performance (Udayasankar, 2008). Turker (2009) finds that these activities can reduce negative stakeholder assessments and foster positive attitudes among employees and customers. Kim et al. (2015) argue that enhancing social performance can lead to increased employee commitment, higher levels of legitimacy within the community, and improved governmental relations.

Table 5.7: Impact of S Score on Intrinsic Value

Panel A: OLS Model

	Market Valuation	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	Tobin's Q	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
S Score	0.161*** (0.047)	-0.025*** (0.006)	0.065 (0.213)	-0.003*** (0.001)	-0.001 (0.010)	-0.235** (0.105)	0.002 (0.002)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1258	518	382	859	1006	573	573
R^2	0.424	0.063	0.417	0.210	0.011	0.268	0.119

Panel B: 2SLS Model

	Market Valuation	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	Tobin's Q	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
S Score	0.203*** (0.057)	-0.006* (0.004)	0.019*** (0.004)	-0.004*** (0.001)	0.008** (0.004)	-0.325** (0.113)	0.004 (0.003)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV	0.003** (0.001)	0.010*** (0.001)	0.010*** (0.001)	0.009*** (0.001)	0.006*** (0.001)	0.005** (0.002)	0.005** (0.002)
J-Test	0.008	-0.000	-0.000	-0.000	-0.001	0.043	-0.000
F-Statistic	43.18***	24.96***	14.74***	16.87***	17.44***	8.848***	7.202**
Observations	1257	519	383	860	972	573	573
R^2	0.421	0.063	0.417	0.210	0.042	0.268	0.140

Panel C: Heckman Correction

	Market Valuation	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	Tobin's Q	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
I.M. Ratio	-0.185** (0.084)	0.016 (0.010)	0.019** (0.009)	-0.005 (0.004)	-0.000 (0.011)	-0.262** (0.106)	-0.002 (0.002)
S Score	0.145*** (0.048)	-0.003 (0.003)	0.010*** (0.003)	-0.003** (0.001)	-0.001 (0.009)	-0.169* (0.102)	0.002 (0.002)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV	0.016*** (0.002)	0.006** (0.002)	0.011*** (0.002)	0.008*** (0.002)	0.032*** (0.001)	0.031*** (0.001)	0.032*** (0.002)
F-Statistic	62.01***	2.487*	4.446**	3.462*	5.971**	12.45***	4.159**
Observations	1257	519	383	860	972	573	573
R^2	0.419	0.067	0.424	0.209	0.008	0.409	0.123

*Description: This table reports the results based on a panel of international PRECs across 2015 and 2021 by using an OLS (Panel A), a 2SLS (Panel B), and a Heckman two-stage correction (Panel C). The dependent variables are NOI/TA, G&A/TA, IE/TA, EBIT/TA, systematic risk, and idiosyncratic risk. The variable of interest is the S Score. We control for size, age, leverage, and asset growth. We also include fixed effects of time and company. IV stands for Instrumental Variable (Country Policy or Google Index). Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

Finally, Table 5.8 presents findings related to the G score. In Panel A, we do not find any significant impact on the valuation or risk of PRECs; however, we do observe a significant negative impact on IE/TA. If we use 2SLS method (Panel B), we note a negative and significant impact of the G Score on NOI/TA, while also observing a negative impact on the systematic risk, but the effect on the systematic risk is rather weak. Different from E and S scores, the G score plays a marginal effect on the market valuation and intrinsic value of the stocks. This can be explained by Siahaan (2013), who notes that the functionality of an audit committee and the proportion of independent commissioners have no significant effect on a company's market value. Similarly, Debby et al. (2014) observe that managerial ownership and the role of an audit committee negatively impact a firm's value.

Table 5.8: Impact of G Score on Intrinsic Value

Panel A: OLS Model

	Market Valuation	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	Tobin's Q	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
G Score	-0.078 (0.054)	-0.005 (0.007)	-0.101 (0.191)	-0.003*** (0.001)	0.000 (0.009)	-0.133 (0.116)	0.003 (0.002)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1258	518	382	859	1002	573	573
R^2	0.415	0.084	0.407	0.203	0.011	0.257	0.121

Panel B: 2SLS Model

	Market Valuation	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	Tobin's Q	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
G Score	0.078 (0.060)	-0.017*** (0.004)	0.003 (0.003)	0.001 (0.001)	-0.005 (0.004)	-0.243* (0.127)	-0.000 (0.002)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV	0.006*** (0.001)	0.004*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.002* (0.002)	0.002* (0.002)
J-Test	0.007	-0.000	-0.000	-0.000	-0.001	0.044	0.000
F-Statistic	42.24***	12.31***	9.523***	8.489***	9.799***	15.18***	15.69***
Observations	1258	519	383	860	972	573	573
R^2	0.382	0.084	0.407	0.203	0.017	0.257	0.121

Panel C: Heckman Correction

	Market Valuation	Panel A: Cash Flow Channel				Panel B: Valuation Channel	Panel C: Idiosyncratic Risk Channel
	Tobin's Q	NOI/TA	G&A/TA	IE/TA	EBIT/TA	Systematic Risk	Idiosyncratic Risk
I.M. Ratio	-0.213** (0.085)	0.017 (0.010)	0.021** (0.009)	-0.003 (0.004)	0.000 (0.012)	-0.296*** (0.106)	-0.002 (0.002)
G Score	-0.084 (0.054)	-0.013*** (0.003)	0.002 (0.003)	0.000 (0.001)	0.001 (0.009)	-0.131 (0.110)	0.003 (0.002)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV	0.016*** (0.002)	0.006** (0.002)	0.011*** (0.002)	0.008*** (0.002)	0.031*** (0.001)	0.031*** (0.001)	0.032*** (0.002)
F-Statistic	3.008*	5.324**	7.657***	5.241**	6.051**	11.89***	6.284**
Observations	1258	519	383	860	972	573	573
R^2	0.412	0.086	0.415	0.201	0.008	0.400	0.123

*Description: This table reports the results based on a panel of international PRECs across 2015 and 2021 by using an OLS (Panel A), a 2SLS (Panel B), and a Heckman two-stage correction (Panel C). The dependent variables are NOI/TA, G&A/TA, IE/TA, EBIT/TA, systematic risk, and idiosyncratic risk. The variable of interest is the G Score. We control for size, age, leverage, and asset growth. We also include fixed effects of time and company. IV stands for Instrumental Variable (Country Policy or Google Index). Standard errors are in parentheses. ***. **, * denotes significance level at 1%, 5% or 10%, respectively.*

5.6 Conclusion

Our paper contributes to the existing literature on the relationship between ESG ratings and the valuation of Public Real Estate Companies (PRECs), by investigating the impact on the market valuation and intrinsic value. The market valuation is quantified by Tobin's Q, while the intrinsic value is measured by cash flow-, idiosyncratic-, and systematic risks. Our instrument-based methodology (2SLS) allows us to mitigate the problems of endogeneity that often arise in the literature. Furthermore, we bolster our results by conducting a Heckman two-stage correction.

We observe a sample of PRECs from 2015 to 2021 in 38 countries and find a positive correlation between overhead ESG metrics (including their sub-components) and firms' market valuation. Furthermore, when it comes to intrinsic value, we find evidence of an impact through the valuation channel. The cash flow channel, which encompasses the profitability and earnings of PRECs, consistently show significant links between ESG factors and earnings before interest and taxes and net operating income. Additionally, the impact of ESG on the other two channels are also marginal. The idiosyncratic risk channel does not reveal any significant impact of ESG or its subcomponents on idiosyncratic risk models. Regarding the valuation channel, the impact on systematic risk is negatively significant in the 2SLS framework. However, after correcting for potential selection bias, this effect disappears.

Thus, by focusing on the aggregated ESG performance, we may conclude that sustainable practices can generate a “Halo Effect”, bolstering a firm's reputation and positively influencing investor perception (Barka et al., 2023). This favourable perception, in turn, fosters investment behaviour and attributes value to companies with high ESG ratings. Investors may also perceive that firms with better ESG ratings will have greater growth opportunities in the future. These expectations of market investors can affect market efficiency and interfere with the rational allocation of resources.

However, we also find noticeable differences in the roles played by the three components in the firms' financial performance. E and S performance are significantly positively related to Tobin's Q, while we do not find any significant results when analysing the impact of the G score on market valuation. Additionally, we also find a significant negative relationship between the S score and systematic risks, indicating that the performance of the S score can positively affect the intrinsic value of the firm by reducing the riskiness of the firm's equity. In other words, the S score influences fundamental value via the valuation channel rather than being linked to stock price misvaluation. However, for the E score, its positive impact on market valuation fails to link to any of the three channels. Hence, activities in the S component show importance for PRECs who aim to enhance both intrinsic value and market valuation.

6. Conclusion

6.1 Summary of Main Results

The four Essays present different aspects of LRE's capability to hedge against inflation, and further, enhance understanding on the systematic risk of tenant industry sectors as well as the impact of ESG on market and intrinsic value. Each Essay offers additional insights into the current research landscape, yet more research and enhancements are necessary to deepen the understanding. Some limitations will be addressed in Section 6.2. Overall, those four Essays contribute to understanding the LRE behaviour and role in a context of protection against inflation. Furthermore, the research helps to understand how the systematic risk of tenant's industry sector is capitalised in real estate equity returns. Last but not least, the impact of ESG scores on the market valuation as well as the intrinsic value are identified.

Essay 1 analyses whether listed real estate could be used to hedge against inflation. Overall, the study confirms the desired inflation-hedging properties of LRE. The finding indicates, that listed real estate is an adequate hedge against inflation, although mainly against expected inflation and in the long-term. However, the short-term hedging ability tends to disappear during turbulent economic periods. The study also found that the inflation hedging capability of LRE varies across different countries. A disaggregation of inflation into its components of energy, food, core, and housing CPIs indicates that LRE adequately hedged against core, food, and housing inflation in Japan. In Australia, positive hedging characteristics are observed in association with energy inflation. Conversely, perverse hedging effects are noted for food and core inflation in the U.S., and for energy inflation in the U.K..

The research furthermore shows that in the long-run hedging quality are mainly attributable to value appreciation rather than from income returns. In the short-run, the capability to hedge against expected inflation is observed in price returns, while income returns display hedging capabilities against unexpected inflation. Robustness tests incorporating a rent-adjusted inflation index reveal a superior hedging ability relative to the case when an unadjusted inflation index is used. This finding suggests that previous studies perhaps downplayed the hedging potential of LRE, and which primarily utilised an unadjusted inflation index. Finally, inflation-hedging portfolios provide more realistic and less extreme allocations to listed real estate than alternatives which use the standard mean–variance approach for portfolio construction.

Essay 2 reveals that the response of LRE returns to inflation shocks is strongly regime-dependent. In stable economic times, LRE returns exhibit a consistent positive relationship with inflation shocks, both over the short- and long-terms. LRE appears to exhibits a better hedging capacity over the long-term than it is the case in the short-term. In the short-term, the model yielded a significant negative inflation-hedging coefficient during more challenging economic environment. However, in the long-term, the model establishes a positive relationship between LRE returns and inflation which persists at all considered times. The research effectively captures the changes in the hedging ability of LRE during economic crises, such as the dot-com bubble, the global financial crisis (GFC), the COVID-19 pandemic, and the start of the war in Ukraine. These crises are visible in the regime-switching analysis, demonstrating the importance of considering economic conditions when assessing LRE’s inflation-hedging properties. It is furthermore found that the direct real estate market displays a delayed albeit a significant response to inflation and where profound effects and responses seem to be emerging approximately six months after a shock occurrence. This lag is attributed to the market’s illiquidity, long-term leases, and information asymmetries. Over time, the impact of inflation on direct real estate varies, with minimal short-term effects but a more substantial long-term impact.

In **Essay 3** the impact of the tenant's industrial sector risks upon the performance of PRECs is examined. The previous academic literature usually attempted to measure asset quality of real estate firms using either tenant credit worthiness or the location of the assets. The research proposes an extension to these measurements by inclusion of the systematic risk of the industry in which the tenants operate, as of a new additional risk factor for assessing PRECs' risk landscape. The findings suggest that the systematic risk of tenant's industry sectors appears to be capitalised, implying that it is being a component of the realised equity returns of PRECs. Furthermore, it also appears that firms exposed to tenants coming from more volatile industries exhibit significantly higher returns as a one-standard-deviation increase in the sector beta of tenants is associated with a 6.18% increase in the equity return. Therefore, a hypothetical long and short trading strategy which is driven by the tenant sector risk in order to test implications of the results is considered. The theoretical implementation of such trading strategy suggests that investors can earn a benchmark-adjusted return of 3.68% per year by holding or buying stocks of companies with high tenant sector risk and selling stocks with low tenant sector risk.

Essay 4 investigates the impact of ESG ratings on the market valuation and intrinsic value of PRECs. The market valuation is quantified by Tobin's Q, while the intrinsic value is measured by cash flow-, idiosyncratic-, and systematic risks. A 2SLS approach is conducted to mitigate endogeneity, while a Heckman two stage correction was employed to correct for a possible selection bias. The model establish a positive association between comprehensive ESG metrics and market valuation. ESG factors appear to significantly impact earnings (cash flow channel), yet their effect on idiosyncratic risk seems not to be insignificant. In the 2SLS model the influence on systematic risk appears to be negative but which disappears after the implementation of the Heckman correction. Sustainable practices appear to generate a "Halo Effect", improving reputation and investor perception, which potentially may be leading to inflated market valuations. Environmental (E) and Social (S) scores significantly boost Tobin's

Q, unlike Governance (G) scores. Additionally, the S score uniquely reduces systematic risks, by augmenting both intrinsic and market values, underlying its' importance. This is in contrast to the E score's limited channel influence.

6.2 Limitations and Avenues for Future Research

When it comes to inflation hedging (**Essay 1 and 2**), it remains to be seen whether central banks' policies are successful in respect of tracking stated targeted inflation of approximately 2%. It is however, increasingly observed that a greater number of investors are adopting machine learning techniques to construct their portfolios. It is anticipated that this trend will continue, potentially for strategies such as building inflation-hedging portfolios. Emerging research, such as that by Mirza et al. (2023), suggests that these innovative techniques may surpass traditional models in performance. However, it's crucial to acknowledge that machine learning techniques can lead to inaccuracies when data is flawed or models are not adequately adapted to market specifics. This evolving trend might be particularly useful for policymakers looking to enhance inflation forecasts and for investors aiming to optimise their portfolio strategies, highlighting the need for careful application and ongoing evaluation

Essay 3 relies on data from PRECs that are willing to disclose tenant information, which may not be fully representative of PRECs true universe. The firms that do not report such details might have systematically different characteristics or performance metrics, potentially implying that a selection bias might have been unknowingly introduced in the research. It is important to note that the study period, spanning from 2010 to 2019, includes the recovery phase following the global financial crisis, thereby covering periods of economic stability. Future research could explore how the capitalization of systematic risk from tenant sectors behaves during periods of economic distress or boom, such as the COVID-19 pandemic or the 2008 financial crisis. This investigation could address additional research gaps and provide deeper insights into sector-specific risk dynamics under varying economic conditions. Furthermore, the study utilises sector betas as a measure of risk, which assumes that the classification of industries (and thus the associated risk profiles) remains stable over time. Therefore, the model does not dynamically account for shifts in economic dynamics or industry characteristics that alter risk profiles. Another limitation of the study is its focus on the correlation between tenant sector risk and PREC performance, where establishing meaningful causality can pose a challenge. Interpreting the direction of the effect may be complicated by potential confounding variables, such as overall economic conditions that could simultaneously influence both tenant risk and PREC performance. Finally, while the trading strategy proposed in the paper is theoretically robust, its implementation in practice may encounter various challenges such as transaction costs, liquidity issues, and the timing of trades - aspects that the paper did not aim to fully explore.

In **Essay 4**, while the use of country-level sustainability policies and ESG awareness as instruments aims to address endogeneity in the analysis of ESG scores and firm performance, these may not completely isolate the ESG effects, due to potential correlations with other unobserved variables affecting firm performance. A more suitable approach might involve using company-level instruments, which could more directly relate to individual firm's activities and decisions, thus providing a clearer, more precise isolation of ESG impacts from other external factors. This adjustment could enhance the robustness of the causal inferences drawn from the analysis and could give more avenues for future research.

6.3 Concluding Remarks

This dissertation makes a significant contribution to the literature on LRE by adopting an unconventional research perspective as its vantage point. The four Essays cover diverse topics, contributing to several distinct streams of LRE literature: LRE's capability to hedge against inflation, the capitalization of tenant sector risk in PRECs returns, and the impact of ESG scores on the valuation of PRECs. Overall, the findings enhance the understanding of LRE in different aspects, benefiting various stakeholders such as corporate decision-makers, investors, and policymakers.

This dissertation deals with many aspects that can be of considerable importance in the practical realm. Firstly, **Essays 1** sheds light on investment strategy components that private and institutional investors can adopt to understand their risk exposure and protect themselves against a real loss. This is followed by **Essay 2**, which looks at a similar topic but focuses more on the effects of inflation shocks. **Essay 3** provides some answers on how investors should look at their allocation to tenant sectors as this is capitalised into the return of PRECs. **Essay 4** discusses the recent trend of ESG and how ESG metrics can impact the valuation of PRECs.

It can be seen from this dissertation that listed real estate vehicles are multifaceted and interesting due to their dual character. I would like to end this dissertation with the appeal for further research detail effort in this growing area of the property industry, not only for reasons of diversification, but also due to the fact that indirect property purchases are also a factor which determine risk structure.

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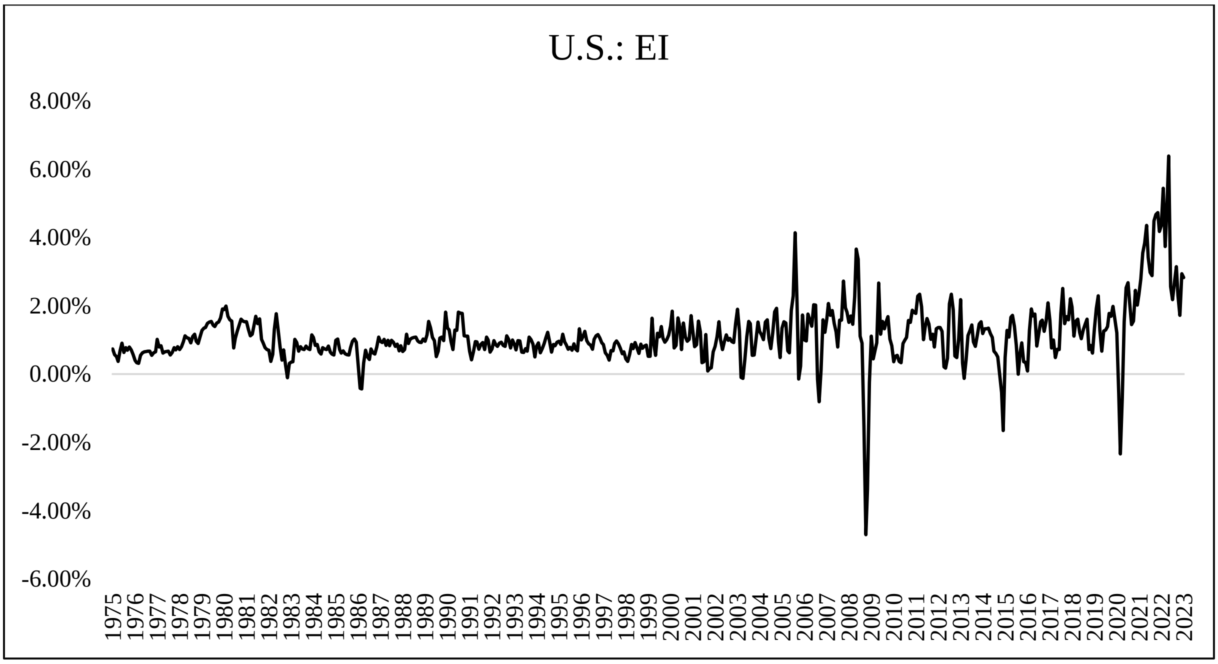
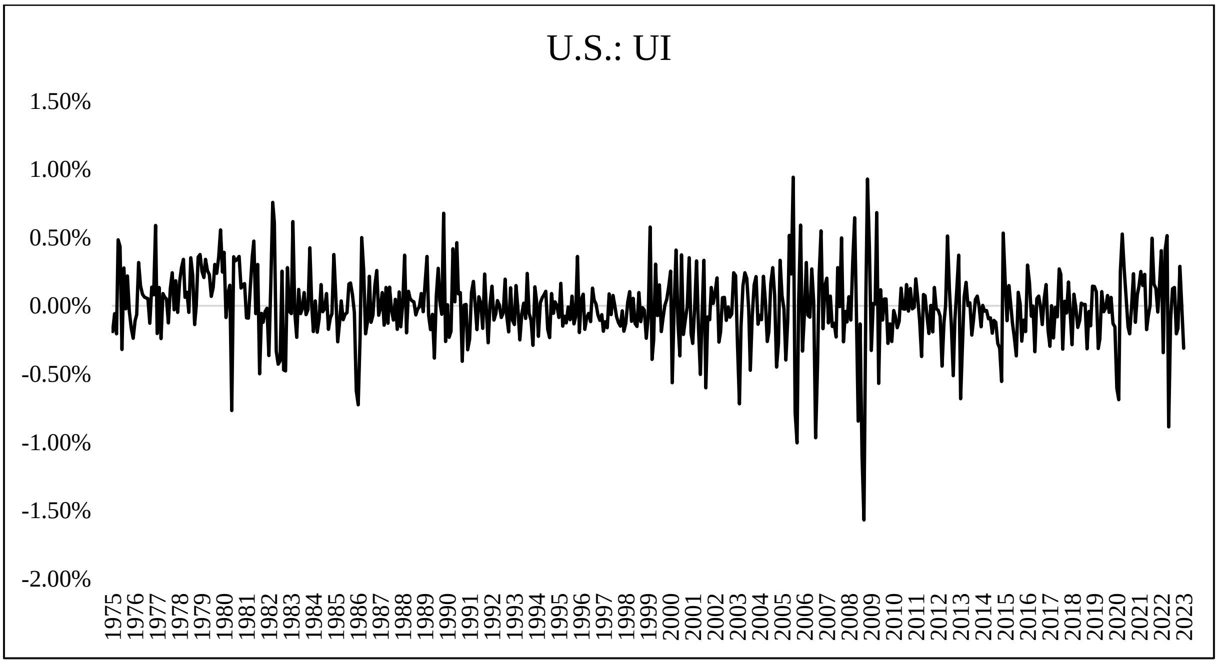
Appendices

Appendix to Essay 1

Appendix A: Decomposition of Inflation Into Its Expected and Unexpected Component

(a)





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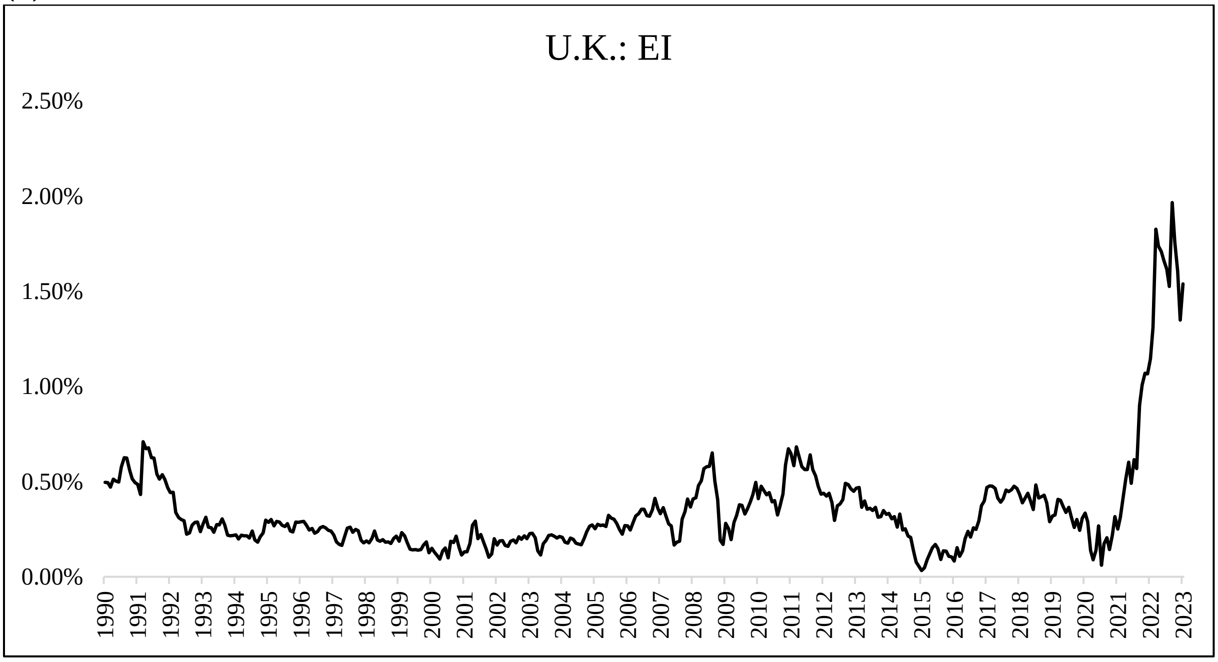
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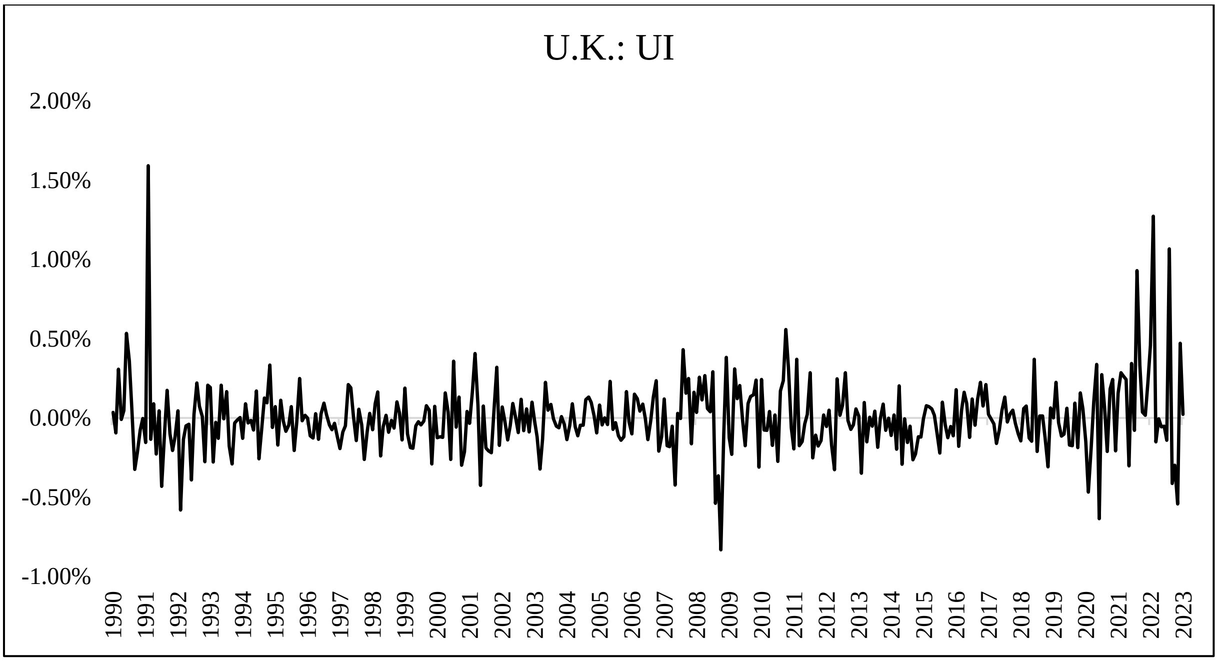
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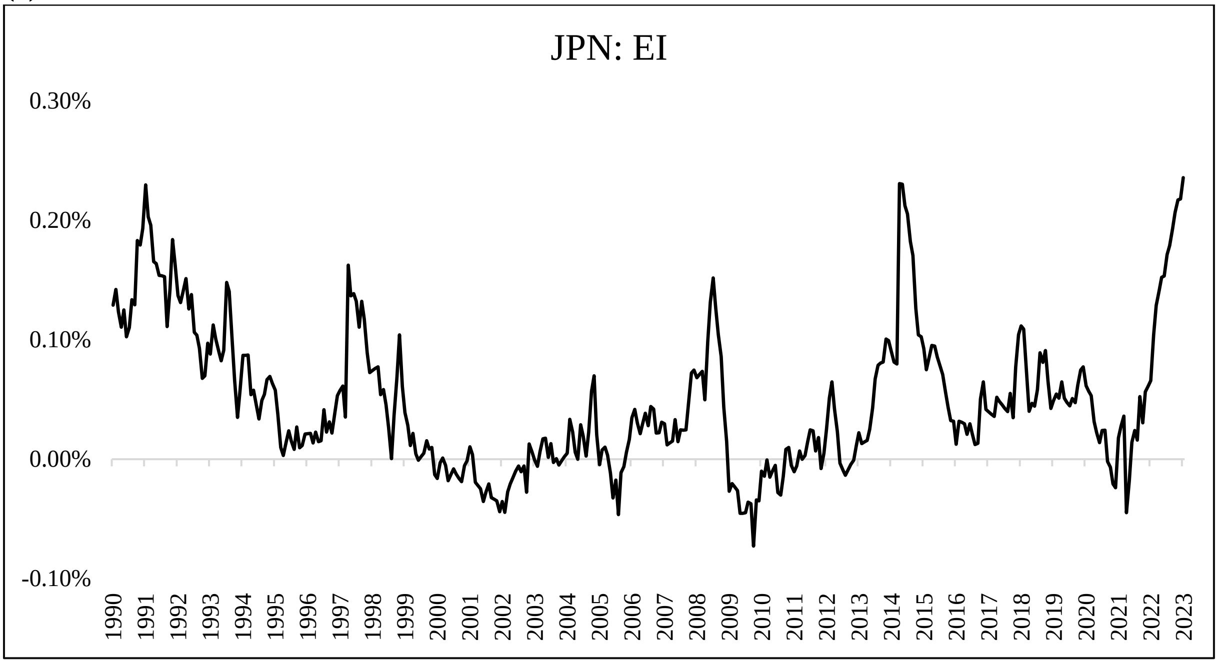
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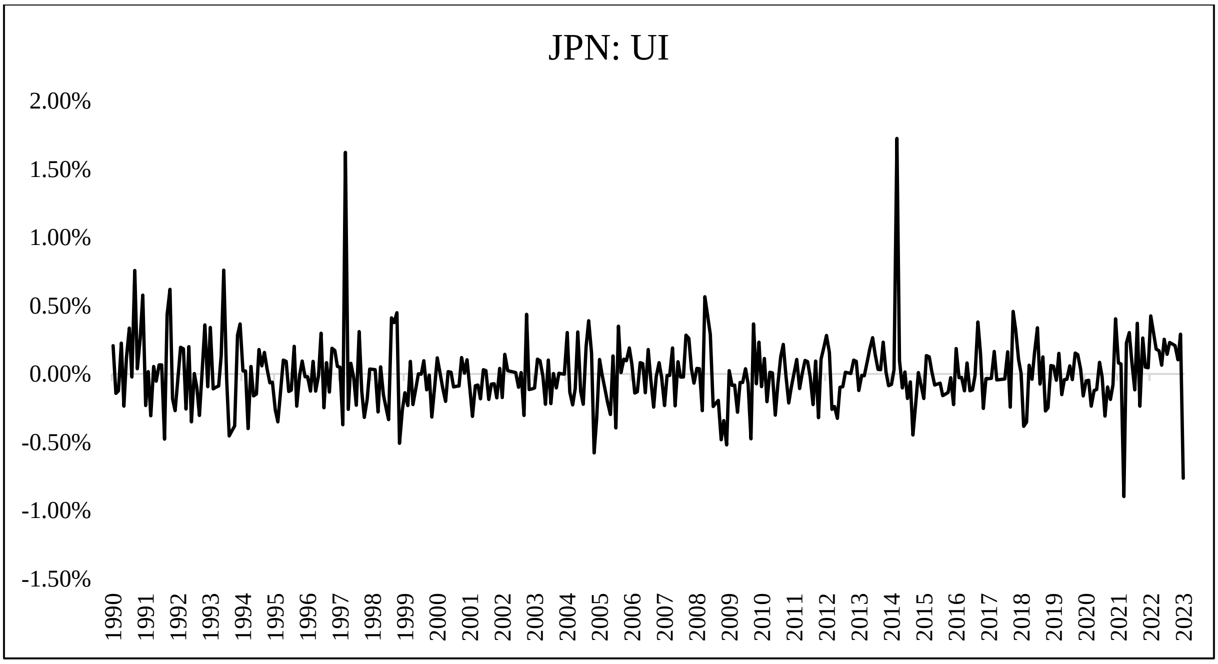
JPN: UI
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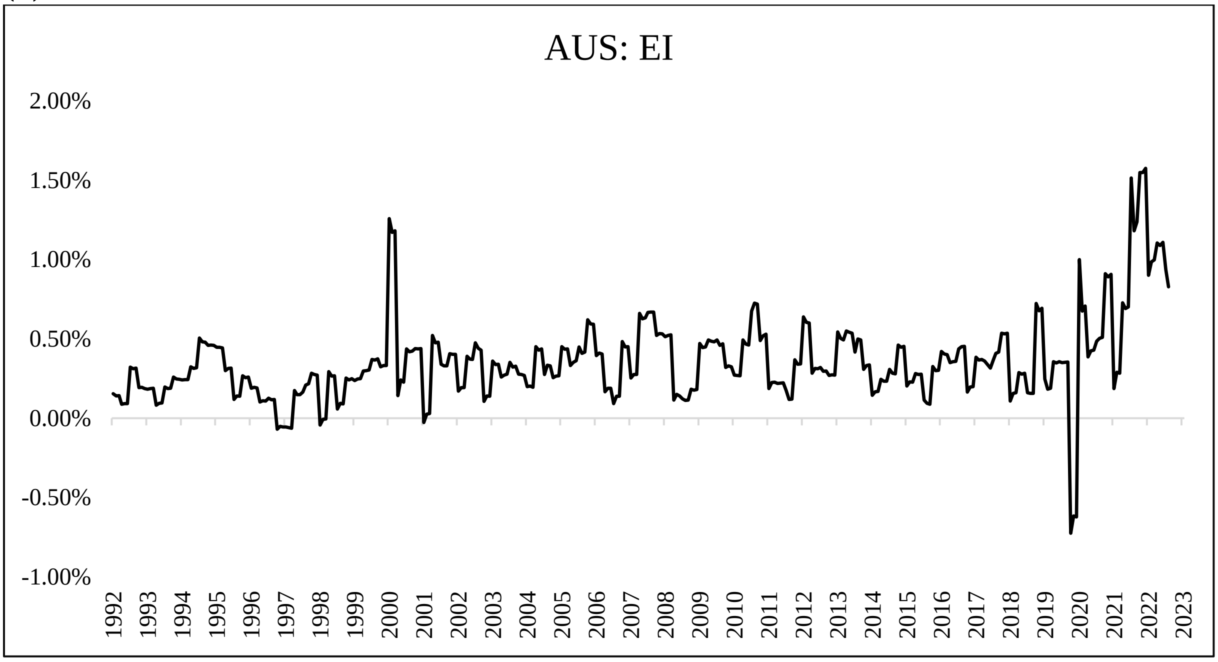
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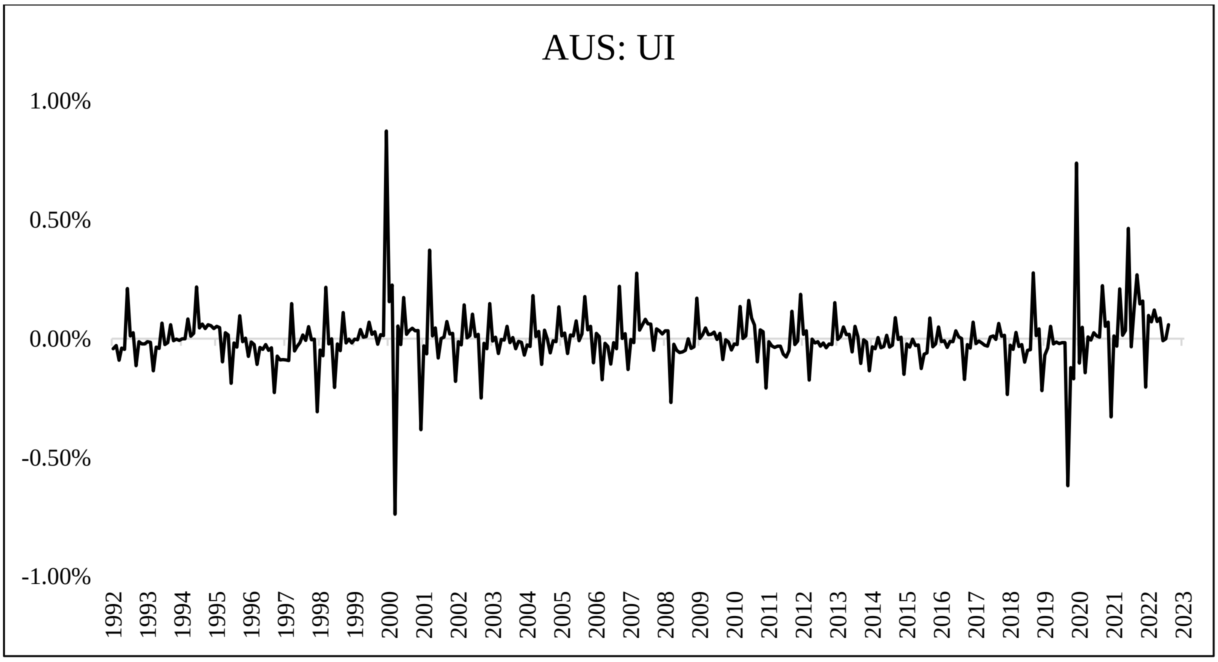
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Appendix B: Results of Kwiatowski-Phillips-Schmidt-Shin (KPSS) Test

		Level	Difference	I(d)		Level	Difference	I(d)
lnLRE	U.S.	8.371***	0.046	1	AUS	4.878***	0.146	1
lnStocks		8.861***	0.052	1		5.618***	0.053	1
lnOil		6.165***	0.088	1		4.960***	0.042	1
lnGold		6.679***	0.270	1		5.972***	0.321	1
lnSilver		3.361***	0.065	1		5.443***	0.076	1
lnAgriculture		3.511***	0.061	1		4.129***	0.078	1
lnGDP		9.031***	0.126	1		6.555***	0.087	1
Interest Rate		6.870***	0.039	1		4.614***	0.152	1
EI index		8.992***	0.171	1		6.741***	0.153	1
UI index		3.409***	0.192	1		2.161***	0.061	1
lnLRE	U.K.	5.545***	0.054	1	JPN	4.9579***	0.168	1
lnStocks		6.583***	0.059	1		0.91248***	0.352	1
lnOil		4.960***	0.042	1		4.9599***	0.042	1
lnGold		5.972***	0.321	1		5.9718***	0.321	1
lnSilver		5.443***	0.076	1		5.443***	0.076	1
lnAgriculture		4.129***	0.078	1		4.1293***	0.078	1
lnGDP		6.451***	0.030	1		1.8306***	0.219	1
Interest Rate		4.799***	0.109	1		2.9121***	0.145	1
EI index		6.627***	0.175	1		5.8351***	0.319	1
UI index		5.169***	0.186	1		5.7779***	0.133	1

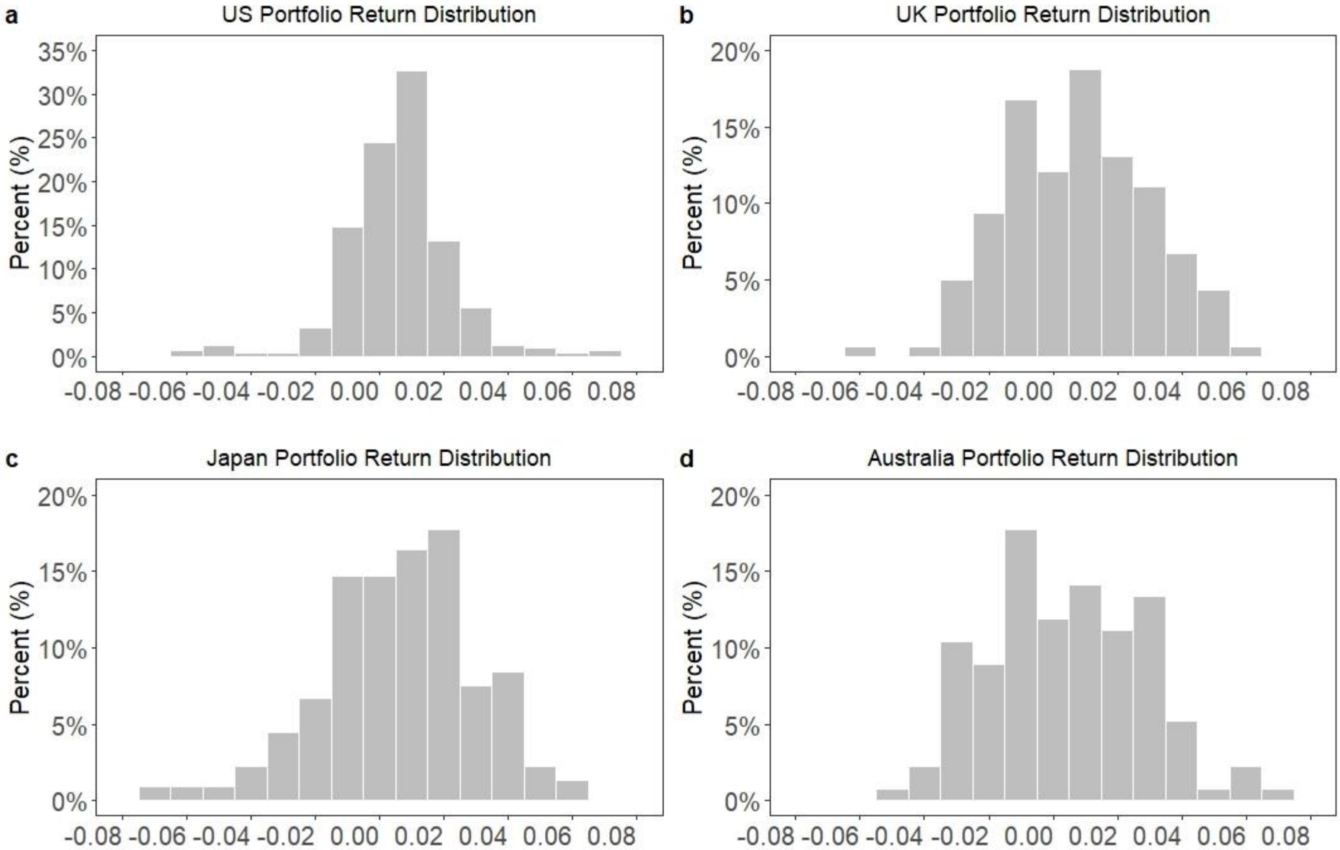
Notes: U.S. stands for United States of America, U.K. for United Kingdom, JPN for Japan, and AU for Australia. LRE denotes the FTSE/EPRA/NAREIT real estate stock total return index. Stocks denotes for each country the corresponding total return of the stock market index. Oil denotes the oil price in U.S. Dollars. Gold denotes the gold price in U.S. Dollars. GDP stands for GDP of each country. Interest rate are the 3-month treasury bill rates. EI index and UI index stand for an index of expected and unexpected inflation, respectively. SP denotes the starting point of the time series and Obs. displays the number of observations. I(1) is given for all variables in all countries.

Appendix C: Average Summary Statistics of Portfolios with Various Minimum Target Returns and Investment Horizons for the US Over the Entire Sample Period

Minimum Target Return	Weights of LRE	Shortfall Probability	Mean	SD	Sharpe Ratio
Rebalanced every 2 years					
r = 0%	6.88%	1.57%	6.36%	16.60%	37.95%
r = 1%	7.43%	1.61%	6.43%	16.81%	38.29%
r = 2%	6.50%	1.70%	6.88%	17.93%	38.37%
r = 3%	8.32%	1.74%	6.98%	17.62%	39.65%
Rebalanced every 5 years					
r = 3%	3.67%	2.33%	6.38%	21.86%	29.19%
Rebalanced every 10 years					
r = 3%	2.67%	2.82%	4.85%	21.43%	22.63%
Rebalanced every 30 years					
r = 3%	6.11%	6.14%	4.50%	17.24%	26.10%

Note: The weights of LRE, the shortfall probability, the mean of portfolio returns, the standard deviation of portfolio returns (SD), and the Sharpe ratios of portfolios are the average values over the entire sample period.

Appendix D: Portfolio Return Distribution



Note: Appendix D plots the distribution of portfolio returns for our inflation hedging portfolios. Panel a) is the distribution of U.S. portfolio returns. Panel b) is based on the portfolio returns of the UK. Panel c) and d) are based on the portfolio returns of Japan and Australia, respectively.

Appendix to Essay 2

Appendix E: Derivation of the Impulse Response Function

Our baseline model is defined as:

$$\Delta Y_{i,t} = \nu(s_j) + \Gamma(s_j)\Delta Y_{i,t-1} + \Pi(s_j)Y_{i,t-1} + \varepsilon_{t,} \tag{A.1}$$

where $\Pi(s_j) = A(s_j)B(s_j)$ and $Y_{i,t} = [Y_{1,i,t}, Y_{2,i,t}, \ldots, Y_{k,i,t}]'$. Consider $Y_{i,t}$ as a $K \times 1$ vector, which encompasses *k* variables for country *i* during the period *t*. s_j represents the dependency on a specific regime.

$$\Gamma(s_j) = \begin{bmatrix} \gamma_{11}(s_j) & \gamma_{12}(s_j) & \cdots & \gamma_{1k}(s_j) \\ \gamma_{21}(s_j) & \gamma_{22}(s_j) & \cdots & \gamma_{2k}(s_j) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{k1}(s_j) & \gamma_{k2}(s_j) & \cdots & \gamma_{kk}(s_j) \end{bmatrix} \tag{A.2}$$

$$A(s_j) = \begin{bmatrix} \alpha_1(s_j) & 0 & \cdots & 0 \\ 0 & \alpha_2(s_j) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_k(s_j) \end{bmatrix} \tag{A.3}$$

$$B(s_j) = \begin{bmatrix} 1 & -\beta_{12} & \cdots & -\beta_{1,k} \\ 1 & -\beta_{22} & \cdots & -\beta_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & -\beta_{k2} & \cdots & -\beta_{k,k} \end{bmatrix} \tag{A.4}$$

$$\Sigma(s_j) = \begin{bmatrix} {\sigma_{11}}^2(s_j) & {\sigma_{12}}^2(s_j) & \cdots & {\sigma_{1k}}^2(s_j) \\ {\sigma_{21}}^2(s_j) & {\sigma_{22}}^2(s_j) & \cdots & {\sigma_{2k}}^2(s_j) \\ \vdots & \vdots & \ddots & \vdots \\ {\sigma_{k1}}^2(s_j) & {\sigma_{k2}}^2(s_j) & \cdots & {\sigma_{kk}}^2(s_j) \end{bmatrix} \tag{A.5}$$

A Cholesky decomposition is employed to generate a lower triangular matrix, described as follows:

$$\textstyle\sum(s_j) = L(s_j)L(s_j)'. \tag{A.6}$$

where $\varepsilon_{i,t}$ has a diagonal or even a unit covariance matrix and is hence contemporaneously uncorrelated (orthogonal): $\varepsilon_{i,t} = \mathrm{L}(s_j)^{-1}u_{i,t}$ and $\mathrm{L}(s_j)\mathrm{L}(s_j)' = \sum(s_j)$.

To formalise impulse response functions, Equation (A.1) can be converted to:

$$Y_{i,t} = \Lambda(s_j) + \left(I + \Pi(s_j) + \Gamma(s_j)\right) Y_{i,t-1} + \varepsilon_{i,t}, \quad \text{(A.7)}$$

where I is defined as an $K \times K$ identity matrix.

Thus, the impulse response function can be represented as:

$$IRF_H(s_j) = L(s_j) \sum_h^H \left((I + \Pi(s_j) + \Gamma(s_j)\right)^h e_k \quad \text{(A.8)}$$

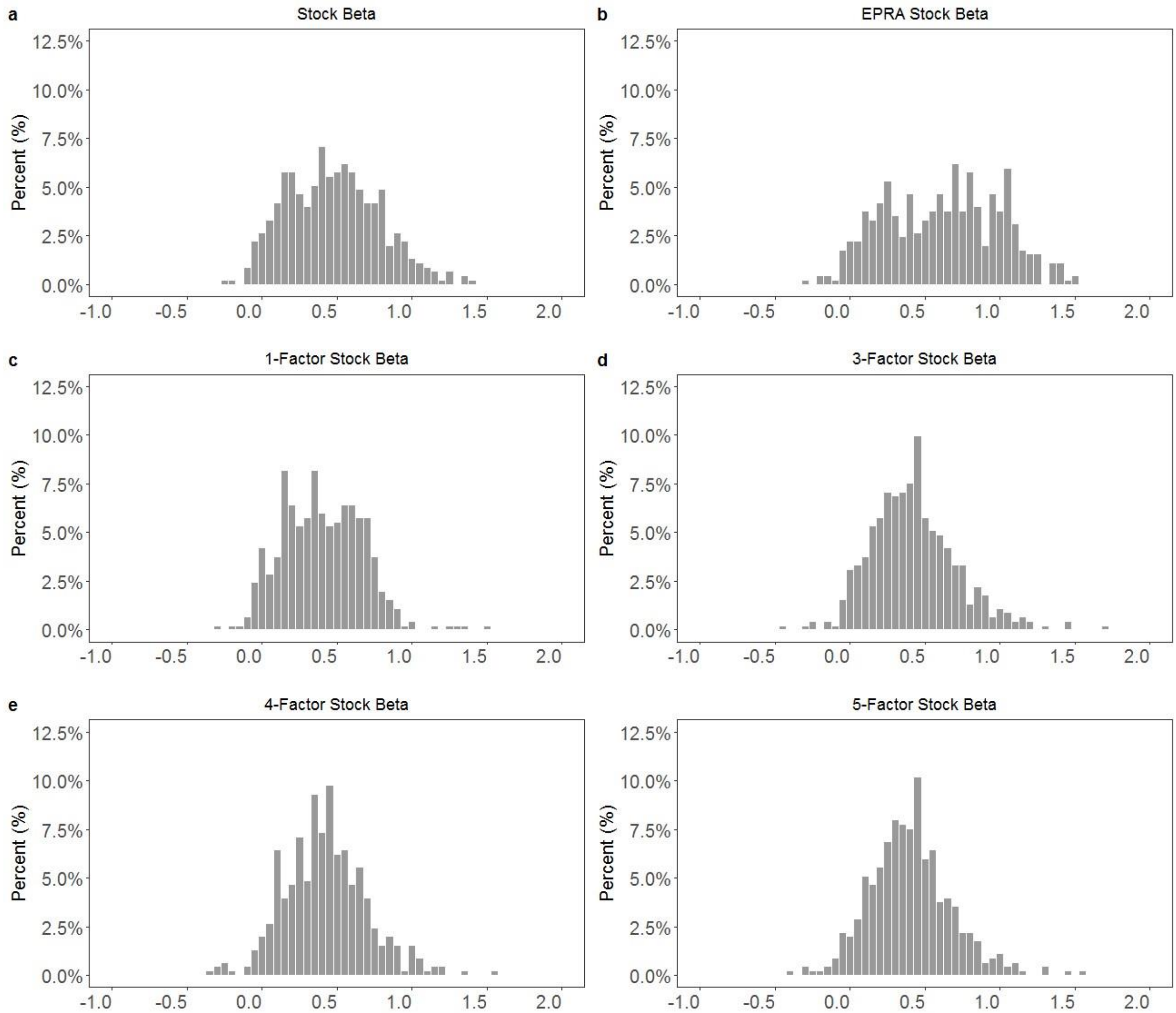
where e_k represent a vector of size $K \times 1$, where k indicates the variable that experiences a shock.

Time-varying impulse response functions are calculated by using the transition probabilities of regimes:

$$IRF_{t,h} = IRF_h(s_1) * p_{1,t} + IRF_h(s_2) * (1 - p_{1,t}) \quad \text{(A.9)}$$

Appendix to Essay 3

Appendix F: Stock Beta Distribution



Description: Appendix F plots the distribution of stock betas in the baseline model and in the robustness tests. Panel a) is the distribution of the stock beta of the baseline model. Panel b) is based on an EPRA index based stock beta. Panel c), d), e), and f) are based on a 1-factor, 3-factor, 4-factor and 5-factor model, respectively.

Appendix G: Unconditional Correlation Matrix

	$\beta_{i,t}^{Sector}$	$\beta_{i,t}^{Sector,\ MKT}$	$\beta_{i,t}^{Stock}$	$\beta_{i,t}^{Epra}$	$\beta_{i,t}^{MKT}$	$\beta_{i,t}^{MKT,\ three}$	$\beta_{i,t}^{MKT,\ four}$	$\beta_{i,t}^{MKT,\ five}$
$\beta_{i,t}^{Sector}$	1.000							
$\beta_{i,t}^{Sector,\ MKT}$	0.905	1.000						
$\beta_{i,t}^{Stock}$	-0.166	-0.191	1.000					
$\beta_{i,t}^{Epra}$	-0.181	-0.192	0.891	1.000				
$\beta_{i,t}^{MKT}$	-0.134	-0.172	0.944	0.831	1.000			
$\beta_{i,t}^{MKT,\ three}$	-0.172	-0.183	0.800	0.703	0.885	1.000		
$\beta_{i,t}^{MKT,\ four}$	-0.200	-0.203	0.694	0.663	0.783	0.898	1.000	
$\beta_{i,t}^{MKT,\ five}$	-0.153	-0.164	0.772	0.677	0.876	0.986	0.892	1.000

Description: This table presents the unconditional correlation matrix of the baseline tenant sector beta, the market factor adjusted tenant sector beta, and various stock beta modifications. $\beta_{i,t}^{Sector}$ is the tenant sector beta of our baseline model, $\beta_{i,t}^{Sector,\ MKT}$ is the adjusted tenant sector beta, while $\beta_{i,t}^{Stock}$, $\beta_{i,t}^{Epra}$, $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{MKT,\ three}$, $\beta_{i,t}^{MKT,\ four}$, $\beta_{i,t}^{MKT,\ five}$ are stock betas and are defined as in Section 4.4.3.2.

Appendix H: Tenant Sector and Tenant Diversification

	HHI_{Sector}				HHI_{TENANT}			
	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Diversified	0.303	0.123	0.110	1.000	0.150	0.087	0.034	0.609
Healthcare	0.795	0.062	0.716	0.883	0.150	0.036	0.120	0.220
Industrial	0.700	0.300	0.266	1.000	0.104	0.056	0.042	0.253
Office	0.280	0.169	0.106	0.698	0.222	0.165	0.059	0.660
Retail	0.707	0.286	0.156	1.000	0.262	0.305	0.033	1.000

Description: This table presents an overview of the diversification of PRECs across tenant sectors (HHI_{Sector}) and tenants (HHI_{TENANT}). We show standard descriptive statistics for the property types of diversified, healthcare, industrial, office, and retail.