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Measuring the interconnectedness and systemic risk in the European listed real estate sector

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EXECUTIVE SUMMARY

Since the early 2000s, globalisation in financial markets has been increasing, affecting the risk-return patterns experienced in different submarkets, such as the listed real estate sector. Macro-economic shocks, such as the global financial crisis (GFC) 2008, COVID pandemic 2020, inflationary pressure, interest rate rises or increases in the global political conflicts from 2022 onwards, have affected all investment sectors and industries. With the increase in global correlation and commonalities the assumption is that diversification benefits have partially diminished. This report aims to bring a deeper understanding into the systemic risks from and to the listed real estate (LRE) sector, and its role in portfolio selection and diversification against system-wide shocks. The findings are aimed to provide LRE investors and equity analysts with new tools and insights to manage their LRE exposure.

- **Systemic importance of European LRE to other sectors:** Findings confirm that when the European LRE sector is under stress, bank and non-bank financial sector equity indices show an increase in tail risk. Overall, firm size (measured by total assets) shows a positive correlation with systemic risk, meaning the larger the firm the more systemically important. While the findings of this study generally confirm the strong relationship between firm size and systemic risk, the data show that even small companies collectively can cause disruption to financial stability.

- **LRE sensitivity to macro-economic shocks and financial market stress:** Our findings suggest that large LRE companies are also more exposed to systemic events. The larger the real estate company, the more external relationships it typically has, hence it becomes more vulnerable to external shocks. Hence, these companies are more vulnerable to external shocks. However, the data show that the LRE sector recovery is quicker than the rest of the financial sector.

- **Firm leverage and sensitivity to external shocks:** Firm level leverage is an important factor, which can increase the vulnerability of a company to external shocks. A level of >50% leverage is typically considered high. However, firms can mitigate their systemic risk vulnerability by increasing their liquidity & income buffer. While net debt to EBITA gives the equity analyst important information about the financial risk of the company such as risk of bankruptcy, the level of LTV (overall leverage) says a lot the companies resilience to external market shocks. Investors and analysts should be aware of high leverage LRE companies, especially large stocks, and those located in markets where the performance of the sector is highly connected with the rest of the financial and macro-economic market of the country.

- **Co-movements among LRE companies within the sector:** Co-movements within the European LRE sector show that especially at times of low or negative returns, systemic risk and co-movement between companies is high. Therefore, a better understanding of dynamic movements in the real estate securities markets' correlation structure and the forces behind market integration is important for investors to evaluate the potential risks and rewards of cross-country real estate diversification. Our findings indicate that the degree of co-movements between both country and sectoral LRE markets increases considerably during recession periods. The subject of interconnectedness is even more relevant now after the pandemic period and the Russia-Ukraine war led European economies into recession.

  According to our estimates, real estate market' systemic risk and exposure indicators were more affected by the war-related uncertainty rather than the pandemic. More specifically, the degree of connectedness across the European LRE market is estimated to be rapidly increasing and has already overcome the 2008 peak value in most of the examined measures. Individual country markets which are less affected by the return and volatility movements of the overall European LRE market are Belgium and the UK. Here, equity analysts need to consider the regulatory and political interaction and integration of the LRE sector into its' national market, when analysing an individual company.

- **Long-term historic changes between systemic risk and LRE:** LRE real estate in mixed asset portfolios can be defensive instrument to protect from systemic risks. Over the examined 20-year time period, times of increased co-movements coincide with periods of distress in the general stock market. However, LRE recovers more quickly than the rest of the financial market after these shocks. It can especially outperform other sectoral stock indices. The research finds that returns of LRE stocks hold up better during and especially after these crisis periods.

For this, LRE stocks have been empirically tested against 11 other industry sector indices. Based on the traditional mean-variance approach (MVT), real estate and healthcare companies account, on average, for 30% of the optimal allocation each followed by financial companies (20%), consumption products (7%), telecommunications (5%) and utilities (4%). Based on our portfolio selection exercise for different time periods, LRE companies perform well after recession periods, especially when the real estate cycle aligns with the economic cycle.

In addition to the mean-variance portfolio, in this study we employ an alternative specification based on minimizing portfolio's systemic exposure. In other words, we construct a portfolio that minimizes the absolute value of the portfolio Value-at-Risk conditional on the market index being at distress, and not dispersion risk. Our findings suggest that LRE is featured in both selection specifications and provides diversification benefits against systemic exposure despite the recent distress in the real estate markets. LRE's weight on the MVT optimal portfolio reached 41% after the sovereign debt crisis and 71% based on the Conditional VaR portfolio allocation. Especially after the period 2011 – 2019 the allocation of LRE in the optimal portfolio has been increasing while exposure to financial companies has been low only increasing again from 2015 onwards. As the inflationary pressures have weakened and interest rates have reached their peaks, we expect the degree of connectedness to decline as well, and the LRE sector to bounce back in 2024.

- **Sector resilience to external shocks and systemic risk:** Sector level differences are more relevant than country differentiation when determining the impact of external shocks to LRE companies. Equity analysts and investors should pay attention to a company's underlying real estate market exposures. The most resilient sectors to external shocks are healthcare and residential LRE, while companies focusing on the classic property sectors office, retail and industrial show high co-movements and spillover risks to external shocks. This is assumed to be caused by the high correlation with financial markets, employment, economic growth overall. This also leads to the conclusion that a diversified LRE company may be more exposed to external shocks than a more specialist one, which stands in contrast to the idea that a company should diversify its real estate portfolio. Over the last ten years residential real estate has become one of the most defensive real estate sectors for companies to invest in, when it comes to vulnerability to external shocks.

Overall investors and equity analysts should consider alternative portfolio optimisation approaches which not only consider risk (volatility of returns) and portfolio return, but also integrate ideas of minimising systemic risk within their portfolios. These approaches can help minimise the vulnerability of the portfolio toward systemic shocks such as a recession, geo-political, macro-economic or financial market risks.

Content table

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Introduction

This report aims to bring a deeper understanding into the interactions between general financial market stability and real estate risk-return profiles. Throughout economic cycles, governments have been concerned about how the real estate sector is affecting the general economy and overall financial market stability, the same is true vice versa. Since the GFC 2008/09 the effects of market globalisation brought the concept of interconnection between markets into further focus.

The Listed Real Estate (LRE) sector provides investors with the opportunity to gain indirect real estate exposure, taking advantage of some diversification benefits direct real estate offers compared to equities and bonds, while benefitting from the liquidity of the listed market. The long-term correlations between securitized real estate returns and direct real estate returns have been researched extensively by Hoesli and Oikarinen (2012).[1] These important features of LRE makes it a valuable component in mixed asset investment portfolios (Boudry et al., 2020; Mensi, 2023). However, since the beginning of the COVID-19 pandemic, the global real estate markets have exhibited clear signs of vulnerabilities. The macroeconomic uncertainty and the monetary tightening over the last years led to significant price corrections in the underlying real estate asset values and to declining market liquidity.

Evidence from previous market cycles have shown that during periods of distress the degree of co-movements among financial institutions is considerably higher. According to Adams et al. (2015), the co-movements among US REITs market can be twice as large when the market is under financial distress. Real estate markets have become a focal point of research for the ECB. According to the ECB's May 2022 issue of the Financial Stability Review, developments in real estate markets are important from a macroeconomic and financial stability perspective. Therefore, a better understanding of systemic importance and exposure of the LRE sector is important not only for policymakers, but also for investors that they need to evaluate the potential risks and rewards of sectoral and cross-country real estate diversification.

This study aims to answer the following research questions:

- Can the systemic importance of listed real estate companies be measured? Which are the main firm characteristics associated with high systemic risk?
- How can the degree of interconnectedness between the European listed real estate sectors be quantified? What was the impact of the recent macroeconomic uncertainty?
- What is the role of LRE in a systemic risk optimal portfolio?

The report is structured into three parts. First, we estimate the systemic importance and exposure of the European LRE market with respect to other financial markets. For that purpose, we use a financial market index that includes banks, insurance companies, financial services companies and other investment firms.

Our empirical results highlight the systemic importance of the real estate sector, and they indicate that when the LRE market is in distress, this has a negative impact on financial markets (Conditional VaR of the financial sector increases, in absolute terms, by 0.42%.[2]). On the other hand, LRE companies exhibit vulnerabilities in periods of distress. According to our results when the financial market index is below its stress threshold (VaR), the tail risk of LRE companies increases by 0.29%.

Secondly, we quantify the connectedness across the European real estate firms and markets. For our empirical analysis we employ several alternative approaches that capture different aspects of connectedness; principal component analysis, Granger causality and a vector autoregressive model approach. Our empirical findings are robust across different methodological approaches and indicate that there is a significant degree of connectedness among the European LRE companies, which increases during recession periods. The degree of connectedness reached its peak over the last year and the start of the Russia-Ukraine war.

Finally, we conduct an empirical exercise to explore the role of LRE in portfolio selection. According to the traditional Markowitz (mean-variance) approach, the risk is measured by the variance of returns. However, the portfolio theory has been extended to downside risks instead of dispersion risk. In this study we employ an alternative specification based on minimizing portfolio's systemic exposure. In other words, we aim to minimize

[1] Listed Real Estate is more liquid and do not entail high transaction costs compared to direct investments to real estate assets.
[2] Despite the fact that LRE is considered a good proxy for the direct real estate market, in the short-term they are more correlated with the stock market (Hoesli and Oikarinen, 2012).

the absolute value of the portfolio Value-at-Risk conditional on the market index at distress (below its VaR). Our findings suggest that LRE is featured in both selection specifications and provides diversification benefits against systemic exposure despite the recent distress in the real estate markets. The weight allocation is higher in the periods after recession, but relatively low during the current economic crisis.

The contribution of this paper is largely empirical, and the results of the research should be of particular interest to both investors and policymakers. A better understanding of dynamic movements in the real estate securities markets' correlation structure and the forces behind market integration is important for international investors to evaluate the potential risks and rewards of cross-country real estate diversification. The high degree of connectedness among LRE companies is associated with weaker sector performance and implies limited diversification opportunities for investors. Our metrics quantifies the degree of connectedness between European markets and can be a useful, since they capture a different aspect of risk.

In addition, the ECB has recently turned its attention to real estate market-related risks, and they have developed a comprehensive framework for identifying the build-up of real estate vulnerabilities that could threaten financial stability. Our research is in line with the ECB's research agenda and our systemic risk metrics provide additional information about the importance and exposure of LRE and they can contribute to the dialogue with policymakers. They may be particularly useful to market regulators who are searching for effective solutions to quantify international transmission of distress across LRE markets and want to promote further development of the LRE industry.

Literature review

In this section we delve into the related literature, and we outline how our paper aligns within this context. A significant contribution of this research is the estimation of systemic risk in the European Listed Real Estate market. Initially, it is essential to distinguish between systematic risk and systemic risk for proper measurement and interpretation. While systematic risks are macroeconomic or aggregate risks that cannot be avoided through diversification, our focus is on systemic risk and systemic exposure, which relate to the risk of breakdown or major dysfunction in financial markets.

Systemic risk became a key concept during the GFC when losses spread across financial institutions, posing a threat to the entire financial system and the real economy (Adrian and Brunnermeier, 2016). Systemic risk metrics are commonly used for macroprudential purposes, and they provide guidance on alternative policies and help anticipate potential breakdowns in financial markets (Hansen, 2013). There are various measures and indicators that analysts and policymakers use to assess and monitor systemic risk, but we focus on two categories; market-based indicators of individual financial institutions and interconnectedness indicators that measures quantify the degree to which financial institutions are linked to each other.

With regards to market-based measures, the literature on systemic risk has mostly focused on the banking sector, but research into systemic risk in relation to the LRE sector is limited. Our study complements and extends existing real estate literature, considering the complexities of the financial market and the challenges in constructing a risk indicator that incorporates all available information. Firstly, we utilize probability distribution measures, CoVaR (Conditional Value at Risk) and MES (Marginal Expected Shortfall) to quantify the systemic importance and exposure of individual firms to financial market variations. These measures focus on quantifying the increased tail co-movements that arise from the spread of financial distress across institutions and markets. The importance of focusing on the tail co-movements has been emphasised before in the literature since there are significant differences in the dynamics between conditional tail dependences and correlations (Hoesli and Reka, 2013).

There are only a few notable examples that examine the systemic risk in the LRE sector. Cao (2021) employs the CoVaR approach to study the dependence structure between the real estate and banking sectors in China. Their empirical findings support the significant contribution of the real estate sector to systemic risk in the banking sector. Similarly, Pavlidis et al. (2021) employ CoVaR to measure systemic risk in the UK REIT market and identify a strong negative relationship between risk and the UK house prices.

The other family of systemic risk measures focus on the interconnectedness across the financial sector. Spillovers between institutions can occur directly through contractual links and heightened counterparty credit risk, or indirectly through price effects and liquidity spirals. As a result, the measured co-movement of institutions' assets and liabilities tends to exceed levels justified by fundamentals alone. While existing literature on systemic risk primarily focuses on cross-country correlations between banks, the importance of studying other asset classes, including REITs, is evident.

Hoesli and Reka (2015) analyse the contagion dynamics between US REITs and the local stock market, identifying several channels that contribute to co-movements beyond economic fundamentals. Liow and Huang (2018) construct a spillovers index for the global REITs market, highlighting the unique aspects of globalization and integration in this market. Their findings highlight the significant role of the local stock market in driving volatility connectedness shocks to the domestic REIT in the majority of cases. Recently, Mensi et al. (2023) explore the interconnectedness of G7 Real Estate Investment Trusts (REITs) markets in the post-COVID period. Their findings suggest that the level of REITs interconnectedness experienced an abrupt increase in the first wave of COVID-19 outbreak (2020Q1), followed by a decline after the initiation of the vaccination programs in end of 2021. The results are in line with the literature that suggests that past economic crises have documented to increase the level of connectedness across financial markets (Maghyereh et al., 2015; Adams et al., 2015; Liow and Newell, 2016). Therefore, the subject of interconnectedness is even more topical now after the pandemic period and the increase in energy prices driven up by the Russia-Ukraine war led European economies into distress.

This paper aims to enhance understanding of the systemic risk and interconnectedness of European real estate markets. To achieve this, we employ alternative methodologies that capture different aspects of risk. More specifically, we adopt three network analysis methodologies, including Principal Component Analysis (PCA), Granger causality, and the VAR-based Spillover index, to assess connectedness and spillovers across real estate markets listed in different countries. Our results indicate that spillovers across financial markets significantly increase during crisis periods when markets tend to move together (Liow and Newell, 2016; Bouri et al., 2022), resulting in the downside that during crisis periods country diversification strategies for investors (Liow and Huang, 2018) are not effective.

Finally, this paper contributes to the literature of portfolio selection under systemic risk focusing mostly on the role of LRE. We provide an empirical analysis of the advantages of including real estate stocks in mixed-asset portfolios, while considering the associated risks. Extensive research has documented the benefits of diversification across different types of real estate or through global investments (Hoesli, et al., 2004; MacKinnon & Al Zaman, 2009). Especially when the economy is under distress, the best portfolio allocation is heavily weighted in listed real estate and precious metals (Sa-Aadu et al., 2010). However, the high unit value and illiquidity of properties pose challenges and increase risk (Hoesli and Reka, 2013). In addition, during periods of distress, REITs may be exposed to spillover risk from other sectors that remains hidden in tranquil periods (Adams et al., 2015) and investors have to consider these co-movements between markets when forming their optimal portfolio-allocations (Begiazi et al., 2016).

In line with our findings, the aforementioned studies indicate that LRE markets were increasingly globalized even before the pandemic which has increased the degree of co-movements between markets. In this empirical exercise we explore the role of LRE in an optimal portfolio allocation based on 20 years of daily data. In addition to the traditional mean-variance approach, we construct a Conditional VaR portfolio. In the latter case the portfolio allocation aims to reduce the risk inherent in in the tails of the distribution of returns conditional on the market being under distress. This novel portfolio selection approach builds upon the CVaR method introduced by Rockafellar and Uryasev (2002). However, in our case we focus on the VaR of the portfolio only during times that the market index is below its VaR threshold to account for systemic risk. Similarly, to our empirical analysis, Haß et al. (2014) study the role of open-ended property funds in portfolio selection employing both the mean-variance and the CVaR approach. They find that property funds are a useful investment vehicle suited to reduce portfolio risk.

Data Summary

This study utilizes data from 88 European listed real estate companies operating in seven countries: the United Kingdom, France, Germany, Spain, the Netherlands, Belgium, and Sweden. The data for these companies is sourced from EPRA's Monthly Statistical Bulletin and provided by EIKON Datastream. The sample period covers 20 years, from January 2003 to September 2023, during which all Euro Area countries had adopted the common currency, and all firms adhered to the regulations set by the ECB's monetary authorities. This period also encompasses significant events such as the Global Financial Crisis, the Sovereign Debt crisis, and the COVID-19 pandemic.

Table 1 presents the summary statistics for all the companies in our sample and provides an overview of the examined countries. The sample is predominantly composed of UK companies, accounting for almost 35% of the European listed real estate market index. German companies make up 20% of the sample, followed by Sweden and France at 15% and 14% respectively.

To estimate the systemic risk and exposure metrics mentioned earlier, it is essential to define the financial market index. For this purpose, the study uses the EIKON Datastream Financials index (FIN), which is a weighted average of banks, insurance companies, financial services firms, and investment trusts. Similarly, to the listed real estate sample, the UK market is substantially larger than the other countries in the sample, accounting for almost 40% of the total market capitalization in 2022. Germany follows with 15%, and France with 14%. In contrast, although Sweden and Belgium represent 15% and 12% respectively in the listed real estate sample's market capitalization, their weighting in the financial market index is only 4% and 10%, respectively.

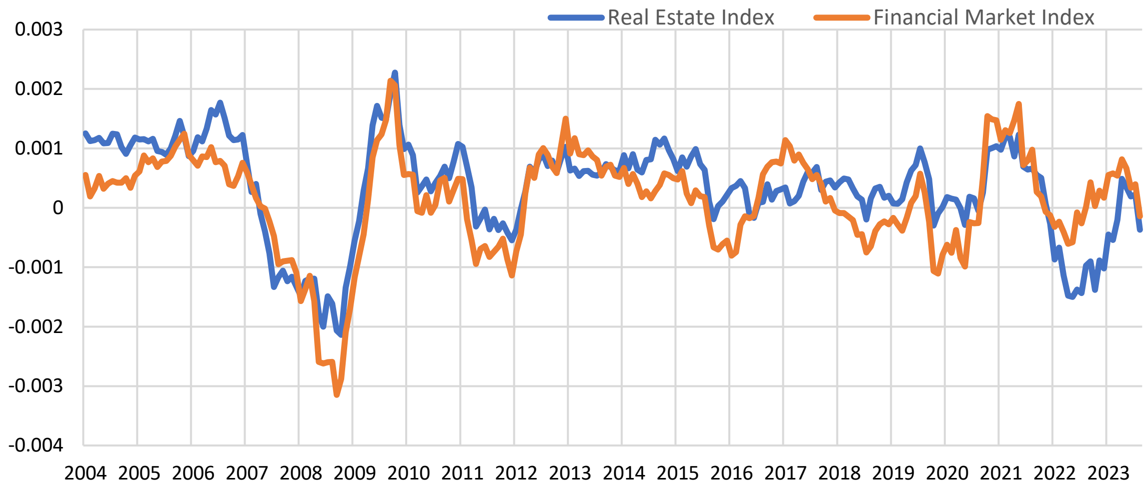
Table 1: Summary statistics

Listed real estate companies				
Countries	No of companies	Market Capitalization 2023	Average company daily returns (2003-2023)	Average company VaR (2003-2023)
UK	41	34.55%	0.030%	-0.426%
Belgium	12	12.26%	0.031%	-0.269%
France	6	13.79%	0.032%	-0.474%
Germany	7	19.33%	0.033%	-0.452%
Netherlands	4	1.42%	0.006%	-0.415%
Spain	3	4.13%	0.018%	-1.064%
Sweden	15	14.53%	0.066%	-0.479%
Total	88	100%	0.036%	-0.370%
Financials				
Countries	No of companies	Market Capitalization 2023	Average index daily returns (2003-2023)	Average index VaR (2003-2023)
UK	218	39.82%	0.010%	-0.384%
Belgium	10	3.80%	0.013%	-0.421%
France	29	14.71%	0.025%	-0.536%
Germany	28	15.31%	0.023%	-0.431%
Netherlands	33	7.40%	0.008%	-0.537%
Spain	12	8.98%	0.015%	-0.589%
Sweden	12	9.97%	0.045%	-0.370%
Total	344	100%	0.016%	-0.420%

Note: The values refer to the average daily returns of a Market Capitalization weighted portfolio for the period January 2003 to September 2023. Market Capitalization is based on data between January 2023 to August 2023. The financial companies are the constituents of the countries' DS Financials indices. The data is provided by EIKON Datastream. In Appendix, Table A displays all the firms used in our analysis.

On average, the listed real estate companies provided positive returns over the 20-year period, with an overall weighted average return of 0.036%. In comparison, the financial market index had a weighted average return of 0.016%. As displayed in Figure 1 the LRE market index outperforms the financial market index for the majority of the examined period. However, the combined impact of the COVID-19 pandemic and the Russia-Ukraine war was more severe on the LRE sector, and more specifically on subsectors such as retail and office LRE companies,[3] than the better diversified financial market index. With regards to volatility, both indices exhibit a standard deviation of 0.24% based on daily returns. In terms of tail risk, the historical Value-at-Risk of LRE companies is lower than the financial market's VaR.

Figure 1: Market Return Indices



Note: The Figure displays the 12-month MA of the monthly average daily returns of the Euro aggregate Listed Real Estate and Financial Market indices. The indices' aggregation is based on Market Capitalization weights. The samples consist of 88 and 344 European listed companies for the Real Estate and Financial Market indices respectively. The examined period is between January 2003 and September 2023. Source: EIKON Datastream and Authors' calculations.

This can be seen by Figure 1 and the sharp decline in the financial market index during the GFC and the Sovereign Debt Crisis. The LRE index also exhibits its lowest returns in 2008, but also during the recent recession after the Russia-Ukraine war. At the country level, market indices with higher returns in Table 1 also exhibited higher risk, as measured by their average historical VaR.

Measuring systemic risk in the European LRE markets

Table 1 illustrates the return-risk characteristics of European LRE companies and of the aggregate financial market in isolation. In this study, we utilize two widely recognized probability distribution measures, ΔCoVaR and MES, to assess LRE firms' systemic risk and its exposure to financial market dynamics. These measures effectively capture the co-movements between individual firms and the broader market movements. Regulators and policy institutions have extensively employed these measures to investigate the systemic importance of individual financial institutions, assess risk spillovers, and identify vulnerabilities to potential stress events.

ΔCOVAR

Adrian and Brunnermeier (2016) introduced Conditional VaR (CoVaR), which measures the tail dependency between the financial system and an examined institution. More specifically, CoVaR is defined as the Value-at-Risk (VaR) of one institution/market index at a specific probability quantile (usually 5%), conditional on the other institution/market index being under distress (at its VaR threshold).

[3] Hoesli and Malle (2022) argue that sectors such as retail, hospitality and office properties have been affected the most by Covid-19, whereas the residential and industrial sectors have been more resilient. Ling et al. (2020) study the impact of COVID-19 on the US REITs market and find that REITs focused on retail and residential properties react more compared to those focused on healthcare which performed well.

The method builds on VaR, which is defined as:

$$P\ (R_t^i < VaR^i) = q \quad (1)$$

The CoVaR of the system *s* with respect to changes in institution *i* is defined as:

$$P\ (R_t^s < CoVaR^{s|i} \,|\, R_t^i = VaR^i) = q \quad (2)$$

$$\Delta \mathrm{coVaR}^{s|i} = \mathrm{CoVaR}^{s|i}_{q=0.05} - \mathrm{CoVaR}^{s|i}_{q=0.5} \ (3)$$

,where R_t is the monthly average of daily returns and *q* the examined quantile.

We capture the systemic importance of each examined institution by estimating the difference between the CoVaR of the system (*s*) when a firm (*i*) is under distress and when it is equal to its median (“*normal times*”). As shown in Equation (3), the difference between the two is defined as ΔCoVaR, where higher values indicate that the examined institution is more systemically important. For our analysis we estimate the $\Delta CoVaR^{FIN|i}$ that measures the conditional VaR of the financial market index (*FIN*) conditional on a company or market (*i*) being under distress. The measure captures the **systemic risk** or **systemic importance** of the examined firm or market.

The estimation of $\Delta CoVaR^{FIN|i}$is based on the following quantile regression model:

$$R_t^s = a_q^{s|i} + \beta_q^{s|i}\ R_t^i + \varepsilon_{q,t} \quad (4)$$

,where R_t is the monthly average of daily returns and *q* the examined quantile (0.05). As above (*s*) and (*i*) stand for system and firm, respectively. The predicted value of the dependent variables from the quantile regression gives the value at risk of the system index conditional on the examined institution.

$$CoVaR_{q,t}^{s|i} \equiv \widehat{R_t^s} = \hat{a}_q^{s|i} + \ \hat{\beta}_q^{s|i}\ VaR_t^i \quad (5)$$

$$\Delta CoVaR_{q,t}^{s|i} = \ \hat{\beta}_q^{s|i}(\ VaR_t^i - VaR_{0.5}^i) \quad (6)$$

It is worth noticing that ΔCoVaR does not distinguish whether the contribution is causal or simply driven by a common factor. According to Adrian and Brunnermeier (2016) this could be an advantage since although a financial firm is small in terms of assets and systemic risk, the measure will capture potential distress that can be caused by a common factor.

MARGINAL EXPECTED SHORTFALL (MES)

The method was introduced by Acharya et al. (2010, 2017) and builds on the concept of Expected Shortfall (ES). ES indicates the expected magnitude of losses when the portfolio is in the tail region of the loss distribution. As the authors point out VaR and consequently CoVaR was never meant for regulatory purposes since it presents two main drawbacks. Firstly, it is asymmetric, and it does not take into account the severity of losses beyond the VaR level. Secondly, the VaR of the sum of two portfolios can be higher than the sum of their individual VaR. Therefore, ES and MES are considered more coherent and more accurate in capturing tail risk. Another difference between the two measures is that MES focuses on the firm returns when the market experiences distress, whereas ΔCoVaR examines the system’s tail risk conditional on an individual firm being under distress.

The mathematical representation of MES is as follows:

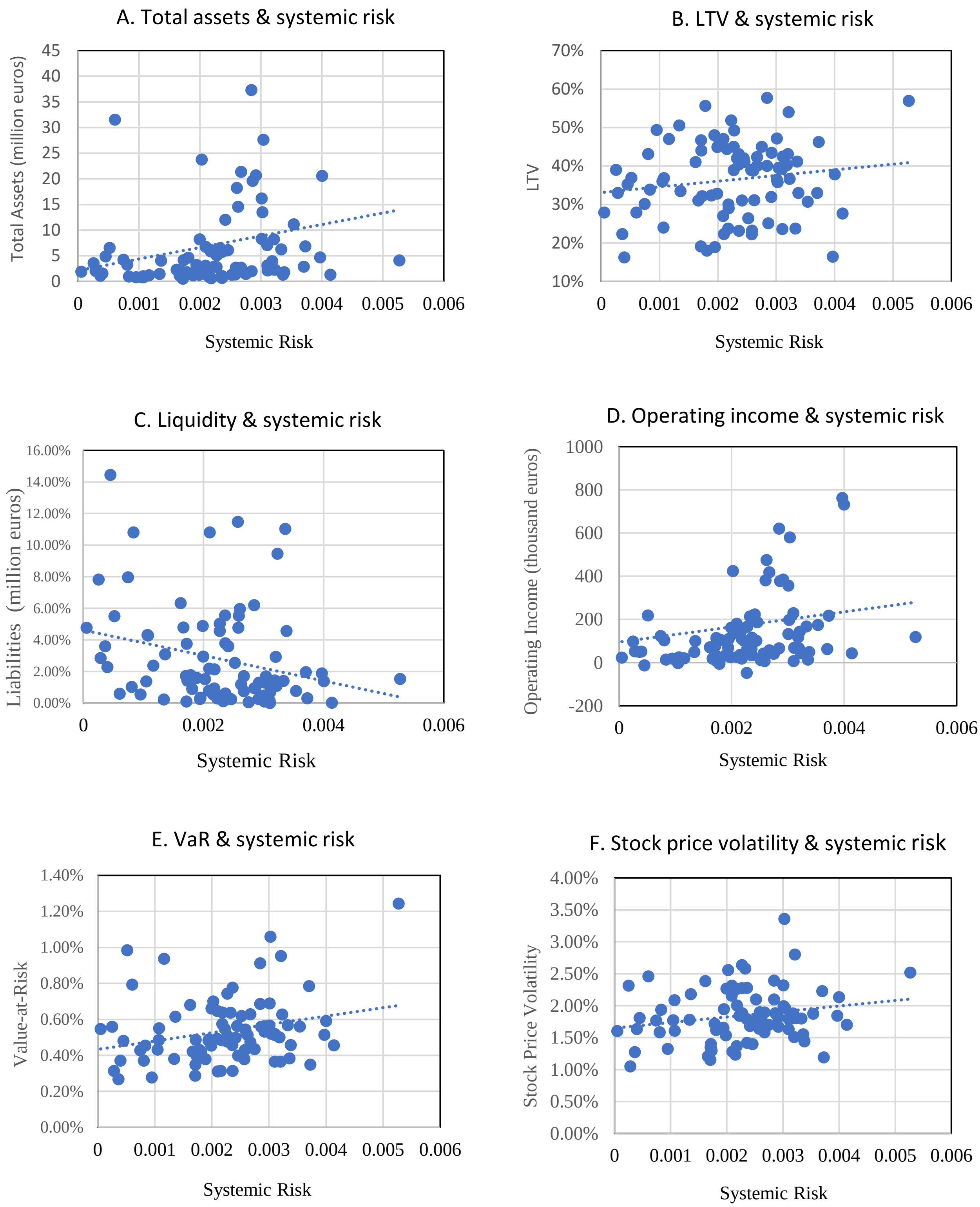
$$MES \ \equiv \ -E\ [R_i\ |R_s\ \le VaR_{s,q}] \quad (7)$$

The stress event threshold is defined at 5% in line with Acharya et al. (2010) who describe it as “*normal tail event*”. MES is equal to the examined firm’s average returns when the market index experiences a tail event or in other words its returns is below the 5% threshold.

FIRM CHARACTERISTICS AND SYSTEMIC RISK METRICS

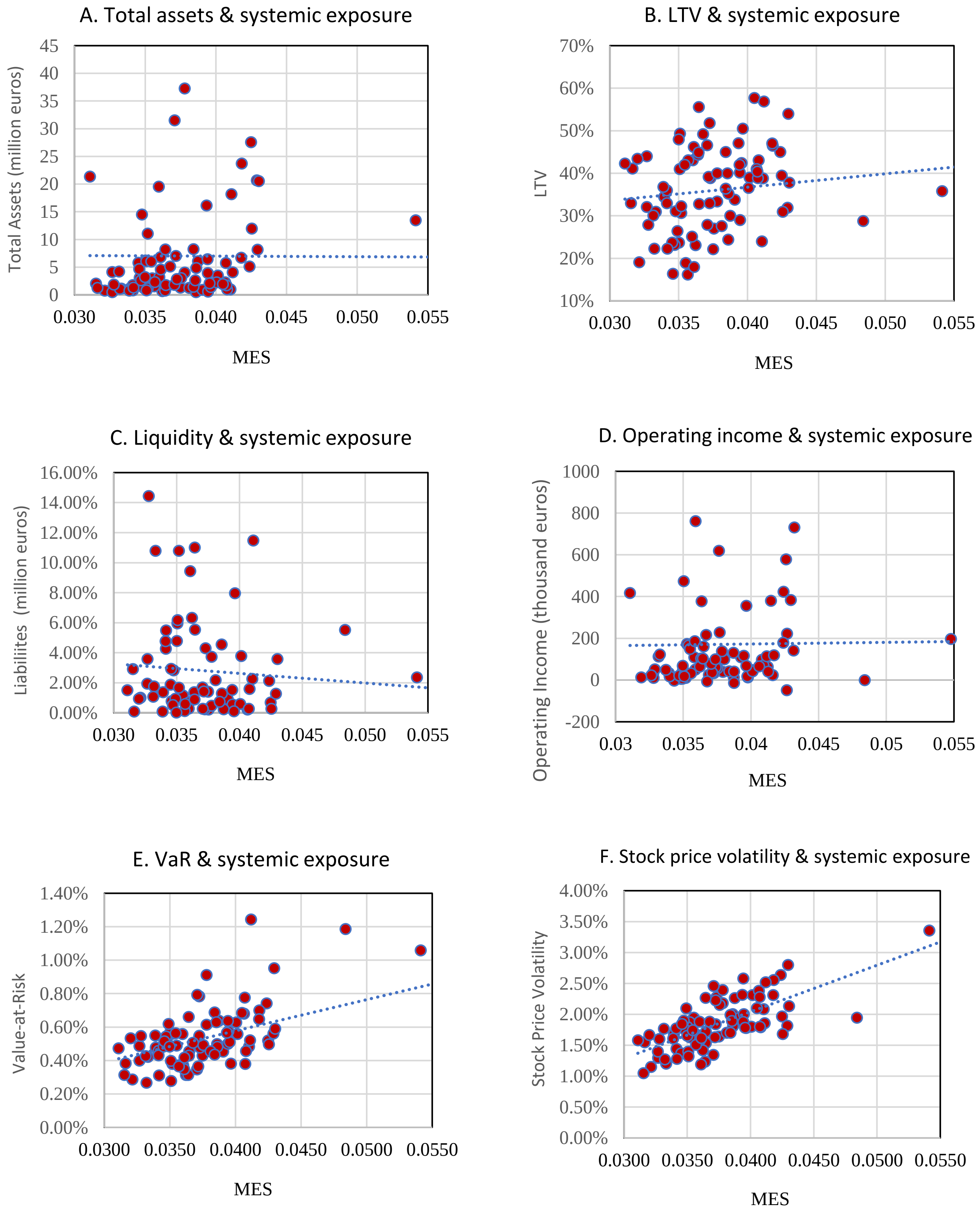
Figures 2 and 3 display the cross-sectional relationship between metrics of systemic risk and firm characteristics. The figures indicate that the size of the company is positively associated with the level of systemic risk, however smaller firms can also pose systemic risks. This is in line with the concept of “*too-big-to-fail*” financial institutions and the empirical evidence of previous studies (Laeven, 2016 ; Varotto and Zhao, 2018).

Figure 2: Firm Characteristics and ΔCoVaR



Note: The Figure shows the correlation between LRE companies' balance sheet characteristics and systemic risk (ΔCoVaR). The data refer to the average value for the period 2003-2023. The data is provided by EPRA, EIKON Datastream and the measures are based on Authors' calculations.

Figure 3: Firm Characteristics and MES



Note: The Figure shows the correlation between LRE companies' balance sheet characteristics and systemic exposure (MES). The data refer to the average value for the period 2003-2023. The data is provided by EPRA, EIKON Datastream and the measures are based on Authors' calculations.

On the other hand, systemic exposure (MES) is not necessarily associated with firm's size (see Figure 3.A). Large real estate companies are not immune to macroeconomics and market fluctuations. This can be attributed to the large market share, since they often have a significant presence in the real estate market, owning a substantial portfolio of properties. In addition, larger real estate companies have more extensive relationships and transactions with other market participants, including lenders, institutional investors, and property owners. Therefore, despite their level of diversification, larger companies appear to be also exposed to financial market fluctuations.

Leverage is another factor associated with higher systemic risk, since it can increase the firm's vulnerability to market downturns or liquidity shocks. The latter argument can be supported by Figures 2.B and 3.B that show the relationship between leverage and systemic risk/exposure. In both cases higher leveraged firms (higher Loans-to-Value ratio) are more exposed to financial risks and are considered a great risk for financial stability in return. The findings are in line with Brunnermeier et al. (2020) who find that higher leverage is associated with greater systemic risk.

On the other hand, firms with high liquidity ratio, defined as cash divided by total assets, are not as systemically important and not as exposed to market risk. Our results are in line with the empirical evidence from the banking sector (Brunnermeier et al. 2020 ; Davydov et al., 2021). With regards to financial health, the literature suggests that (non-interest) income is positively associated with higher systemic risk (De Jonghe, 2010 ; Brunnermeier et al., 2020). Our data suggests that there is a positive relationship between operating income and systemic risk, whereas the association with MES is weak but also positive, since higher operating income can be used as a buffer against financial market risks and reduce the probability of default and market exposure.

Lastly, we present the relationship between systemic risk indicators and two key metrics: VaR and stock price volatility. Our findings reveal a weak correlation between systemic risk and both metrics, underscoring the need for additional metrics to comprehensively assess the risk profile of a company or market. This outcome aligns with the findings of Adrian and Brunnermeier (2016). In contrast, Figures 3.E and 3.F illustrate that real estate companies with high tail risk (VaR) and stock price volatility tend to exhibit greater MES and therefore exposure to adverse developments in the financial markets. However, it is important to note that this does not necessarily imply a threat to financial stability.

TIME-VARYING SYSTEMIC RISK MEASURES

To investigate the evolving dynamics among the variables and systemic risk, it is necessary to estimate the dynamic version of systemic risk. We accomplish this by employing a quantile regression model, following the approach of Adrian and Brunnermeier (2016), and incorporating a set of country-level state variables.

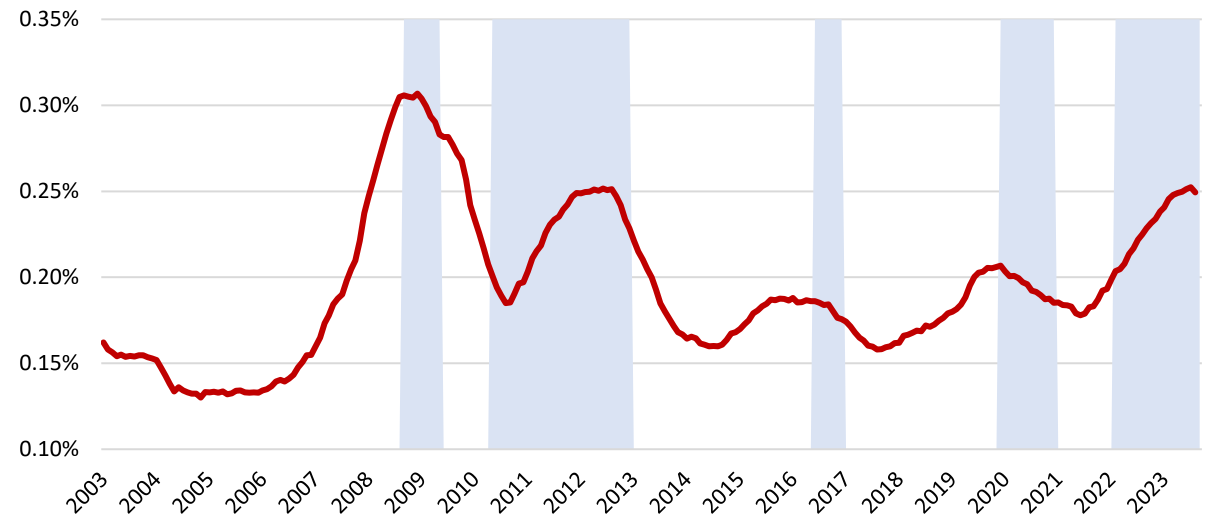
The dynamic ΔCoVaR, as illustrated in Equation (2), represents the Conditional VaR of the market index, indicating the fifth percentile returns of the system when the examined company's returns align with its VaR. In our analysis, we utilize a set of state variables at the country level to capture the fluctuations in conditional moments. These include stock market returns and volatility, the spread between the 10yr AAA corporate and the 10-year government bond, and the credit spread between AAA and BBB corporate bonds. For a detailed step-by-step explanation of the estimation process, please refer to the Appendix.

Figure 4 presents the systemic risk index for the European LRE (Listed Real Estate) market spanning the period 2003-2023. Systemic risk refers to the susceptibility of the domestic financial market to the potential transmission and amplification of adverse effects arising from a downturn in the LRE sector. The estimation of systemic risk is based on the weighted average of individual LRE companies' market capitalization. This approach is based on the analysis conducted by Rodriguez-Moreno and Peña (2013), who estimated an aggregate ΔCoVaR to gauge the collective spillover impact in a portfolio comprising both US and European firms. Similarly, Skouralis (2023) employed a similar methodology to estimate a systemic risk index for the Euro Area, combining the individual company-level risks of banks, insurance companies, financial services firms, and investment trusts.

In addition, in Figure 5 we present the aggregate MES. The index measures the average returns of LRE companies when the financial market index is below its VaR threshold. The aggregation is based on a market capitalization weighted average of all the companies in our sample. Contrarily to ΔCoVaR, we calculate MES using daily returns and a monthly sample. For illustration purposes and consistently with all the measures presented in this paper, we present a 24-month rolling window MES.

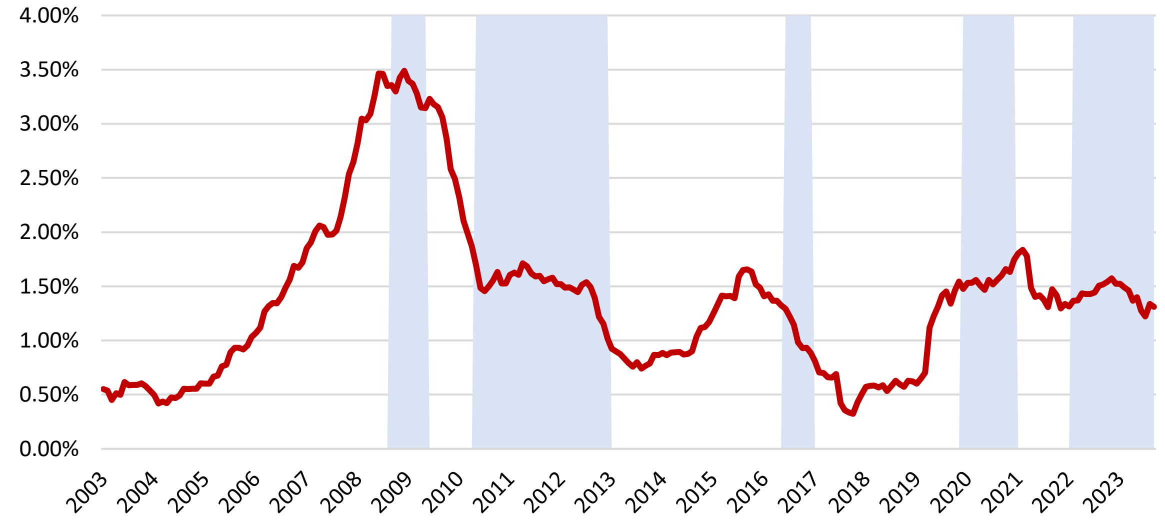
When comparing the two charts, we can identify common patterns as well as noteworthy differences. Initially, both indicators started at low levels, indicating a period of low stress. However, following the collapse of Lehman Brothers in 2008, we observe peak values in both indicators during the six months that followed. This suggests a significant increase in systemic risk during that period. During the sovereign debt crisis, LRE companies experienced a spike in their systemic importance, mirroring the behaviour of the majority of financial firms that were impacted by the widespread macroeconomic and political uncertainty. However, the LRE companies demonstrated relative resilience to the market's distress.

Figure 4: Systemic risk in the European LRE market



Note: The Figure displays the 24-month MA of the European LRE aggregate ΔCoVaR. The aggregation is based on a MCap-weighted portfolio of a sample of 88 LRE companies. The examined period is between 2003 and 2023 and the data is provided by EIKON Datastream and Authors' calculations.

Figure 5: European LRE market Aggregate MES



Note: The Figure displays the 24-month MA of the European LRE aggregate MES. The aggregation is based on a MCap-weighted portfolio of a sample of 88 LRE companies. The examined period is between 2003 and 2023 and the data is provided by EIKON Datastream and Authors' calculations.

In the subsequent years, both measures displayed low levels of risk, until the occurrence of the Brexit referendum in 2016, when both indicators reached a local maximum point. This indicates a heightened level of risk during that particular event. Another peak is observed in the first months of the COVID-19 pandemic, where the MES of LRE companies increased significantly from 1.5% to 2.5%.

This notable rise in the exposure of LRE companies can be attributed to the adverse developments in the financial markets during the early phase of the pandemic. Finally, both measures display a rapid increase over the last year as expected due to the Russia-Ukrainian war. Similarly, to the GFC, LRE market becomes more systemically important, and its exposure to the financial market has also been increasing. In other words, the LRE market is progressively more vulnerable to exogenous shocks.

Measuring interconnectedness in the European LRE markets

REAL ESTATE EXPOSURE ΔCOVAR

The above systemic risk metrics focus on the importance and the exposure of the listed real estate market with regards to the financial system. In this section we investigate the degree of connectedness across real estate companies. For that purpose, we use ΔCoVaR, which is bidirectional and we can estimate the exposure ΔCoVaR as the change in the tail risk of an examined firm when another firm or a market index is under distress.

We focus on the tail dependencies across the European real estate markets. In other words, we calculate the conditional VaR of the examined company or market (*i*) conditional on the European aggregate Real Estate market index being under distress. We define the new measure as **real estate exposure ΔCoVaR** and it captures the real estate systemic exposure of the examined firm or market. The measure can be also adjusted to captures the co-movements and tail dependency between the two listed companies or markets.

In this case the CoVaR of the examined LRE company *i* with respect to changes in European Real Estate aggregate index (*RE*) is defined as:

$$P\,(R_t^i < CoVaR^{i|RE}\,|\,R_t^{RE} = VaR^{RE}) = q \quad (9)$$

$$\Delta \mathrm{CoVaR}^{i|RE} = \mathrm{CoVaR}_{q=0.05}^{i|RE} - \mathrm{CoVaR}_{q=0.5}^{i|RE} \quad (10)$$

Table 2 presents the summary statistics of all systemic risk metrics. All the returns are estimated as the monthly average of daily returns and the sampling period is 2003-2023. In line with our previous analyses, the risk metrics are expressed as positive values. Therefore, an increase in VaR indicates higher tail risk. We observe that tail risk (VaR) in the European REIT market varies between 0.4% and 0.7%. However, VaR focuses on the risk of an individual institution in isolation and largely ignores risk spillovers. The fourth column displays the average ΔCoVaR of the domestic financial market index when a listed real estate company is under distress. Our findings from the countries' data average suggest that when the listed real estate market experiences distress, the tail risk (VaR) of the financials index increases, on average, by 0.22%.

Note that VaR and all metrics based on VaR are not additive. The summary statistics in Table 2 and Table 3 refer to the average value of all firm-level risk based on our sample, but not the market/portfolio risk. As expected, the systemic importance of the LRE market is lower at the less leveraged markets such as the UK. On the other hand, LRE companies in Sweden are more leveraged and thus more systemically important for the domestic financial market stability.

The last two columns present the metrics for the systemic exposure of LRE companies. Firstly, we present the summary statistics for MES with respect to the financial market. The measure shows the average returns of a LRE company, when the financial markets is below its 5% threshold (VaR). As observed in Table 1, the average returns of the LRE companies for the entire sample period is below but close to zero, however when the financial market index is distressed, the average return is -3.82%, as displayed in Table 2.

The more exposed markets are in Spain and France, which were the two countries that faced severe economic downturns in the period 2008-2014 and they exhibit high average individual VaR. The high exposure is observed in Sweden driven by the weak performance of the market in the last two years. In the last column we present the average Conditional VaR of a LRE company when the European LRE market is under distress. For instance, the VaR of UK LRE sector is estimated at 0.51%, however, this increases to 0.78% when the domestic financial market index is at is below its VaR. threshold.

Table 2: Systemic risk and exposure metrics: Country summary statistics

	Individual VaR	Leverage (Dec. 2022)	ΔCoVaR	MES	RE Exposure CoVaR
UK	0.51%	30.21%	0.19%	3.63%	0.78%
BEL	0.39%	42.96%	0.22%	3.64%	0.61%
FRA	0.63%	36.92%	0.27%	4.78%	1.02%
GER	0.60%	38.53%	0.22%	3.42%	0.86%
NLD	0.48%	38.80%	0.33%	3.89%	0.83%
ESP	0.65%	35.23%	0.27%	4.58%	0.97%
SWE	0.70%	45.07%	0.26%	4.09%	1.06%
All	0.54%	36.15%	0.22%	3.82%	0.84%

Note: The values refer to the daily average metrics of our sample of 88 European LRE companies and the period January 2003 to September 2023. DS Financials index is the market index used in the estimation of systemic risk metrics. Source: EPRA, EIKON Datastream and Authors calculations.

Table 3 displays the systemic risk summary statistics for companies with low (<30%), medium (31%-49%) and high (>50%) LTV based on EPRA's December 2022 data. We observe that the level of firm leverage is positively associated with LRE companies' tail risk and exposure to the financial markets, whereas the degree real estate exposure is homogeneous across all LTV levels. The results are in line with Figures 1 and 2.

Table 3: Systemic risk and exposure metrics: Sectoral summary statistics

Measure:	Number of firms (%)	VaR	ΔCoVaR	MES	RE Exposure CoVaR
Low LTV (<30%)	26.1%	0.51%	0.21%	0.32%	0.81%
Medium LTV (31%-49%)	64.8%	0.54%	0.22%	0.37%	0.82%
High LTV (>50%)	9.1%	0.60%	0.27%	0.44%	0.80%

Note: The values refer to the daily average metrics of our sample of 88 European LRE companies and the period January 2003 to September 2023. DS Financials index is the market index used in the estimation of systemic risk metrics. The LTV data is provided by EPRA for December 2022.

Table 4 presents the summary statistics at selected sectoral levels. The sectoral classification follows previous publications by EPRA. In the case a company is categorised as Industrial/Office mixed; we included only in the Industrial category. Based on our findings the strong demand for housing makes residential LRE companies to be amongst the most resilient subsectors. The outcome is based on the fact that the housing market is one of the few real estate markets not affected as much by the COVID-19 pandemic.

Healthcare and Self-Storage REITs also present low exposure. The latter two subsectors display the lowest tail risk (VaR), and it are not as vulnerable to fluctuations in financial and real estate markets. These companies benefit from the stability of the respective industries, especially in the recent years and the steady-cash flows from long-term leases.

Table 4: Systemic risk and exposure metrics: Sectoral summary statistics

Measure:	VaR	LTV	ΔCoVaR	MES	RE Exposure CoVaR
Residential	0.57%	37.54%	0.17%	3.57%	0.77%
Retail	0.51%	39.29%	0.21%	4.14%	0.84%
Offices	0.62%	32.04%	0.30%	3.93%	0.97%
Industrial	0.59%	38.31%	0.22%	3.94%	0.90%
Healthcare	0.38%	33.70%	0.12%	3.61%	0.58%
Self -Storage	0.50%	20.77%	0.27%	3.59%	0.89%
Diversified	0.52%	35.78%	0.25%	3.71%	0.78%

Note: The Table displays the daily firm-average risk metrics for the period 2003-2023. The sample consists of 88 European LRE companies and DS Financials index is used as the market index for the estimation of systemic risk metrics. The LTV data is provided by EPRA for December 2022. The systemic risk metrics are based on EIKON Datastream data and Authors 'calculations.

The VaR of Retail-focused LRE companies is among the lowest driven by the strong performance of supermarket REITs. However, Retail is one of the most vulnerable sectors with regards to systemic risk with average returns of -4.14% in the periods when the financial market index was distressed. This result highlights the importance of systemic risk indicators that capture another aspect of risk. Industrial and Office LRE companies have a share of 18.5% and 11.3% of the market in terms of market capitalization and as expected are amongst the most exposed subsectors. The office property sector, which is commonly used to track developments in the commercial real estate market is also the most systemically important subsector. It is worth noticing that the sectional metrics is not directly comparable since we have to take into consideration the country where each LRE company is located. Finally, diversified LRE companies have among the lowest VaR compared to the core subsectors, however their exposure to more than one sector makes them more systemically important and more vulnerable to adverse developments in the financial and real estate markets.

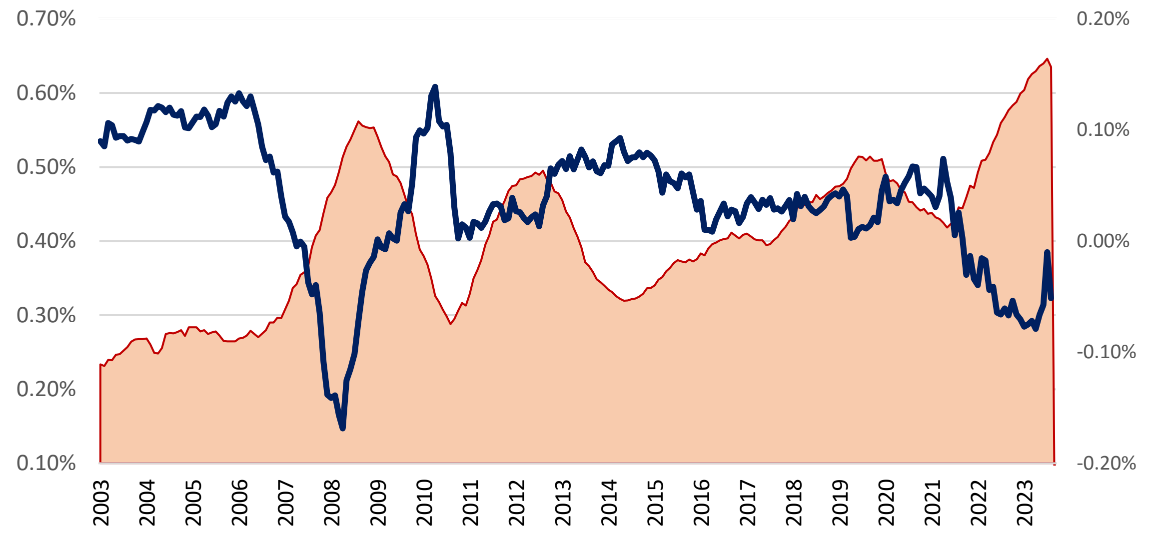
LRE SYSTEMIC EXPOSURE ΔCOVAR OVER TIME

Figure 6 presents the average systemic exposure of a LRE company to the European real estate market. In other words, this index captures the aggregate tail dependency across LRE companies. Our findings indicate that there is a strong negative association between the sector's returns and the degree of connectedness among LRE companies. In the period 2003-2019, we observe three peaks during the GFC, the debt sovereign crisis and the period after the Brexit referendum. However, over the last years, two more local maximum values are observed during the pandemic and in the most recent case of the start of the Russia-Ukraine war when the peak value was the highest since GFC. This is not unexpected since the economy-wide distress in the market result in more common patterns and an increase in tail dependency between real estate companies.

Network measures of connectedness

The aforementioned aggregate measurements of systemic risk and exposure present some limitations since aggregation typically tends to average away risk or dispersion in a data set. (Bisias et al., 2012). Therefore, in addition to cross-sectional measures we adopt several econometric techniques and metrics to capture different aspects of the degree of interconnectedness in the LRE sector. More specifically we employ three network measures, namely the Principal Component Analysis (PCA), the Granger-causality based Dynamic Causality Index (DCI) and the VAR-based Spillover Index (SI). These measures quantify the commonalities and the statistical connectivity within a system of financial institutions. These approaches are complements rather than substitutes and provide us with additional empirical evidence regarding the degree of connectedness in the European LRE market.

Figure 6: Aggregate Real Estate Exposure ΔCoVaR



Note: The Figure displays the average systemic exposure of a LRE company to the European real estate market for the period 2003-2023. The estimation is based on the MCap-weighted average aggregate real estate exposure ΔCoVaR. The data is provided by EIKON Datastream and Authors' calculations.

PRINCIPAL COMPONENTS ANALYSIS (PCA)

Potential increased commonality amongst LRE companies can be captured by network measures such as Principal Component Analysis (PCA). PCA is a statistical procedure that allows you to summarize the information content in large panel datasets by means of summary indices that can be more easily visualized and analysed. In our case, it is used to capture the dynamic commonality among the asset returns and the number and importance of common factors that drive the returns of the European LRE markets. PCA offers a more direct indications of linkages between markets and are easily aggregated to produce overall measures of "*tight coupling*" (Bisias et al., 2012).

Given a matrix of LRE market indices $(R_{i,t})$, $\overline{R_t}$ the vector average returns and t the number of days in the estimation the mathematic representation is the following:

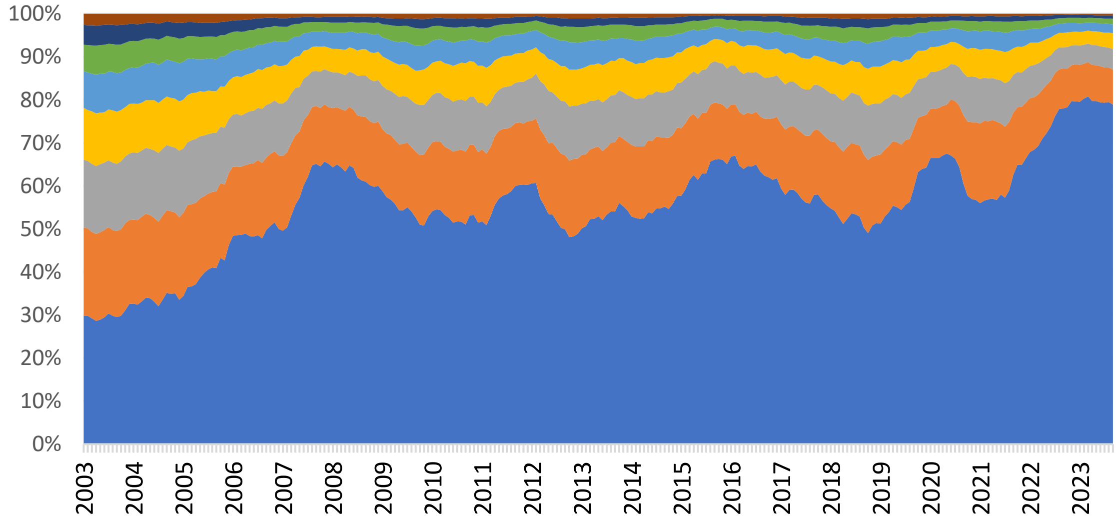
$$\hat{\Sigma} = \frac{1}{t-7} \sum_1^t (R_{i,t} - \overline{R_t})(R_{i,t} - \overline{R_t})' \quad (11)$$

PCA provides us with the decomposition of the variance-covariance matrix of the returns of the European LRE market indices into the orthonormal matrix of loadings[4] and the diagonal matrix of eigenvalues Λ. The first eigenvalues capture a larger portion of the total volatility when the market indices tend to move together and exhibit common patterns, as is with crisis periods. (Billio et al., 2012).

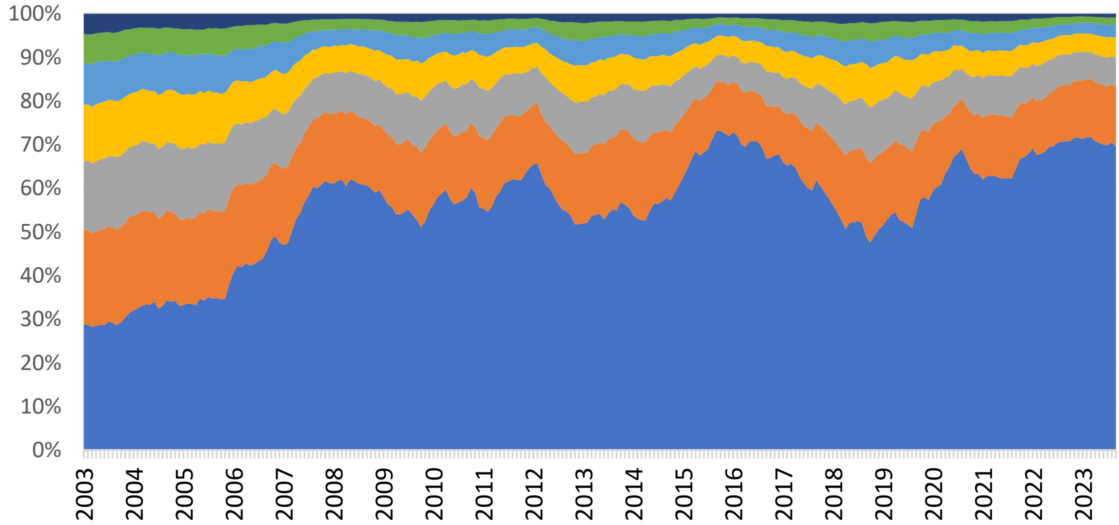
Figure 7 displays the explanatory power of the first principal components. The higher the fraction of the total variation that can be explained by the first components, the greater is the degree of interconnectedness amongst the European LRE markets. The results are homogeneous between sectoral and country co-movements, and they show that the first principal component captures 30%-70% of the total return variation. It started to increase in 2007/08 and the Global Financial Crisis and the following Eurozone Sovereign Debt Crisis. Then, it declined slightly over the next years up until the Brexit referendum when the degree of commonalities presents a local maximum especially for the country co-movements. The degree of connectedness remained high in the COVID-19 period and it started to rapidly increase again since the start of the Russia-Ukraine war and the associated macroeconomic uncertainty.

[4] Eigenvectors of the correlation matrix of returns.

Figure 7: Principal Components Analysis



A. European LRE Sectors



B. Country LRE market indices

Note: The Figure displays the 24-month MA of the first principal components of daily returns and the period 2003-2023. In Figure (A) we present the results for 8 LRE sectors and in Figure (B) of 7 country indices.

DYNAMIC CAUSALITY INDEX (DCI)

Following Billio et al. (2012, 2016), we explore the dynamic propagation and direction of shocks to the system by using Granger causality. Granger causality is a statistical concept that is used to determine the causal relationship between two time series variables. In essence, Granger causality tests whether the past values of one variable can provide useful information for predicting another variable, beyond what can be predicted using the past values of that variable alone. It is based on the idea that if time series *i* "Granger causes" time series *j*, then the past values of *i* should improve the predictions of *j* compared to using only the past values of *j*.[5] Billio et al. (2012) focus on 25 large entities in four different sectors and they choose to ignore smaller firms that ae not as systemically important. We follow a different approach, and we implement the method for the market capitalization weighted portfolios of LRE companies for each country. The main advantages are that we do not have any data gaps[6] and we can examine the cross-country shock propagation.

[5] It is important to note that Granger causality does not imply a direct causal relationship or provide information about the underlying mechanism of causality. It only suggests that one variable provides useful predictive information for another variable based on the observed data patterns.

[6] Around one third of the companies in our sample were founded in the last ten years.

The mathematic formulation is as follows:

$$R_{i,t} = \sum_1^L b_{1,1} r_{i,t-1} + \sum_1^L b_{1,2} R_{j,t-1} + e_{i,t} \quad (12)$$

$$R_{j,t} = \sum_1^L b_{2,1} r_{j,t-1} + \sum_1^L b_{2,2} R_{i,t-1} + e_{j,t} \quad (13)$$

i ≠ j and L is the maximum number of lags and $e_{i,t}$ and $e_{j,t}$ are uncorrelated white noise processes. $R_{i,t}$ causes $R_{j,t}\ (a_{j,i} = 1)$ if $b_{1,2} \neq 0$ and $b_{2,1} = 0$. If both $b_{1,2} \neq 0$ and $b_{2,1} \neq 0$ then there is a feedback relationship between the two time-series ($a_{j,i} = a_{i,j} = 1$).

Based on the above we estimate the Dynamic Causality Index (DCI) that is calculated as the number of causal relationships divided by total possible number of causal relationships.

The mathematical representation of DCI is the following:

$$DCI_t = \binom{v}{2} \sum_{i=1}^{v} \sum_{j=1}^{n} a_{i,j,t} \quad (14)$$

Where v is the number of series/variables considered. In Figure 8 we display the results. The index presents its highest values during the GFC the Sovereign Debt Crisis and the Brexit referendum. Our results from the DCI analysis suggest that the pandemic had a strong effect on the degree of co-movements between countries, but not among LRE sectors. Despite the fact that PCA and DCI are both network measures, they do not present perfect correlation since they capture different facets of connectedness (Billio et al., 2012). However, in both cases, the COVID-19 period resulted in a maximum point indicating strong associations amongst the LRE markets, followed by the latest geopolitical tensions and from the Russia-Ukraine war that impacted investor sentiment in the European real estate markets.

SPILLOVER INDEX (SI)

The Granger-causal approach is directional, but it has some limitations since it only focuses on two time-series and testing zero against non-zero coefficients with arbitrary significance levels and without tracking the importance and size of non-zero coefficients (Diebold and Yilmaz, 2014). To provide robust results against these drawbacks, we adopt the spillover index methodology introduced by Diebold and Yilmaz (2009, 2012). This method models stock market returns in a vector autoregressive framework (VAR) to empirically measure the volatility spillovers across markets. Diebold and Yilmaz (2009) introduce a spillover index using the forecast error variance decompositions of VAR model following Sims (1980) and the Cholesky decomposition. The main disadvantage of the latter is that it is sensitive to the variable ordering. For that purpose, we follow Diebold and Yilmaz (2012) and we employ a generalised VAR (1) model in which forecast-error variance decompositions do not depend on the variable ordering.

The VAR model takes the following form:

$$X_t = \sum_{i=1}^{Lags} \Phi_i X_{t-i} + e_t \quad (15)$$

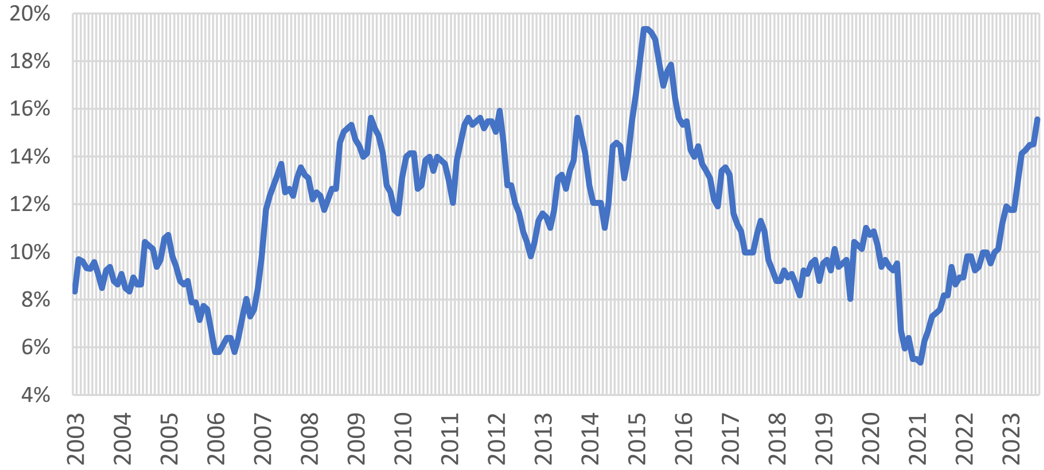
Where e ~ (0, Σ) is a vector of independently and identically distributed disturbances.

The moving average representation is as follows:

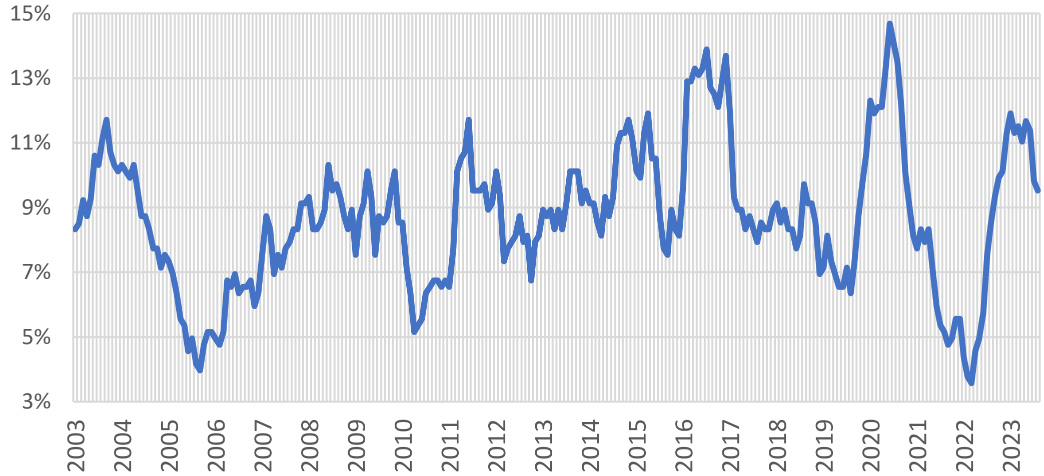
$$X_t = \sum_{i=0}^{\infty} A_i\, e_{t-i} \quad (16)$$

Following Diebold and Yilmaz (2012) and Koop et al. (1996) we use a generalised VAR which produces variance decomposition that does not depend on the variable ordering. This approach allows for correlated shocks, contrarily to orthogonalized shocks, using the error distributions.

Figure 8: Dynamic Causality Index



A. European LRE Sectors



B. Country LRE market indices

Note: The Figure displays the Dynamic Causality Index (DCI) for the period 2003-2023. In Figure A we present the results for 8 sectoral indices and in Figure B for 7 country indices. The estimation is based on daily returns of 88 LRE companies provided by EIKON Datastream.

The H-months ahead error variance decomposition of x_i due to shocks in x_j is defined as:

$$\theta_{i,j}(H) = \frac{\sigma_{i,j}^{-1}\sum_{h=0}^{H-1}(u_i' A_h \Sigma u_j)^2}{\sum_{h=0}^{H-1}(u_i' A_h \Sigma A_h' u_i)^2} \quad (17)$$

Σ is the variance matrix and $\sigma_{i,j}^{-1}$ is the error term standard deviation. As the shocks are not orthogonalized, the sum of the variance decomposition is not necessarily equal to one. We then normalize the elements of the variance decomposition matrix:

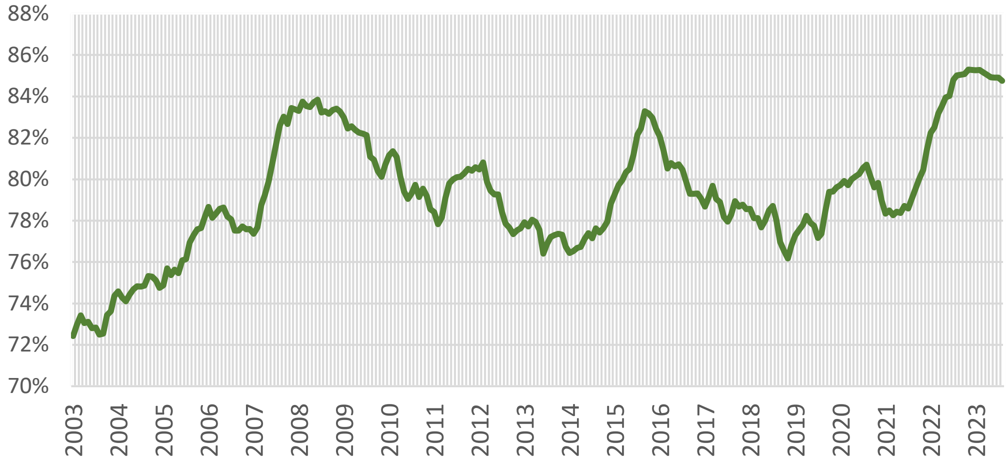
$$\widetilde{\theta_{i,j}}(H) = \frac{\theta_{i,j}(H)}{\sum_{j=1}^{N}\theta_{i,j}} \quad (18)$$

The total volatility index is estimated as follows:

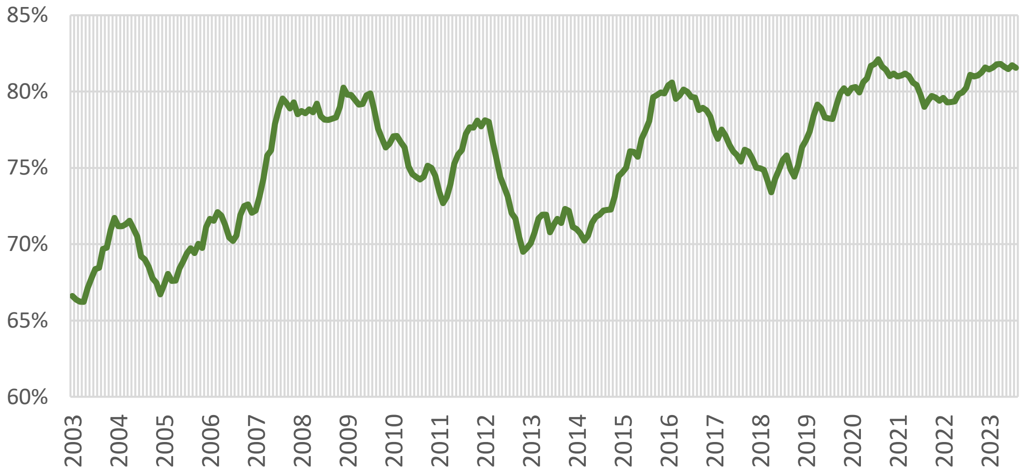
$$\text{SI (H)} = \frac{\sum_{i,j=1\ with\ i\neq j}^{N}\widetilde{\theta_{i,j}}(H)}{Number\ of\ vars} \quad (19)$$

SI (Spillover Index) captures the contribution of spillovers across market to the forecast error variance. In Figure 9 we present the total net spillovers amongst the seven country and eight sectoral-level European LRE indices.

Figure 9: Spillover Index



A. European LRE Sectors



B. LRE Market Indices

Note: The Figure displays the Spillover index for the period 2003-2023. In Figure A we present the results for 8 sectoral indices and in Figure B for 7 country indices. The estimation is based on daily returns of 88 LRE companies provided by EIKON Datastream.

With regards to the cross-country analysis, the degree of connectedness is considerably high and varies from 67% in the period before the GFC and peaks at above 80% in the last observations. The time variation follows closely the PCA methodology with high values in 2008 and 2014. However, the common pattern across all measures presented in this paper is the rapid increase in interconnectedness caused by the Russia-Ukraine war.

Table 5 displays the country level spillovers from and in a country. The estimation is based on a VAR(1,1) model and the seven LRE market country indices. The results suggest that the UK is the stronger net contributor followed by France. The results are in line with our expectations since one out of three LRE in the sample is located in the UK. On the other hand, Germany, Spain and Sweden are net shock receivers, despite the fact that their shock transmission to the other European countries is amongst the highest.

Table 5: Total Spillovers

	UK	Belgium	France	Germany	Netherlands	Spain	Sweden
FROM	0.642	0.822	0.765	0.845	0.808	0.735	0.876
TO	1.179	0.744	1.044	0.603	0.910	0.363	0.649
Net	0.538	-0.078	0.279	-0.242	0.102	-0.372	-0.226

Note: The Table displays the total spillovers to and from each country's LRE sector. The estimation is based on the Diebold and Yilmaz (2009) Spillover index and a sample of daily returns of 88 LRE companies over the period 2003-2023.

Portfolio Exercise

Our findings indicate that LRE returns are negatively correlated with sector's systemic exposure. However, periods of high systemic exposure for LRE companies are coincide with periods of distress in the financial markets. In this section we examine the role of LRE in a portfolio optimization exercise. The traditional portfolio selection approach by Markowitz (1952) is based on assets' returns and risk (variance). For a given set of assets the Mean-Variance theory (henceforth MVT) provides us with an efficient frontier that represents combination of assets with minimum risk for different levels of returns.

Despite the fact that this quantitative selection presents weaknesses, MVT is still the most popular approach in the portfolio selection theory. One of its main drawbacks is that MVT evaluates portfolios based on variance rather than downside risk. Therefore, two portfolios with the same variance will be considered to be equally risk despite the fact one of them may exhibit only small, but frequent losses and the other suffered rare, but sizeable declines.

In addition to the MVT portfolio, we also construct a Conditional VaR portfolio that aims to minimize the VaR of the portfolio conditional on the market index being under distress (below its VaR). Our empirical approach builds upon the modern portfolio theory of CVaR (Conditional Value-at-Risk) optimization, which uses the expected returns (losses) of the portfolio that occur beyond its VaR threshold. In our paper, we use the CVaR of the portfolio but only for periods that the market index is below its VaR to capture portfolio's systemic exposure. Our aim is not to capture tail as in the case of CVaR, but we want to measure the tail dependencies between markets.

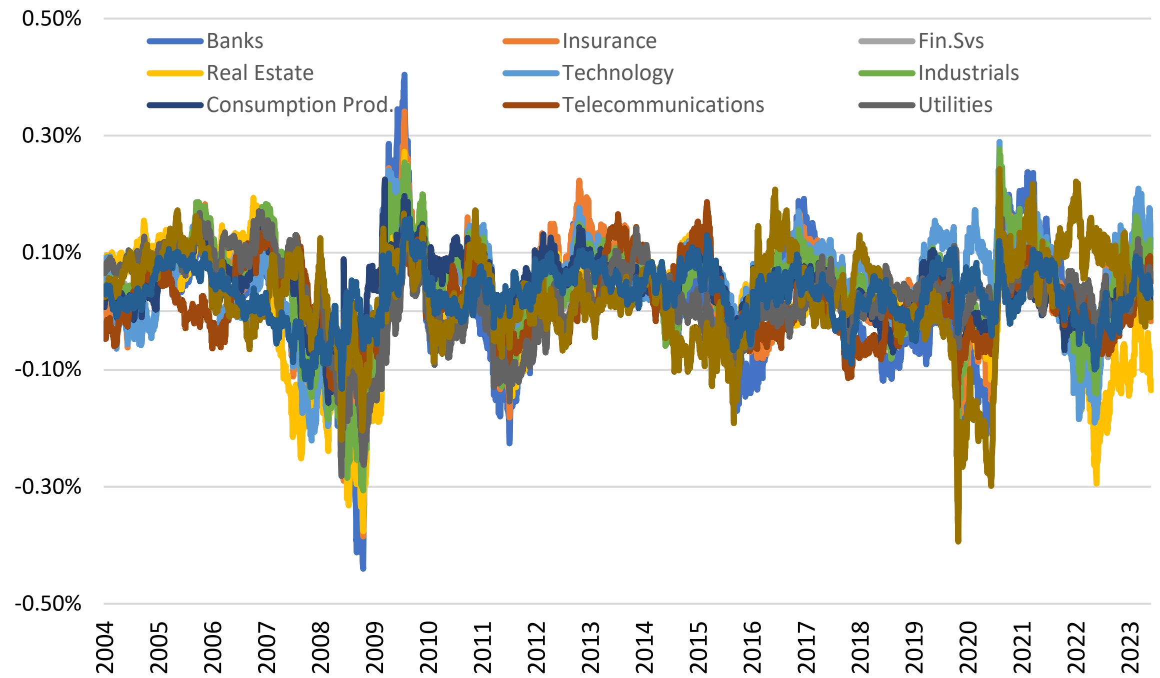
For our analysis we use 20 years of data (2004-2023) and 11 market indices. More specifically, we use Datastream market aggregates for the following sectors: Banks, Insurance, Financial Services, Technology, Industrials, Consumer products, Telecommunications, Utilities, Energy, Healthcare and our LRE market index. The Datastream indices are provided for each country, and we construct a European index based on Market Capitalization weights. Figure 9 displays the 200-day moving average of daily returns of all sector indices and Table 6 presents the summary statistics. As a benchmark and market index we use the STOXX600 index. Technology and consumption products companies outperformed the STOXX600 market index, whereas banks performed poorly due to the large declines the sector suffered during the GFC and the sovereign debt crisis.

Based on this sample of 20 years of historical returns we estimate the optimal weight allocation using both the MVT and the Conditional VaR approach. We don't use simulated returns or moving averages because we want to capture the historical tail dynamic between the market index (STOXX 600) and sectoral indices. In Figure 10 we present the efficient frontier as estimated by the approaches. In the MVT, investors base their decision solely on the risk-return trade-off and risk is measured by the returns' standard deviation as shown in the following equations:

$$E(R^P) = \sum_{i=1}^{11} w_i * E(R_i) = \sum_{i=1}^{11} w_i * \mu_i \quad (19)$$

$$\sigma^2{}_P = \sum_{i=1}^{11} \sum_{j=1}^{11} w_i * w_j * \sigma_i * \sigma_j * Corr(i,j) \quad (20)$$

Figure 9: Sectors Returns



Note: The Table depicts the 12-month MA of daily returns of 11 European sectoral market indices. The indices are calculated as the MCap-weighted average of the 7 Datastream country and sector aggregate indices. The sample covers the period 2003 and 2023. The Real Estate index is the MCap-weighted index of 88 LRE companies that have used in our previous analyses.

Table 6: Markets' Returns Summary Statistics

Sector	Mean	Min	Max	Standard Deviation
Banks	0.01%	-11.40%	13.85%	1.41%
Insurance	0.03%	-14.30%	14.52%	1.54%
Fin. Services	0.03%	-9.60%	9.00%	0.98%
Real Estate	0.01%	-10.40%	8.20%	1.20%
Technology	0.05%	-10.40%	9.70%	1.31%
Industrials	0.04%	-11.30%	9.40%	1.23%
Cons.Prod.	0.04%	-8.70%	29.20%	1.10%
Telecomm.	0.01%	-10.70%	10.00%	1.10%
Utilities	0.02%	-11.70%	15.20%	1.09%
Energy	0.02%	-17.20%	18.40%	1.52%
Healthcare	0.03%	-8.30%	8.20%	0.96%
STOXX600	0.02%	-11.48%	9.87%	1.13%

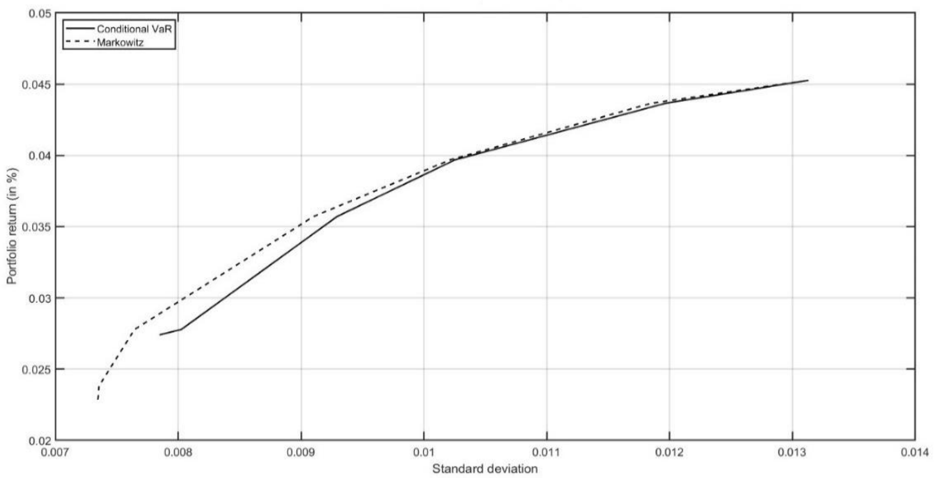
Note: The Table presents the summary statistics of the daily returns of the 11 European sectoral indices. The indices are calculated as the MCap-weighted average of the 7 Datastream country and sector aggregate indices. The sample covers the period 2003 and 2023. The Real Estate index is the MCap-weighted index of 88 LRE companies that we have used in our previous analyses.

The expected returns of the portfolio $E(R^P)$ is the weighted sum of the mean return of the individual assets, in our case the market indices. In the MVT approach, the portfolio risk is measured by its standard deviation as shown in Equation (20). Our alternative measure of risk is Conditional VaR which is calculated as the tail risk (VaR) of our portfolio when the market index is below its VaR threshold as shown in Equation (21).

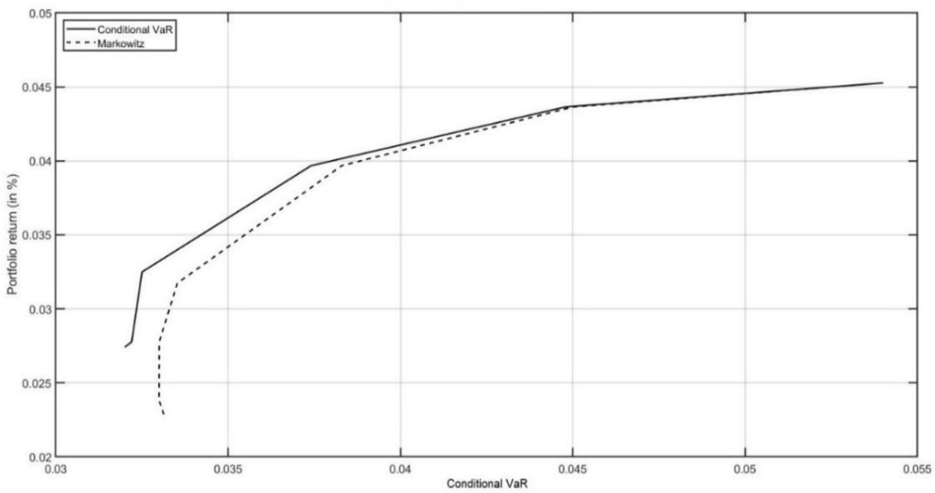
$$Conditional\ VaR_{0.05}^{P} = VaR_{0.05}^{P} \mid R^{Market} \leq VaR_{0.05}^{Market} \quad (21)$$

In this empirical exercise we want to calculate the weights for which we obtain the minimum tail risk (VaR of the portfolio) conditional on the market being below its VaR. The approaches provide different results as displayed in Figure 10. In the Figure 10.A we present the optimal portfolios for different levels of risk measured by their standard deviation. The MVT portfolios outperform, by construction, all the portfolios based on the Conditional VaR approach. On the other hand, the latter method provides portfolios with lower tail risk in periods of market distress compared to MVT as displayed in Figure 10.B.

Figure 10: Efficient Frontiers



A. Mean-Variance Theorem Approach



B. Conditional Value-at-Risk

Note: The Figures shows the efficient frontier based on the A) Mean-Variance and the B) CVaR optimization approach. The frontier includes all the optimal portfolios with the highest return for any given level of risk. In the Figure A risk is measured by portfolio's standard deviation, whereas in Figure B, risk is measured by Portfolio's Conditional Value-at-Risk. The sample consists of 11 sectoral indices and covers the period 2004-2023.

Based on the MVT approach, LRE and healthcare companies account, on average, for 30% of the optimal allocation each followed by financial companies (20%), consumption products (7%) and telecommunications (5%) and utilities (4%).

Based on the Conditional VaR approach, the weight on LRE is lower, but still one of the highest (17%). Consumption products and Healthcare are the two sectors with the highest weight allocation with 25% each, followed by financials (21%). Interestingly, this portfolio allocation against market tail risk includes more utilities companies (13%). However, the portfolio allocation varies considerably depending on the selected time period. For that purpose, we apply the portfolio optimization exercise for different time periods between 2004 and 2023.

The results are presented in Table 7. The LRE portfolio allocation is among the highest across the examined period, second only to Healthcare companies. The crisis caused a sizeable drop to the weights of financial companies, however LRE proved to be resilient. The sector increases again its share on portfolio allocation up until 2021. During the pandemic period (2020-2021), LRE and Healthcare outperform the other sectors and their share in the optimal portfolios has increased. However, LRE share dropped significantly in the last two years and since the beginning of the Russia-Ukraine war. During this period sectors such as Utilities, Energy and Telecommunications have increased their portfolio allocation.

Table 7: Portfolio Allocation

MVT									
Period	All Fin	LRE	Tech	Ind	Cons	Telec	Util	Energy	Health
2004-2007	16%	29%	0%	0%	0%	1%	18%	2%	33%
2008-2010	0%	27%	6%	0%	15%	0%	0%	0%	51%
2011-2014	38%	38%	0%	0%	0%	1%	0%	0%	24%
2015-2019	44%	41%	0%	0%	0%	0%	10%	0%	5%
2020-2023	0%	17%	2%	0%	24%	7%	31%	0%	19%
Conditional VaR									
Period	All Fin	LRE	Tech	Ind	Cons	Telec	Util	Energy	Health
2004-2007	6%	27%	0%	0%	0%	5%	0%	1%	61%
2008-2010	13%	41%	0%	0%	40%	0%	0%	0%	6%
2011-2014	35%	12%	0%	0%	0%	21%	0%	0%	32%
2015-2019	0%	71%	0%	0%	0%	0%	16%	13%	0%
2020-2023	0%	5%	1%	0%	45%	0%	0%	0%	49%

Note: The Table displays the optimal weight allocation based on our sample of 11 sectoral indices and the period 2004-2023. Data is provided by EIKON Datastream and Authors' calculations. The MVT optimal portfolio based on the highest Sharpe ratio, whereas the optimal Conditional VaR is based on the Sortino ratio.

The results vary with regards to LRE and the Conditional VaR optimization approach. During the GFC and in the period between 2015 and before the pandemic, LRE was one of the more resilient sectors in terms of systemic exposure. Similarly, to MVT, the optimal portfolio allocation during the last three years does not include financial and LRE companies, but healthcare and consumption products. Interestingly, over this period, Utility companies' weight in the MVT portfolio is 31%, but the sector exhibited tail dependency with the market index and therefore its weight on the Conditional VaR portfolio is close to zero. As interest rate and inflation has been stabilised, the expect the share of Consumer products and Utility companies to decline and the one of financial institutions and LRE to increase in 2024 back to its original levels.

Conclusions

This paper aims to quantify systemic risk and connectedness in the European LRE markets. Our empirical results indicate that when the LRE sector is under distress the (daily) tail risk of the financial market index increases by 0.42%. At the same time, LRE sector is significantly vulnerable to distress in the financial markets. In periods that the financial market index performs poorly, the VaR of the daily LRE index increases by 0.29%. However not all LRE companies are systemically important. Systemic risk is positively correlated with total assets/liabilities and leverage and negatively associated with profitability and liquidity. Hence, from an investors' point of view, firm size and leverage matter, especially at times of economic and financial stress. Individual firm level balance sheet analysis including operating income buffer, liquidity and the level of liabilities can help making an informed decision. In addition, there are also differences in how the different real estate sectors have affected by external shocks. Healthcare focused companies are more resilient to external shocks and also show less sensitivity to co-movements within the real estate market. Companies invested primarily in residential property, however, are resilient to external shocks however, are more influenced by movements in the real estate market.

To support the robustness of the findings, we provide a series of test and alternative methodologies to quantify the degree of connectedness in the European LRE markets. Our results show that the degree of co-movements in the LRE market exhibits significant variation depending on the state of the economy. Over the last 3 years the European economies experienced two major shocks, namely the COVID-19 pandemic and the Russia-Ukraine war. According to our estimates, real estate market' systemic risk and exposure indicators were more affected by the war-related uncertainty and the monetary tightening shortly after, rather than the pandemic. More specifically, the degree of connectedness across the European LRE markets rapidly increased over the last 12 months in 2022 and has already overcome the 2008 peak value in most of the examined measures. On one hand, our analysis shows a general increase in market connectedness from 2011 onwards, confirmed by the principal component analysis, however, secondly economic driven events seem to have a higher impact on LRE performance than financial market stress alone. This is derived from our analysis comparing the impact of the GFC versus recent events of the Ukraine-Russian war and inflation.

Finally, we demonstrated in a portfolio optimization exercise that there are distinct periods when LRE allocation is a beneficial and important diversification tool. Our findings suggest that LRE is featured in both the MVT and the Conditional VaR selection specifications and provides diversification benefits against systemic exposure despite the recent distress in the real estate markets. Overall, our results show that the LRE sector requires separate attention for monitoring market integration by policymakers and for implementing portfolio optimization by investors.

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Appendix

APPENDIX A: TABLES

Table A: Listed Real Estate Sample

Aedifica	Helical Bar	Retail Estates
Aroundtown	Home Invest Belgium REIT	Safestore Holdings
Ascencio	Home REIT	Sagax AB
Assura	Hufvudstaden	Schroder Real Estate Inv. Trust
Atrium Ljungberg AB	Icade	SEGRO
Big Yellow Group	Impact Healthcare REIT	Shaftesbury
BMO Commercial	Inmobiliaria Colonial	Shurgard Self Storage
BMO UK Real Estate Investments	Intervest Offices	Sirius Real Estate
British Land	Klépierre	Stendorren Fastigheter
Carmila	Landsec	Supermarket Income REIT
Castellum	Lar Espana Real Estate SOCIMI	TAG Immobilien
Civitas Social Housing	LEG Immobilien	Target Healthcare REIT
CLS Holdings Plc	LondonMetric Property	Triple Point Social Housing REIT
Cofinimmo	LXi REIT	Tritax Big Box REIT
Corem Property Group	Mercialys	Tritax EuroBox
Covivio	Merlin Properties	UK Commercial Property REIT
Custodian REIT	Montea	Unite Group
Derwent London	NewRiver REIT	Urban Logistics REIT
Deutsche EuroShop	Nextensa	Vastned Retail
Deutsche Wohnen	NP3 Fastigheter AB	VGP N.V.
Dios Fastigheter	NSI	Vonovia
Empiric Student Property	Nyfosa	Wallenstam
Eurocommercial	Pandox	Warehouse REIT PLC
Fabege	Phoenix Spree Deutschland	WDP
Fastighets Balder	Picton Property	Wereldhave
Gecina	Platzer Fastigheter Holding	Wihlborgs Fastigheter
Grainger	Primary Health Properties	Workspace Group
Great Portland Estates	PRS REIT	Xior Student Housing
Hamborner REIT	Regional REIT	
Hammerson	Residential Secure Income PLC	

Source: EPRA Monthly Statistical Bulletin, December 2022

APPENDIX B: DYNAMIC ESTIMATION OF ΔCOVAR

Following Adrian and Brunnermeier (2016) we employ a quantile regression model to estimate the dynamic ΔCoVaR and exposure-ΔCoVaR. The standard OLS regression model yields the median return of the market index conditional on a tail event in the examined institution, whereas quantile regressions allow us to explore the additional tail risk conditional upon a distressed company.

The time-series estimation is based on a country-level set of state variables that capture the variation in conditional moments, but they are not factors of systemic risk. For our analysis, we use stock market returns and volatility, the spread between a AAA corporate bond and the 10-year government bond and the credit spread between a AAA and a BBB corporate bond. The estimation is based on the fifth percentile of the quantile regression model to predict the additional tail risk in the financial markets conditional on the examined firm being under distress.

For the estimation we run the following quantile regressions:

$$R_t^i = a_q^i + \gamma_q^i \; StateVars_{t-1}^{country} + \; \varepsilon_{q,t} \quad (1)$$

$$R_t^s = a_q^{s|i} + \beta_q^{s|i} \; R_t^i + \; \gamma_q^{s|i} \; StateVars_{t-1}^{country} + \; \varepsilon_t^{s|i} \quad (2)$$

,where R_t is the monthly average of daily returns of the institution *i* and the market index *s*, and *q* the examined quantile (0.05). By replacing back the estimated values of the coefficients we obtain:

$$VaR_{q,t}^i \equiv \widehat{R_t^i} = \hat{a}_q^i + \; \hat{\gamma}_q^i \; StateVars_{t-1}^{country} \quad (3)$$

$$CoVaR_{q,t}^{s|i} \equiv \widehat{R_t^s} = \hat{a}_q^{s|i} + \; \hat{\beta}_q^{s|i} \; VaR_t^i + \hat{\gamma}_q^i \; StateVars_{t-1}^{country} \quad (4)$$

$$\Delta CoVaR_{q,t}^{s|i} = \; \hat{\beta}_q^{s|i} (\; VaR_t^i - VaR_{0.5}^i) \quad (5)$$