Master

Quantilograms: Concept and use in empirical finance

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Abstract

This paper is written to highlight a rather novel statistical methodology called Quantilogram/ Cross-Quantilogram/ Partial Cross-Quantilogram. The purpose is to make the method more accessible for someone without a master's degree in statistics or a phd in finance, e.g. a master student of economics or someone working within finance. The method is very useful when working with financial data, since it does not require data to be normally distributed. Financial data are frequently known to not have finite fourth moments due to heavy tails. The cross-quantilogram can reveal nonlinear and/or asymmetric relationships under varying market conditions. It can detect directional predictability and tail dependency between two time series, for arbitrary lags, and model how the dependency varies over time. The method is based on a quantile hit process, where the quantilogram is the correlogram of this quantile hit process.

The paper uses quantilograms to explore two cases from empirical finance. The first case examines the cross-quantile dependence structure between Brent crude oil, S&P 500 and OSEBX, to see which of the former two has the most spillover effect on the latter. The paper reveals that both Brent and S&P 500 have spillover effects on OSEBX, with S&P 500 being the strongest influencer. S&P 500 shows positive predictability for OSEBX for most quantiles at lag 1. A partial cross-quantilogram reveals that S&P 500 has a moderating effect on the spillover effects from Brent to OSEBX, whereas Brent has negligible effect on the relationship between S&P 500 and OSEBX. In general, the effects are not very persistent.

The second case study explores the directional predictability between 3 stocks from the aerospace industry; Lockheed Martin, Intuitive Machines and Astrotech. The industry is very diverse, and this is reflected in the results from the analysis. There is a surprising lack of cross-quantile correlation between the three. We find the strongest connectedness between Lockheed Martin and Intuitive Machines, which makes sense considering that their business models have the most in common. A lack of positive correlation in the medium-to-lower quantiles for Astrotech and Intuitive Machines at lag 1 makes them good hedges for each other.

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Chapter 1

Introduction

There are two main elements to concider for every investment decision:

1. What is the expected return?

2. What risk is associated with that expected return?

There are two major flaws with standard entry- to mid-level econometric methods. The first being that they generally model risk as variation around the mean. The second being that they often assume normality in the (joint) distributions. First of all, would it not be more interesting to model correlation depending on market conditions? From a risk management point of view, it feels more relevant to consider how two distributions correlate in times of distress, as opposed to whether or not one is above its mean when the other is below. If the returns of stock A are below the 0.1 quantile, is it likely that the returns of stock B will also below the 0.1 quantile. In other words, does risk, in the traditional sense of correlation, differ under normal circumstances and extreme conditions?

It has always appeared as somewhat of a conundrum to this author how we repeatedly continue to analyze time series using standard econometric methods that assume normality, even though we know that the bivariate normality assumption on the joint distributions does not hold. Even after examining the time series both visually and formally, and concluding that they are clearly not normally distributed, we still proceed to apply the aforementioned techniques, simply providing some precautionary statement about how one should be aware that the results might not be valid due to the assumptions not being fulfilled.

The quantilogram was first introduced by Linton and Whang in 2007 [35], and later extended to the cross-quantilogram (CQ) by Han, Linton, Oka and Whang (hereafter Han et al.) in 2016 [23]. Han et al. included an extra dimension as well, the partial cross quantilogram (PCQ), which allows for controlling for intermediate factors so one reveal the true direct underlying relationship. The original quantilogram is now considered a special case of the cross-quantilogram, and the PCQ is a multivariate version. The quantilogram is analogous to the autocorrelation or correlogram, the CQ is analogous to a bivariate cross-correlation, and the PCQ is equivalent to a multivariate partial cross-correlation function. The difference being that, where the autocorrelation models behavior around the mean, the quantilogram models autocorrelation, quantile to quantile using quantile hits. The quantilograms measure lead-lag dependencies between two time series. These lead-lag dependencies are referred to with different terminology throughout the literature, e.g directional predictability, spillover effects, interconnectedness, nonlinear dependencies etc. Essentially they all refer to the same thing, how the quantiles of one time series are connected to the quantiles of another lagged time series. In other words, does one time series influence the other, or can it predict future behaviour of another time series.

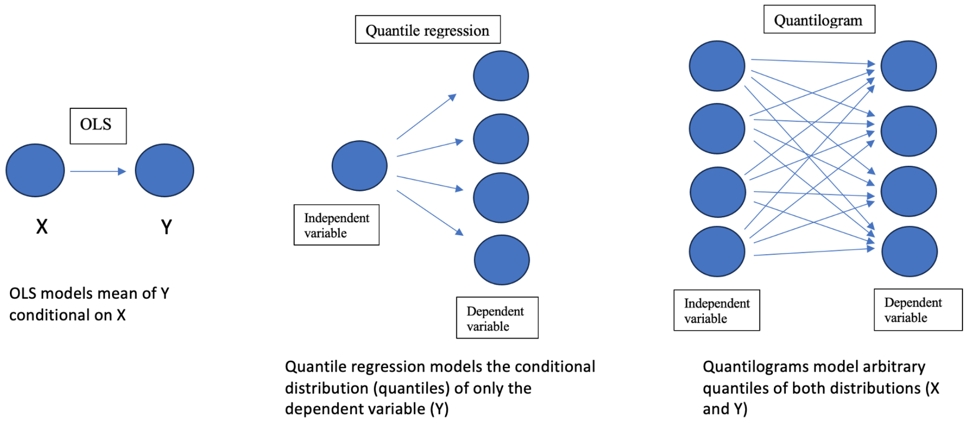

Figure 1.1: OLS vs Quantile regression vs Quantilogram (produced by author)

1.1 Logic & Assumptions

The logic behind the method is to first register if a realization of the first time series is below some predefined arbitrary quantile τ_1. The formula (see methodology section) includes an indicator function which takes the value 1 if the condition is true, 0 otherwise. If an observation is below the predefined quantile, the value of the quantile hit is $1 - \tau_1$. If it is above the quantile it takes the value $-\tau_1$. The same applies for the second time series. The two values are then multiplied together. There is a scaling element in the denominator, similar to the standard correlation, to ensure that the value lies in the interval [-1, 1]. The cross-quantilogram is then given as the correlogram of this quantile hit process.

Condition 1: Observation 1 $\leq$ quantile 1	Condition 2: Observation 2 $\leq$ quantile 2	Correlation value
True	True	Positive
True	False	Negative
False	True	Negative
False	False	Positive

Table 1.1: Logic behind positive/negative values for the cross-quantile correlation of the quantile hit process

Instead of meeting the normality assumptions, the only strict requirement to employ the CQ method is that the analyzed time series must be stationary. Financial time series are typically not normally distributed due to infinite fourth moments, and may behave very different in a normal market versus an extreme market. Quantilograms can measure correlation at the tails of the distribution or under different market conditions, be it bearish, normal, or bullish markets. This allows for capturing non-linear, asymmetric behavior of financial time series. On average, two variables might correlate in a certain way, but in case of extreme events that correlation might change. Measures such as Value at Risk (VaR) and Expected Shortfall address this by estimating tail risk/potential loss, but they are still often calculated under the assumption of normality.

Linear regression obviously assumes that the true underlying relationship between the dependent variable and the independent variables is linear, which most often is not the case. Quantile regression allows us to model conditional quantiles of the dependent variable, but still only using one value of the independent variable. The traditional quantile estimator is not based on time-dependent conditions and is unable to generate confidence intervals [50]. Using the CQ, we expand the universe since it allows us to model the $\tau - th$ quantiles of both variables, allowing for a more comprehensive understanding of the underlying relationship under different circumstances [11]. Commonly used models, such as multivariate GARCH models, generally also assume the existence of finite fourth moments.

Neither the Pearson correlation coefficient nor covariance can be used to assess non-linear relationships, or those stemming from non-normal data. Figure 1.2 shows several cases where traditional correlation does not provide a good description of the underlying data. In the first example (a), there is clearly a relationship, but since it is non-linear the correlation coefficient does not capture this. In the second example (b), we see that one extreme outlier leads to a correlation coefficient of 0.71. Whereas if you remove this one data-point, the correlation is close to 0. In the lower left-hand corner (c), we see two subgroups, typically male&female. If you evaluate the entire dataset as a whole the correlation appears to be close to 1, but within each subgroup there is practically no correlation. If you did not visually inspect this dataset you would not know that there were two subgroups. The final example (d) shows a heteroskedastic dataset.

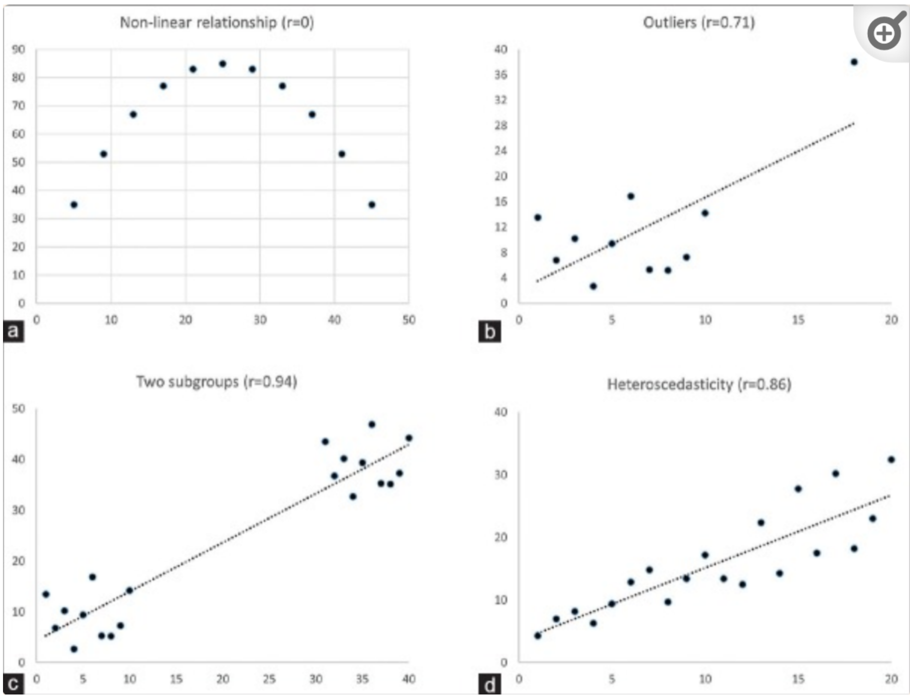

Figure 1.2: When correlation should not be used, reproduced from [2]

One of the most important advantages of using the cross-quantilogram, mentioned in several research papers, is its ability to capture the direction, duration and magnitude of the relationship between two time series. Other advantages include: (1) Using block bootstrapping for the directional predictability test allows for arbitrary long lags to be estimated. (2) It captures the properties of a joint distribution. (3) The methodology is robust to misspecification errors since it is a nonparametric statistic based on quantile hits. (4) Quantilograms are invariant to any strictly monotonic transformation applied to both series, e.g., taking the log. (5) The CQ can also measure contemporaneous effects by setting the lag to 0. (6) By using a rolling window one can capture the time-varying nature of the correlation.

A drawback of the quantilograms is that they, contrary to a VaR or expected shortfall, produce a unit-less output. Which in turn means that the output does not necessarily have direct interpretability in form of a monetary unit for instance, which of course is also true for traditional correlation. However, it can be integrated into more complex models such as network approaches. Generally, the magnitude of the correlation is rather small compared to a standard correlation coefficient, but when you accumulate the values over several lags the total effect is potentially much larger. Finally, the simplicity of the model, applying the quantile hit process, also means that you give up some information about the observations.

1.2 Case study - OSEBX, Brent oil and S&P500

As an example of how the CQ and PCQ can be applied, we are going to conduct a case study of the directional predictability of the returns on Oslo Stock Exchange (OSEBX) from Brent crude oil and the S&P 500. Our study is, to the best of our knowledge, the first to apply this cross-quantile dependency technique to quantify the dependency or predictability from Brent and S&P 500 to OSEBX. Earlier studies have typically used ordinary linear regression (OLS). We find that there is positive directional predictability in similar quantiles at lag 1 from Brent to OSEBX, and that the effect is mostly gone after 5 days. We similarly find positive directional predictability from S&P 500 to OSEBX, and that the effect is stronger than for Brent. Applying a PCQ, we find that the S&P 500 has a moderating effect on the relationship between Brent and OSEBX, but that there is still some spillover effect from Brent to OSEBX. Brent has negligible moderating effect on the relationship between S&P 500 and OSEBX.

1.3 Case study - Aerospace stocks

The second case study takes a closer look at the quantile correlation between certain companies from the aerospace industry. Specifically, we examine the connectedness between Astrotech, Intuitive Machines and Lockheed Martin. Both standard correlation and cross-quantile correlation is very weak, and in some cases negative. This is likely due to the discrepancies between the business models. Lockheed Martin is the most influential out of the three, as it has some positive predictability for both Astrotech and Intuitive Machines. Astrotech and Intuitive Machines can serve as hedges for each other, as they have insignificant or negative cross-quantile correlation across all quantiles at lag 1 (with one exception).

The rest of this paper is organized as follows: Chapter 2 gives a review of the existing literature on quantilograms and certain papers that are relevant background material for the case studies. Section 3 covers the concept and use of quantilograms in empirical finance. The methodology including mathematical notation is introduced in Section 4. Section 5 reveals the results from our case studies. Section 6 offers discussions surrounding our findings. Finally, Section 7 gives a brief summary and conclusion of the paper.

Chapter 2

Literature review

The literature review is organized according to which topics quantilograms were used to examine. At the end there are two sections that refer to the specific topics for the case studies.

2.1 General finance

Baumöhl & Lyocsa (2017) [5] use cross-quantiles to study the directional predictability from stock market sector indices to gold. They split the sample into two periods, to evaluate if there is a change in the directional predictability before and after the financial crisis in 2008. They find significantly different results for the entire sample, before and after the crisis. There is limited quantile dependence from gold to all sectors, except Industrials, both before and after the crisis. There are only three sectors for which gold exhibits safe haven attributes for the entire sample period (1999-2016), namely IT, Healthcare and Telecommunication services. Baumöhl & Lyocsa define gold as a safe haven if extreme negative returns to the stock market are followed by positive gold returns, or if the heatmap is entirely empty, meaning there is no relationship. Their findings reveal how dependencies can vary over time and how the financial crisis caused a change in these dependencies.

Todorova (2017) [65] uses the CQ to examine the intraday directional predictability of large Australian stocks. Specifically looking at intraday reactions to overnight news. The evidence indicates the existence of intraday reversals when overnight news has been very bad, but there are mixed results when the news was good. Joaqui-Barandica et al. (2023) [27] use a CQ to study if there is a predictive relationship between interest rates and the Stoxx 600 Banks index. According to them, the Stoxx 600 Banks index receives shocks during a financial crisis, whereas the World Interest Rate transmits them.

Mensi et al. (2023) [37] use a combination of a CQ and a quantile connectedness approach to study dependencies and spillovers between uncertainty indices of stocks (VIX), economic policy uncertainty (EPU) and oil, gold, and various stock markets, under varying market conditions. The uncertainty indices are net transmitters of spillovers to the stock market under bearish and bullish markets. Furthermore, they uncover strong quantile dependency from the US to other stock markets in the shorter time frames.

Lindman et al. (2020) [34] use a cross-quantile approach to compare the quantile dependence between stock returns in Germany and the UK, with three distinct countries within the European Monetary Unit (Euro-countries), two global leading markets (USA and Japan) and two emerging markets (the worlds most populated countries, China and India). Key takeaways are that common currency groups are more financially integrated than others, that dependencies are heterogeneous (especially between UK/Germany and developed markets

(USA/Japan) and emerging markets (India/China)), and that the correlation varies over time, particularly in the higher and lower quantiles. Indicating that financial integration increases during times of financial and economic turbulence.

Qian et al. (2022) [48] use PCQ networks to measure quantile connectedness of 30 of China's financial institutions, finding that they are more connected at the extreme quantiles than at the median. Using the relative centrality measurement they identify the financial institutions with the largest potential to trigger or transfer systemic risk. Demirer et al. (2020) [14] apply a CQ to investigate the time-varying risk aversion and profitability from carry trades, uncovering that risk aversion can predict carry trade returns during periods of medium to high risk aversion.

Baumöhl et al. (2022) [6] measure the systemic risk in the global banking sector, including 83 of the largest banks from 24 countries across Europe, the US and Asia. To do so they construct a network by computing the bivariate CQ for all pairs of banks. They propose a systemic risk index based on the sum of all the pairs. They only consider the lower quantiles of the distributions because they are only interested in downside risk. The results show a massive increase in systemic risk during the Covid-19 pandemic compared to the global financial crisis in 2008. US banks are the most influential risk transmitters, whereas Asian banks are major risk receivers.

Deev et al. (2022) [13] study the time varying left-tail exposure of Chinese stocks to Evergrande. The results show that the companies that were most exposed were the companies with the largest market capitalization, and those in the real estate and utilities industries. Which is as expected considering Evergrande was the second largest property developer in China. Hung (2023) [63] examines the Covid pandemics effect on the G7 stock markets, finding that the stock markets react negatively and disproportionately to increases in confirmed Covid cases.

2.2 Cryptocurrencies

Corbet et al. (2020) [12] implement a quantile Granger-causality test to measure the directional predictability between cryptocurrencies and traditional financial assets. They find significant bi-directional causality between Bitcoin and other financial assets in the tails of the distributions, but Bitcoin is a strong safe haven for oil, and a weak safe haven for S&P 500. Naeem et al. (2023) [38] inspect the relationship between oil and cryptocurrencies. Using a CQ they discover a nonlinear and asymmetric relationship between oil shocks and cryptocurrencies. Sohag & Ullah (2022) [59] use a CQ to examine Bitcoins response to social media sentiment. Using daily high-frequency data from Twitter-based economic uncertainty, they find significant predictability with 1 and 5 days lag for the lower quantiles of both variables.

Hampl et al. (2024) [22] examine the behaviour of cryptocurrencies during the Russian invasion of Ukraine. They follow the safe-haven definition by Shahzad et al. (2019) [56], stating that an asset is a strong safe-haven if there is only negative correlation in the lower quantiles during market stress. Whereas a weak safe-haven asset displays only insignificant correlation in the lower quantiles. Cryptocurrencies exhibit weak safe-haven properties for commodities and strong safe-haven properties for foreign exchange currencies, but can not serve as safe-havens against other cryptocurrencies. However, every cryptocurrency asset considered in the paper served as a strong safe-haven for USD.

2.3 Currencies

Laurini et al. (2008) [33] use both quantilograms and quantile regression to study the spread between bid and ask for the BRL/USD exchange market. They found that for the lower percentiles there was low persistence, but as the percentiles increased, so did the persistence. This asymmetry shows that there is higher persistence for higher spreads, typically due to unanticipated shocks. Shahzad et al (2021) [55] use the CQ to measure how the quantiles of investor sentiment affect the quantiles of the dollar-pound exchange rate. They demonstrate a positive effect in the lower quantiles and a negative effect in the median to upper quantiles.

Rehman et al. (2022) [51] use CQs and PCQs to study the directional predictability between foreign exchange rates in emerging markets. Using the CQ, they find that the Mexican peso, Brazilian real and Turkish lira are the most significant emerging market currencies for investors looking for hedging opportunities. The structural inter-dependencies are evident at lag 1, but weaken quickly, and there is no consistently significant predictability at the median quantile. The PCQ, somewhat surprisingly, reveals that oil is not a driving force of the interconnectedness between the exchange rates. Finally, using a recursive subsample, Rehman et al. show that the CQ varies over time, predominantly in the extreme quantiles.

Cho & Han (2021) [11] apply a CQ analysis to study the tail behavior of safe haven currencies in extreme markets. Specifically, they study the effect of FX volatility on currencies when they are below the 5th quantile or above the 95th quantile. Their research shows that the Japanese yen is the strongest safe haven currency, thereafter the Swiss franc and the euro. Furthermore, they discover that different shocks have asymmetric effects on the currencies.

Shahzad et al. (2018) [56] use a CQ network approach to investigate risk transmitters and receivers in 25 developed, emerging, Middle Eastern and North African markets. Developed markets act predominantly ask risk transmitters, while smaller currencies act as receivers. They model bearish, normal and bullish markets for the entire sample, pre-crisis period, during the global financial crisis, and after the crisis. The Canadian and Australian dollars are the main risk transmitters (USD not included in the paper).

Chang et al. (2024) [9] inspect the impact of Taiwanese dollars on Taiwanese stock markets during the Covid-19 pandemic. They find that Taiwanese dollars Granger cause returns on the Taiwanese stock market in a negative way. Hung & Vinh (2023) [26] use cross-quantilograms to examine the impact of Covid-19 on foreign exchange markets. They find that changes in confirmed Covid-cases can predict changes in currency markets under all market conditions.

2.4 Energy / Fossil fuels

Tiwari et al. [64] use CQs and PCQs to study directional predictability from energy markets to exchange rates and stock markets in emerging market countries. Their findings show that implementing the PCQ is beneficial, as including general geopolitical risk and geopolitical risk threats in the PCQ approach greatly improves the predictability. All time series were non-normally distributed, stationary and auto-correlated. Underlining why it is necessary to use a statistical method such as the QC/PCQ, which does not rely on the Gaussian assumptions. Similarly, Zhou et al. (2019) [71] examine if oil volatility has directional predictability for stock returns in the BRICS countries (Brazil, Russia, India, China and South Africa). According to them, if oil volatility is lower than its 0.1 quantile, then it is less likely to experience large losses or gains in the stock markets. On the other hand, there is an increased likelihood of experiencing large losses or gains if oil volatility is above its 0.9 quantile. The directional predictability for the respective countries also depends on whether they are a net exporter or net importer of oil.

Okhrin et al. (2023) [41] also research the interconnectedness of oil with financial commodity markets using a CQ, paired vine-based copulas and copula vine-based regression. During Covid-19 the connectedness increased significantly, and it also intensified after the Russian invasion of Ukraine. The connectedness is asymmetric, due to the stronger tail dependence in the lower tail.

Kumar et al. (2021) [32] research a similar topic, namely if geopolitical risk improves the directional predictability from oil to stock returns in 14 emerging markets, also differentiating between oil exporters and oil importers. Without controlling for geopolitical risk they find no significant predictability, but after controlling for geopolitical risk they find positive quantile dependence when both are in the same quantiles in the lower to middle quantiles. Also, oil shocks have a much larger effect on stock markets in oil exporting countries as compared to oil importing countries. Kartal et al. (2024) [30] use CQ to study the relationship between energy security risk and financial markets in South Korea, finding that financial development indicators are strong predictors of energy security risk. Sinha et al. (2022) [58] examine the dependence between Indian financial markets and energy commodities using DCC-Garch, CQ and Wavelet Coherence, showing that there is an asymmetric negative effect from market returns to energy commodities.

Uribe et al. (2018)[67] is the only paper implemented in this literature review that uses prices instead of returns for their analysis. Uribe et al. use gas and electricity prices in the US to uncover nonlinear dependencies, which increase for prices above the median, and work in both directions. The authors state that using quantiles is a motivation for the paper, because it allows them to model seasonality. The dependency is lower from electricity to gas than from gas to electricity. Scarcioffolo & Etienne (2021) [54] investigate directional predictability and spillover effects between natural gas, oil, and electricity, using returns from the respective time series. Implementing a quantile Granger causality test, they find bi-directional causality between gas and electricity under different market conditions. They also find spillover effects from oil to gas under adverse market conditions.

Alomari et al. (2022) [3] investigate the connectedness and return spillovers between oil and precious metals futures. Oil produces significant spillover effects to precious metals during an extremely negative market, but under normal market conditions the effect is insignificant. The dependency of oil on precious metals is mostly insignificant, confirming that the relationship is heterogeneous and asymmetric. The conclusion from the paper is that precious metals are good for diversifying oil portfolios. Raggad (2023) [49] uses implied volatility to predict returns in the oil market. There is evidence of predictability when volatility is high, but no evidence when volatility is low or normal.

2.5 Renewable energy/Green markets

Uddin et al. (2019)[66] use a CQ-based correlation approach to examine the dependence between renewable energy stocks and other asset classes, such as oil, gold, and exchange rates. They found that there is some predictability from the Renewable Energy Index (REI) to oil when both are in their lower quantiles. The dependency is strongest at a lag of 1 day, still present after 5 days, before it dissipates thereafter. On the other hand, the spillover effect from oil to REI is positive across quantiles for similar quantiles, but not when they are in opposite quantiles. The relationship is asymmetric. This indicates that when oil prices increase so does the REI, but not the other way around. This is probably due to the substitution effect. Renewable energy is more expensive than oil. Therefore, as the price of oil rises, more energy demand can be met by renewable energy. The strength of the dependency decreases rapidly, but is still vaguely present after 66 days (a quarter) in the lower quantiles.

Karim et al. [29] apply cross-quantilograms to evaluate whether or not energy metals can predict climate change risk, and if so, how it could be possible to diversify away from the risks. They uncover predictability between the two at higher lags, as well as in the tails of the distributions. As extreme climate events become more frequent, business owners can use energy metals to hedge their exposure to climate risks, both over the short- and long-term. Yahya et al. (2020) [68] use a CQ to see if there is cross-quantile dependency between non-ferrous metals and clean energy indexes. Using time-varying copulas and a quantile Granger-causality test, they find that the interconnectedness is asymmetric and increasing with the number of lags. Razzaq et al. (2022) [50] test the directional predictability from carbon trading to stocks from different sectors in China. They find negative predictability from carbon trading prices to stock markets in bull markets, and positive predictability in bear markets. In other words, this dependence is also asymmetric. They also found that it varies substantially across sectors. "The results imply that higher carbon trading prices lead to higher production costs, lower output, lower profitability and a reduction in stock prices" [50]. Qi et al. (2024) [47] do something similar, except they are comparing the correlation between green bond markets and carbon trading markets. They find that there is some positive predictability from green bonds to carbon trading markets, but that the effect is most pronounced at 1 days lag and is gone after 5 days.

Borg et al. (2022)[7] use a CQ and a PCQ to study the dependence of renewable energy production-related critical metal futures and producer equity returns, and compare them to non-renewable energy and other commodity markets. They find that relationships that appear similar when evaluating the traditional correlation metric, can be both asymmetric and non-linear, but also that the dependencies run in opposite directions. With similar correlations of around 0.55, the dependency runs from the precious metals index to silver, but for the the agricultural index the dependency runs predominantly from corn futures to the index. The CQ reveals the true nature of the underlying relationship, providing valuable insight for market participants.

On a similar note, Zhang et al. (2023) [69] combine a CQ with a TVP-VAR based connectedness approach to study the dependence and connectedness of returns to renewable energy stocks and fossil energy markets. The CQ approach allows them to model various market conditions and varying time frames. The results show that renewable energy stocks are heavily dependent on fossil energy markets under extreme market conditions, whereas they are decoupled under normal conditions. After the financial crisis in 2008, they find an abrupt jump in both the connectedness and dependence of renewable energy stocks on fossil energy, which was pronounced during extreme market conditions. Pham (2021) [44] studies integration within green equity markets. US markets are the primary driver, as they can predict movements in both the European and Asian markets.

Sohag et al. (2022) [60] also combine a TVP-VAR connectedness approach and a CQ to see whether or not geopolitical events transmit opportunities or threats to green markets. They also include a quantile-on-quantile approach to check the robustness of their findings. Geopolitical risks transmit positive shocks to green equities and bonds, throughout the quantiles.

2.6 Others

Other implementations of the CQ include a study on the interconnectedness of international tourism demand in Europe by Lyocsa et al. (2019) [36]. They find asymmetric demand depending on what market state is prevalent, and that international tourism demand tends to be bidirectional. Finally, in bad times the demand tends to increase for Central and Eastern Europe.

2.7 Case study: OSEBX, Brent and S&P 500

Heggen (2019) [24] uses a two-factor capital asset pricing model to investigate the influence from oil returns to stock returns of the 25 largest companies on OSEBX, known as the OBX index. She found that 12 out of 25 stocks were significantly affected by oil returns at a 5% significance level. Unsurprisingly, an increase in oil prices had a positive effect on all five oil related stocks included in the OBX index, but interestingly it had a negative effect on six out of the seven other stocks. These stocks included consumer goods (seafood), telecommunications, and one industrial company. A distributed lags model, found little evidence that oil returns affected future stock returns.

Running a regression with nine explanatory variables, Hovden & Batalden (2017) [25] found that there are four factors that had a significant effect on the returns of OSEBX. The primary effects came from oil and the S&P 500, and the effect was positive. They also found less important and negative effects from VIX and SMB (fear index and a small vs big index). Using a co-integration test they found that the causal relationship between oil and OSEBX changed after 2014, and that there no longer exists a long-term relationship.

Fosby & Dahl (2016) [19] use OLS to see how oil returns affected OSEBX over the time period 1996 - 2015. Their findings reveal that the oil returns and the Morgan Stanley World Capital Market Index have significant impact on OSEBX, whereof the latter is the most significant. Using an extended model, they find that OSEBX is more sensitive to negative than positive impulses from both explanatory variables, showing an asymmetry in its response. Næs et al. (2008) [39], using monthly data from 1980-2006, find that most of the worlds stock markets fall with an increase in oil prices, as opposed to OSEBX which rises with an increase.

2.8 Case study: Aerospace

Mattedi et al. (2004) [42] use Value-at-Risk (VaR) and Tsallis statistics to conduct a risk analysis of the aerospace sector. Their sense of the interpretation of financial risk is defined as "the degree of uncertainty about future returns", generally referring to increased volatility. I would like to emphasize that this paper is 20 years old and that more evolved measures of risk are available today. Nevertheless, VaR continues to be a highly used risk measurement to this day, given that it is easy to compute and has good interpretability. As Mattedi et al. point out, the VaR computes the maximum potential loss given some probability (typically 1% or 5%) under normal market conditions. They construct their own aerospace index and find that it follows a Tsallis distribution, and that it is more volatile than comparable indices such as Dow Jones or S&P500.

A more recent paper by Singh et al. (2022) [57] looks in to investor preference in relation to the ongoing war in Ukraine. They report some interesting results indicating spillover effects from ESG to the aerospace and defence sector after the invasion. Investor interest in these sectors has spiked since the invasion, which is no surprise considering the massive increases in domestic spending on defense budgets, particularly across Europe. The authors apply the return spillovers framework introduced by Diebold & Yilmaz (2012) [15] for their analysis. Do et al. (2023) [16] also investigate the aerospace sector in relation to war, this time with special emphasis on before and after the dissolution of the Soviet Union. Their paper focuses on market reactions to satellite launches. The main finding is that on days of satellite launches investors are distracted, so there is a larger degree of co-movement between stocks and the market in general.

Due to increased spending in the aerospace and defense sector (A&D) after Russia's invasion of Ukraine, the A&D sector has outperformed the market. Bouri et al. (2024) [8] use a quantile-based connectedness method to measure spillovers from one company to another under different market conditions (bearish, normal and bullish), while also accounting for exogenous factors such as geopolitical risk. They find increased spillover effects from both returns and volatility under extreme market conditions.

Zheng & He (2021) [70] attempt at share price prediction within the aerospace industry using recurrent neural networks (RNN). They also emphasize that aerospace stocks are more volatile than the average stock. They have mixed results depending on whether or not the stock is in a stable or volatile state.

2.9 Summary

The literature review showcases the wide range of research problems that quantilograms can be applied to. The method gives a more comprehensive insight into the underlying nature of relationships within topics such as stock markets, commodities, currencies, banks, energy, and tourism demand. The literature review reveals how quantilograms can be used to model directional predictability/spillover effects/tail dependence under various market conditions. Relationships that were previously often studied at or around the mean can now be modelled for the entire range of quantiles. Next, we will take a look at the technicalities behind the quantilogram methodology.

Chapter 3

Methodology

3.1 Quantilogram

Suppose that random variables $y_1, y_2, ...$ are from a stationary process whose marginal distribution has quantiles μ_τ for $\tau \in (0,1)$. Under the null hypothesis that some conditional quantiles are time invariant

$$H_0 : E[\psi_\tau(y_t - \mu_\tau)|\mathscr{F}_{t-1}] = 0 \tag{3.1}$$

where $\psi_\tau(x) = \tau - 1(x < 0)$ is the check function and $\mathscr{F}_{t-1} = \sigma(y_{t-1}, y_{t-2}, ...)$, if you are below the unconditional τ-quantile today, the chance is no more than τ that you will be below it tomorrow. Otherwise there is some predictability in the process.

We define the quantilogram as

$$\rho_{\tau k} = \frac{E[\psi_\tau(y_t - \mu_\tau)\psi_\tau(y_{t+k} - \mu_\tau)]}{E[\psi_\tau^2(y_t - \mu_\tau]}, k = 1, 2, ... \tag{3.2}$$

of the stationary time series y_t for any τ. Under the null hypothesis in Equation 3.1, the population quantity

$$E[\psi_\tau(y_t - \mu_\tau)\psi_\tau(y_{t+k} - \mu_\tau)] = E[\psi_\tau(y_t - \mu_\tau)]E[\psi_\tau(y_{t+k} - \mu_\tau)|\mathscr{F}_{t+k-1}] = 0 \tag{3.3}$$

for all k Therefore, $\rho_{\tau k}$ is zero for all k. Under the alternative hypothesis (H_1), $\rho_{\tau k}$ can take a variety of shapes across τ and k; however, under mixing, $\rho_{\tau k} \to 0$ as $k \to \infty$ for all τ [35].

3.2 Cross-Quantilogram CQ

Let $\{(y_t, x_t) : t \in \mathbb{Z}\}$ be a strictly stationary time series with $y_t = (y_{1t}, y_{2t})^\top \in \mathbb{R}^2$ and $x_t = (x_{1t}, x_{2t}) \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$, where $x_{it} = [x_{(1)it}, \ldots, x_{(d_i)it}]^\top \in \mathbb{R}^{d_i}$ with $d_i \in \mathbb{N}$ for $i = 1, 2$. $F_{y_i|x_i}(\cdot|x_{it})$ denotes the conditional distribution function of the series y_{it} given x_{it}, with density function $f_{y_i|x_i}(\cdot|x_{it})$, and the corresponding conditional quantile function is defined as $q_{i,t}(\tau_i) = \inf\{v : F_{y_i|x_i}(v|x_{it}) \geq \tau_i\}$ for $\tau_i \in (0,1)$, for $i = 1, 2$. Let T be the range of quantiles we are interested in evaluating the directional predictability for. For simplicity, we assume that T is a Cartesian product of two closed intervals in $(0,1)$, that is $T \equiv T_1 \times T_2$, where $T_i = [\tau_i, \tau_i]$ for some $0 < \tau_i < \tau_i < 1$.

Let us consider a measure of serial dependence between two events $\{y_{1,t} \leq q_{1,t}(\tau_1)\}$ and $\{y_{2,t-k} \leq q_{2,t-k}(\tau_2)\}$ for any arbitrary pair of $\tau = (\tau_1, \tau_2)^\top \in T$ and for an integer k. Generally, $\{1[y_{i,t} \leq q_{i,t}(\cdot)]\}$ is referred to as the quantile-hit or quantile-exceedance process for $i = 1, 2$ where

$$\psi_{\tau_1}(y_{1,t} - q_{1,t}(\tau_1)) = \begin{cases} 1 - \tau_1 & if \quad (y_{1,t} \leq q_{1,t}(\tau_1)) \\ -\tau_1 & if \quad (y_{1,t} > q_{1,t}(\tau_1)) \end{cases} \tag{3.4}$$

and

$$\psi_{\tau_2}(y_{2,t} - q_{2,t}(\tau_2)) = \begin{cases} 1 - \tau_2 & if \quad (y_{2,t} \leq q_{2,t}(\tau_2)) \\ -\tau_2 & if \quad (y_{2,t} > q_{1,t}(\tau_2)) \end{cases} \tag{3.5}$$

The cross-quantilogram is defined as the cross-correlation of this quantile-hit process [23]:

$$\rho_\tau(k) = \frac{E[\psi_{\tau_1}(y_{1,t} - q_{1,t}(\tau_1))\psi_{\tau_2}(y_{2,t-k} - q_{2,t-k}(\tau_2))]}{\sqrt{E[\psi^2_{\tau_1}(y_{1,t} - q_{1,t}(\tau_1))]}\sqrt{E[\psi^2_{\tau_2}(y_{2,t-k} - q_{2,t-k}(\tau_2))]}} \tag{3.6}$$

for $k = 0, \pm1, \pm2, ...$, where $\psi_{\tau_i}(y_{i,t} - q_{i,t}(\tau_i)) = 1[y_{i,t} \leq q_{i,t}(\tau_i)] - \tau_i$. If $\rho_\tau(k) = 0$, knowing whether an event $y_{2,t-k}$ was below(above) $q_{2,t-k}(\tau_2)$ at time $t-k$ does not reveal anything as to whether or not another event $y_{1,t}$ will be below(above) $q_{1,t}(\tau_1)$ at time t. If $\rho_\tau(k) \neq 0$, there exists quantile dependence or directional predictability between the two events.

The sample counterpart is given as:

$$\hat{\rho}_\tau(k) = \frac{\sum_{t=k+1}^{T} \psi_{\tau_1}(y_{1,t} - \hat{q}_{1,t}(\tau_1))\psi_{\tau_2}(y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2))}{\sqrt{\sum_{t=k+1}^{T} \psi^2_{\tau_1}(y_{1,t} - \hat{q}_{1,t}(\tau_1))}\sqrt{\sum_{t=k+1}^{T} \psi^2_{\tau_2}(y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2))}} \tag{3.7}$$

Cho & Han (2021) [11] suggest an alternative formulation of the quantile hit process, which some might find easier to interpret. Instead of two events $y_{1,t} < q_{1,t}(\tau_1)$ and $y_{2,t-k} < q_{2,t-k}(\tau_2)$, it might be more intuitive to find the dependence between two events $q_{1,t}(\tau_1^l) < y_{1,t} < q_{1,t}(\tau_1^h)$ and $q_{2,t-k}(\tau_2^l) < y_{2,t-k} < q_{2,t-k}(\tau_2^h)$ for arbitrary quantile ranges $[\tau_1^l, \tau_1^h]$ and $[\tau_2^l, \tau_2^h]$. To calculate the dependence of such events, you can use a different variant of the cross-quantilogram that is defined by replacing $\psi_{\tau_i}(y_{it} - q_{i,t}(\tau_i))$ in Equation 3.2 with

$$\psi_{[\tau_i^l, \tau_i^h]}(y_{it} - q_{i,t}([\tau_i^l, \tau_i^h]) = 1[q_{i,t}(\tau_i^l) < y_{it} < q_{i,t}(\tau_i^h)] - (\tau_i^l, \tau_i^h) \tag{3.8}$$

For more information, see footnote 4 in Han et al.(2016) [23]. As before, if $\rho_\tau(k) = 0$, there is no dependence or directional predictability from an event $q_{2,t-k}(\tau_2^l) < y_{2,t-k} < q_{2,t-k}(\tau_2^h)$ to an event $q_{1,t}(\tau_1^l) < y_{1,t} < q_{1,t}(\tau_1^h)$. If $\rho_\tau(k) \neq 0$, there exists quantile dependence or directional predictability between the two events. If $\rho_\tau(k)(s) > 0$, it is more likely for $y_{1,t}$ to be located in the range $[q_{1,t}(\tau_1^l), q_{1,t}(\tau_1^h)]$ when $y_{2,t-k}$ is located in the range $[q_{2,t-k}(\tau_2^l), q_{2,t-k}(\tau_2^h)]$. If $\rho_\tau(k) < 0$, it is less likely for $y_{1,t}$ to be located in the range $[q_{1,t}(\tau_1^l), q_{1,t}(\tau_1^h)]$ when $y_{2,t-k}$ is located in the range $[q_{2,t-k}(\tau_2^l), q_{2,t-k}(\tau_2^h)]$. Since the asymptotic distribution of the CQ contains nuisance parameters, Han et al. (2016) [23] suggest obtaining critical values using the stationary random block bootstrap introduced by Politis & Romano (1994) [46], where pseudo samples of blocks of data with random lengths are constructed.

The cross-quantilogram is very useful for modelling financial time series because it provides a complete picture of the directional dependencies and spillovers between two time series, since it, due to its non-parametric nature, can take into account arbitrary lags and a full range of quantiles. The method, however, can also be applied to capture the correlation between two contemporaneous events. This reduces the method to a measure of cross-quantile correlation, but without any predictability, since the events happen simultaneously. If you wish to examine the likelihood that two time series will be below (above) the same quantile at the same time, you can set $\tau_1 = \tau_2$ and $k = 0$, i.e., $y_{1,t} \leq q_{1,t}(\tau)$ and $y_{2,t} \leq q_{2,t}(\tau)$. In this special case, the cross-quantilogram is defined as:

$$\rho_{12,\tau} = \frac{\sum_{t=1}^{T} \psi_\tau(y_{1,t} - q_{1,t}(\tau))\psi_\tau(y_{2,t} - q_{2,t}(\tau))}{\sqrt{\sum_{t=1}^{T} \psi_\tau^2(y_{1,t} - q_{1,t}(\tau))\sum_{t=1}^{T} \psi_\tau^2(y_{2,t} - q_{2,t}(\tau))}} \tag{3.9}$$

where T represents the number of observations [48].

Since the introduction of the cross-quantilogram, the quantilogram has now become a special case of the cross-quantilogram, where the respective time series are set to the same time series. The cross-quantilogram is well-defined even for non-normal distributions with infinite fourth moments, as is very common with financial data. The cross-quantilogram is also invariant to any strictly monotonic transformation applied to both series, such as the logarithmic transformation. If you take the logarithm of both time series, it does not change the output of the quantilogram.

When applying the cross-quantilogram, we can conduct Portmanteau tests to test the hypothesis that all correlations coefficients are 0. Suppose that $\tau \in \mathbb{T}$ and p are given. One might be interested in testing:

$$H_0 : \rho_\tau(1) = \ldots = \rho_\tau(p) = 0 \quad vs \quad H_1 : \rho_\tau(k) \neq 0 \,\text{for some k} \in 1, \ldots, p. \tag{3.10}$$

While the Box-Pierce type test statistic $\hat{Q}_\tau^{(p)} = T\sum_{k=1}^{p} \hat{\rho}_\tau^2(k)$ can be used for this test, the Ljung-Box version $\check{Q}_\tau^{(p)} = T(T+2)\sum_{k=1}^{p} \hat{\rho}_\tau^2 \frac{(k)}{(T-k)}$ is the preferred alternative in practice due to its out-performance with finite samples [11].

3.3 Partial cross-quantilogram PCQ

The partial cross-quantilogram was also introduced by Han et al. in their seminal 2016 paper [23] to estimate the correlation between two time series, accounting for intermediate, exogenous events between time $t - k$ and t. This means that when calculating the dependence between two quantile hit processes, the effects of external events are removed. The controlling events could include variables other than y_{1t} and y_{2t}, events of the lagged predicted variables $\{y_{1,t-1}, \ldots, y_{1,t-k}\}$, or events of intermediate predictors $\{y_{2,t-1}, \ldots, y_{1,t-k-1}\}$. We let $\{y_{3t}, \ldots, y_{lt}\}$ for $l \geq 3$ be the variables for the controlling events and let $z_t \equiv [\psi_{\tau_3}(y_{3t} - q_{3,t}(\tau_3)), \cdots, \psi_{\tau_l}(y_{lt} - q_{l,t}(\tau_l))]^\top$ be an $(l-2) \times 1$ vector of controlling hit processes.

The correlation matrix of the hit processes and its inverse can be formulated as:

$$\mathbf{R}_{\bar{\tau}} = \mathbb{E}[h_t(\bar{\tau})h_t(\bar{\tau})^\top] \text{ and } \mathbf{P}_{\bar{\tau}} = \mathbf{R}_{\bar{\tau}}^{-1} \tag{3.11}$$

where $h_t(\bar{\tau}) = [\psi_{\tau_1}(y_{1t} - q_{1,t}(\tau_1)), \ldots, \psi_{\tau_l}(y_{lt} - q_{l,t}(\tau_l))]^\top$. For $(i, j \in 1, \ldots, l)$, let $(r_{\bar{\tau},ij})$ and $(p_{\bar{\tau},ij})$ be the $((i, j))$ elements of $(\mathbf{R}_{\bar{\tau}})$ and $(\mathbf{P}_{\bar{\tau}})$, respectively. The cross-quantilogram in Han et al. (2016) is identical to $(r_{\bar{\tau},12}/\sqrt{r_{\bar{\tau},11}r_{\bar{\tau},22}})$, and the partial cross-quantilogram is defined as:

$$\rho_{\bar{\tau}|z} = -\frac{p_{\bar{\tau},12}}{\sqrt{p_{\bar{\tau},11}p_{\bar{\tau},22}}}. \tag{3.12}$$

For more detail, see Han et al. (2016, Section 4). To obtain the sample analogue of the partial cross-quantilogram, we construct a vector of hit processes, $\hat{h}_t(\bar{\tau})$, by replacing the population quantiles in $(h_t(\bar{\tau}))$ with the sample analogues $(\hat{q}_{1,t}(\tau_1), \ldots, \hat{q}_{l,t}(\tau_l))$. Next, we obtain the estimator for the correlation matrix and its inverse as follows:

$$\hat{\mathbf{R}}_{\bar{\tau}} = \frac{1}{T}\sum_{t=1}^{T} \hat{h}_t(\bar{\tau})\hat{h}_t(\bar{\tau})^\top \text{ and } \hat{\mathbf{P}}_{\bar{\tau}} = \hat{\mathbf{R}}_{\bar{\tau}}^{-1} \tag{3.13}$$

The sample equivalent of the partial cross-quantilogram is defined as:

$$\hat{\rho}_{\bar{\tau}|z} = -\frac{\hat{p}_{\bar{\tau},12}}{\sqrt{\hat{p}_{\bar{\tau},11}\hat{p}_{\bar{\tau},22}}}. \tag{3.14}$$

where $(\hat{p}_{\bar{\tau},ij})$ denotes the $((i, j))$ element of $(\hat{\mathbf{P}}_{\bar{\tau}})$ for $(i, j \in \{1, \ldots, l\})$. Han et al. (2016) also propose that one uses the stationary bootstrap procedure and a self-normalized approach to construct the confidence intervals for the partial cross-quantilogram [11].

Another way to formulate the partial cross-correlation is:

$$\rho_{\bar{\tau}|z} = \delta\sqrt{\frac{\tau_1(1-\tau_1)}{\tau_2(1-\tau_2)}}, \tag{3.15}$$

where δ is a scalar parameter defined in the following regression:

$$\psi_{\tau_1}(y_{1t} - q_{1,t}(\tau_1)) = \delta\psi_{\tau_2}(y_{2t} - q_{2,t}(\tau_2)) + \gamma^\top z_t + u_t, \tag{3.16}$$

with an $(l-2)\times 1$ vector γ and an error term μ_t. Thus, testing the null hypothesis of $\rho_{\bar{\tau}|z} = 0$ can be viewed as testing predictability between two quantile hits with respect to information $\bar{z}$, as in a Granger causality test based on the regression form [20]. One can use $\rho_{\bar{\tau}|z}$ for the purpose of testing for Granger causality, by choosing relevant variables $\bar{z}$ [45].

Chapter 4

Use in empirical finance

The main organizing premise of the summary in Table 4.1 was based on; (1) if the terminology, or similar phrasing or content, was mentioned in the title, abstract or introduction, then it was characterized as motivation for applying the CQ. (2) If the attribute was mentioned in the methodology section, it was counted as stating a property of the method. The elements section refers to whether or not the element was visually included in the paper in the form of heatmaps or such. In the case of Granger causality, it was whether or not causality in any way was referred to within the results. X+ denotes that formal testing for Granger causality was conducted, whereas X- denotes that the results were referred to with respect to causality, but no formal tests were conducted.

The table will include raters error, meaning that if others were to conduct a similar evaluation, the results would differ due to the individuals interpretations and the possibilities for overlooked information. The average citation index and impact factor was 9.6 and 7.5, respectively. The averages were generally influenced in an upward manner by journals related to renewable energy, and downwards by finance related journals. The three seminal papers at the top of the summary are not included in the frequencies in the following section.

The most frequently stated motivations for applying the cross-quantilogram were, in descending order; modelling market regimes/tail dependencies (83%), directional predictability (80%), being able to reveal asymmetric dependencies (56%), modelling arbitrary long lags (51%), modelling non-linear relationships (49%), applicability to non-normal distributions that lack finite fourth moments (41%), the possibility to model how the dependencies change over time (39%), and finally, the implementation of the PCQ being able to account for exogenous effects (29%).

With regards to properties of the CQ the respective authors highlighted in their methodology sections, the main attributes of the techniques were that it was conceptually appealing and offers a complete perspective of the connectedness of two time series (66%),the ability to model arbitrary lags (56%), modelling non-normal distributions (46%), that it is robust to misspecification error (34%), that it can model asymmetric dependencies (24%), and that it is invariant to any monotonic transformation applied to both time series (12 %).

Paper	Citation Index (CI)	Impact Factor	Non-linear	Asymmetry	Modeling market regimes/ Tail Dependence	Directional predictability	Moments/ Non-normal	Lag	PCQ	Time-varying	Robust to misspec/outliers	Consistent/ Asymptotic valid	Moments/ Non-normality	Invariant to mono. transf.	Lags	Asymmetric	Conceptually appealing/ complete perspective	Heatmap	CQ	PCQs	Recursive subsampling/ Rolling window	Q-test/ Ljung-Box	Granger causality	Combinations/ extensions	Title
			Motivation								Properties							Elements included in paper							
FOUNDERS																									
Linton & Whang 2007	7,2	6,3					x	x				x										x			*Quantilogram: With an application to evaluating directional predictability*
Han, Linton, Oka & Whang 2016	7,2	6,3					x	x						x			x								*The Cross-Quantilogram: Measuring quantile depence and testing directional predictability between time series*
Lee, Linton & Whang 2019	2,3	1,3																							*Quantilograms under strong dependence*
VERY IMPORTANT																									
Lindman et al 2020	4,5	2,6		x	x	x				x		x	x		x			x			x			DCC-EGARCH	*Market impact on financial market integration: Croos-quantilogram analysis of the global impact of the Euro*
Uddin et al 2019	14,7	12,8		x	x	x	x	x	x	x						x	x	x		VIX, EPU, OVX, TECH	x		x-		*Cross-quantilogram-based correlation and dependence between renewable energy stock and other asset classes*
Rehman et al 2022	5,8	5,2	x	x	x	x		x	x	x	x		x				x	x		Oil	x				*Directional predictability in foreign exchange rates of emerging markets: New evidence using a cross-quantilogram approach*
Uribe et al 2018	14,7	12,8	x	x		x		x					x	x					x			x	x-		*Uncovering the nonlinear predictive causality between natural gas and electricity **prices***
Baumöhl & Lyocsa 2017	10,8	10,4				x	x								x		x	x					x-	Bonferroni correction (p-val)	*Directional predictability from stock market sector indices to gold: A cross-quantilogram analysis*
Cho & Han 2021	5,3	4		x	x	x	x		x		x		x		x	x	x		x	VIX					*The tail behavior of safe haven currencies: A cross-quantilogram analysis*
Borg et al 2022	16,1	8,7		x	x	x		x	x	x		x						x		EPU	x				*Dependence between renewable energy related critical metal futures and producer equity markets across varying market conditions*
Mensi et al 2023	5,6	3,6		x	x	x			x	x					x	x	x	x		VIX, GVZ, OVX				Quantile connectedness	*Extreme dependence and spillovers between uncertainty indices and stock markets: Does the US market play a major role?*
Scarcioffolo & Etienne 2021	11,3	10,2	x		x	x	x				x		x		x		x	x	x		x		x+		*Testing directional predictability between energy prices: A quantile-based analysis*
Qian et al 2022	5,6	3,6		x	x		x	x	x	x	x					x	x			PMFG				Total connectedness	*Partial cross-quantilogram networks: Measuring quantile connectedness of financial institutions*
IMPORTANT																									
Corbet et al 2020	9,1	8,2			x	x	x	x					x		x		x		x				x+	GCD-/GCQ tests	*Measuring quantile dependence and testing directional predictability between Bitcoin, altcoins and traditional financial assets*
Laurini et al 2008	6,5	4,8		x							x					x	x		x					VECM	*Empirical market microstructure: An analysis of the BRL/US$ exchange rate market*
Joaqui-Barandica et al 2023	10,8	10,4	x	x		x											x		x			x		QVAR	*Directional predictability between interest rates and the Stoxx 600 Banks index: A quantile approach*
Pham 2021				x	x	x	x	x	x				x		x			x		VIX,OVX,EPU			x+		*How integrated are regional green equity markets*
Kumar et al 2021	11,3	10,2	x		x	x	x		x						x	x	x	x		GPR	x		x-		*Does geopolitical risk improve the directional predictability from oil to stock returns? Evidence from oil-exporting and oil-importing countries*
Chang et al 2024	5,6	3,6	x			x	x	x		x	x		x		x			x							*Revisit the impact of exchange rate on stock market returns during the pandemic period*
Todorova 2017	6,6	4,7			x	x	x					x					x		x					Intraday	*The intraday predictability of large Australian stocks: A cross-quantilogram analysis*
Yahya et al 2020	14,9	9		x	x	x		x		x						x	x	x			x		x+	Time-varying copula	*Evaluation of cross-quantile dependence and causality between non-ferrous metals and clean energy indexes*
Demirer et al 2020		2,6			x	x	x			x			x						x			x			*Time-varying risk aversion and the profitability of carry trades: Evidence from the cross-quantilogram*
Zhou et al 2019	6,6	4,7	x	x	x	x	x						x	x			x		x						*Does international oil volatility have directional predictability for stock returns? Evidence from BRICS countries based on cross-quantilogram analysis*
Sinha et al 2022		4,8			x	x		x										x		x				DCC-Garch, Wavelet	*Dependence structure between Indian financial market and energy commodities: a cross-quantilogram based evidence*
Shahzad et al 2021	10,8	10,4	x		x	x			x	x			x		x		x								*Investor sentiment and dollar-pound exchange rate returns: Evidence from over a century of data using a cross-quantilogram approach*
Sohag et al 2022	14,7	12,8	x		x	x		x			x		x		x		x	x			x			Q-Q (Quantile on quant)	*Do geopolitical events transmit opportunity or threat to green markets? Decomposed measures of geopolitical risks*
OK/GOOD																									
Baumöhl et al 2022	6,6	4,7			x	x				x				x	x		x	x			x			Network analysis, Bonferroni corr(p-val)	*Measuring systemic risk in the global banking sector: A cross-quantilogram network approach*
Shahzad et al 2018	10,8	10,4	x		x	x					x				x		x							Bonferroni corr(p-val)	*Risk transmitters and receivers in global currency markets*
Karim et al 2023	10,8	10,8	x		x	x	x	x							x		x	x			x		x-		*Asymmetric relationship between climate policy uncertainty and energy metals: Evidence from cross-quantilogram*
Razzaq et al 2022	17,2	12	x	x	x	x				x					x			x			x		x+		*Testing the directional predictability between carbon trading and sectoral stocks in China: New insights using cross-quantilogram and rolling window causality approaches*
Tiwari et al 2022	3,7	2,9	x		x	x	x	x	x		x		x				x	x		x	x		x-		*Directional predictability from energy markets to exchange rates and stock markets in the emerging market countries (E7+1): New evidence from cross-quantilogram approach*
Lyócsa et al 2019	7,5	3,3		x		x		x							x				x				x+	ERGM Networks	*Interconnectedness of international tourism demand in Europe: A cross-quantilogram network approach*
Qi et al 2024	17,2	12	x		x	x		x	x									x		x	x				*The correlation between the green bond market and carbon trading markets under climate change: Evidence from China*
Deev et al 2022 (Lyocsa/Vyrost)	10,8	10,4			x				x	x										x	x			Contemporaneous	*The looming crisis in the Chinese stock market? Left-tail exposure analysis of Chineses stocks to Evergrande*
Alomari et al 2022	11,3	10,2		x	x	x	x	x			x		x		x		x	x						Quantile VAR connectedn.	*Extreme return spillovers and connectedness between crude oil and precious metals futures markets: Implications for portfolio management*
Sohag & Ullah 2022													x	x	x		x	x					x-		*Response of BTC market to social media sentiment: Application of cross-quantilogram with bootstrap*
Hung 2023			x	x	x			x		x	x		x				x	x			x		x+		*What effects will Covid-19 have on the G/ stock markets? New evidence from a cross-quantilogram approach*
Hung & Vinh 2023	1,5	0,9		x	x	x	x			x	x		x	x	x	x	x	x					x+	Dynamic connectedness	*Asymmetric impact of the COVID-19 pandemic on foreign exchange markets: Evidence from an extreme quantile approach*
Hampl et al 2024	5,6	3,6	x		x										x					x	x			Contemporaneous	*Crypto havens during war times? Evidence from the Russian invasion of Ukraine*
Raggad 2023	11,3	10,2	x	x	x	x		x			x						x		x			x	x-		*Can implied volatility predict returns on oil market? Evidence from cross-quantilogram approach*
Zhang et al 2023	9,1	8,2		x	x	x		x					x		x		x	x		x	x			TVP-VAR	*Does the connectedness among fossil energy returns matter for renewable energy stock returns? Fresh insights from the cross-quantilogram analysis*
Kartal et al 2024	21,1	11,2	x	x	x			x			x		x		x	x		x							*Energy security risk and financial development nexus: Disaggregated level evidence from South Korea by cross-quantilogram approach*
Naeem et al (Karim) 2023	9,1	8,2	x	x	x	x	x	x		x					x		x	x			x				*Non-linear relationship between oil and cryptocurrencies: Evidence from returns and shocks*
Okhrin, Uddin, Yahya 2023	14,7	12,8	x	x	x											x			x					Copulas, Contemp.	*Nonlinear and asymmetric interconnectedness of crude oil with financial and commodity markets*
Total	376,3	305,8																							
Mean	9,6	7,5																							

Figure 4.1: Summary of 45 research papers on Quantilograms

Certain visual elements are typically included in research papers, depending on the purpose of the paper. The most common graphical element to include is the heatmap (61%). This is quite understandable. The heatmap presents the results in a easily interpretable and visually appealing way, which was also part of the motivation for Han et al. to develop the cross-quantilogram in the first place. After the heatmap comes recursive subsampling or rolling window (44%), PCQ (34%) and CQ (29%). Only four papers (10%) include plots of the Q-statistic from the Ljung-Box tests. The final element, which is non-graphical, is whether or not the paper uses the terminology "causality". 16 papers mention causality with those exact words. Out of those 16 papers, 8 papers perform a Granger causality in quantiles test. The others simply refer to the dependence as causal without providing more evidence. That being said, Han et al. (2016) themselves refer to the PCQ as a way to test for Granger causality if one includes relevant exogenous variables [23].

A finding that appears in most papers is that the dependency is generally not very persistent. It tends to dissipate rather quickly. For the majority of studies using daily data, there were very few significant results after a month or a quarter. This indicates that new information is quickly absorbed by the market.

One recurring issue that was encountered while writing this thesis was the ambivalence amongst research papers on how to interpret the results from CQ estimates or heatmaps. A fair amount of papers refer to their findings as if they happened at the same time, for instance as "when variable a is in some market state and variable b is in some market state". Even though the events happen at different times. This can be very confusing to the reader. Several papers are careless in the way they refer to their results in relation to which test they have actually performed. In the methodology section we introduced two different alternatives for estimating the cross-quantile correlation. The main method introduced by Han et al. in 2016 tests whether or not an observation is less than or equal to some quantile [23]. Whereas Cho & Han introduced an alternative test in 2021, where they test whether or not an observation is in some interval, between a lower and upper quantile [11]. Many papers refer to their findings as if they applied the second method, when in fact they used the first. This is something to be aware of.

4.1 Examples from empirical finance

We will now present some carefully selected examples from empirical finance. The examples are chosen to showcase the diverse applicability of quantilograms and also to emphasize some of the characteristics that make them so useful.

4.1.1 Example 1

The first example is from Borg et al. (2022) [7] who use a CQ and a PCQ to study the dependency structure between renewable energy production-related critical metal futures and producer equity returns, and comparing them to the dependency structure between non-renewable energy and other commodity markets, and their respective indexes. This specific example was chosen to illustrate the information available to you when using quantilograms, that you will not get using standard correlation.

Figure 4.2 shows how valuable a cross-quantilogram can be when trying to understand the underlying nature of a relationship between two time series. The upper table displays your standard correlation metric. Notice the correlation of 0.553 between silver and its corresponding precious metals index. It is roughly the same as the correlation between corn,

ii) Unconditional correlation matrix between producer index returns and relevant futures market returns

Producer Index\ Futures market	Crude Oil	Natural Gas	Gold	Silver	Platinum	Copper	Corn	Wheat	Coffee
S&P Producers Oil and Gas	0.916	0.448							
S&P Producers Gold			0.133						
Dow Jones Precious Metals				0.553	0.826	0.673			
S&P Producers Agribusiness							0.542	0.565	0.574

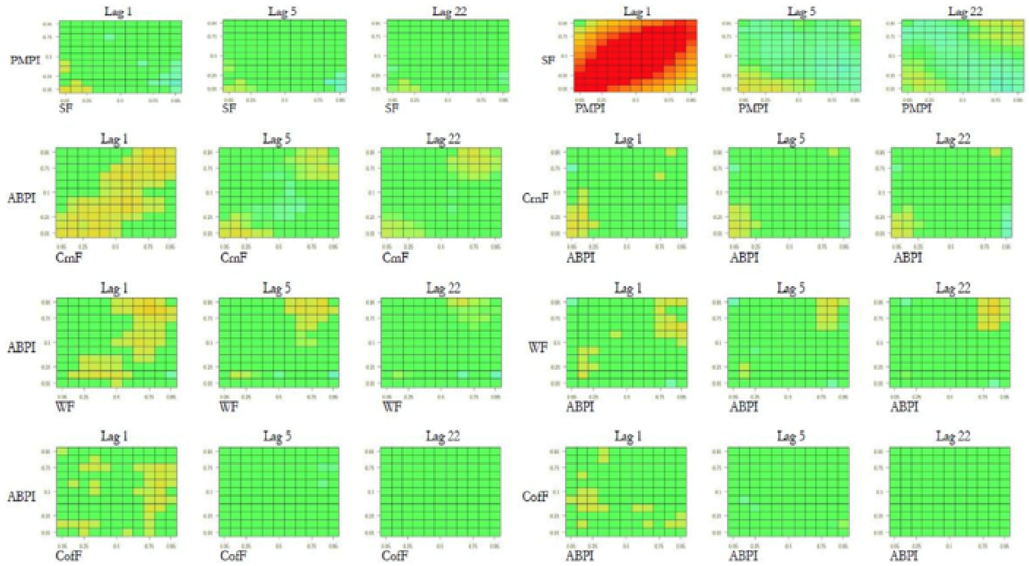

Figure 4.2: Stereotypical example from Borg et al. [7]

wheat, coffee, and their corresponding agricultural producers indexes. So if the standard Pearson correlation was all the information you had available to you, you would assume that the nature of the underlying relationship was similar. But as the heatmaps reveal, this could not be further from the truth.

The heatmaps in the lower part of Figure 4.2 reveal that both the magnitudes and directions of spillovers or predictability are both in the opposite direction, and of very different strength. The first row shows directional predictability from silver to the precious metals index for 1, 5 and 22 lags on the left-hand side, and vice versa on the right-hand side. Similarly, we have equivalent heatmaps for the commodities and their index on the 3 bottom rows. We see that there is practically no predictability from silver to the index, apart from in the extreme lower quantiles. From the index to silver however, there is positive predictability more or less across the board. The intensity of the red colour shows that it is a strong spillover effect as well.

For commodities however, the spillover effect is significantly weaker **and** it runs primarily in the opposite direction. The cross-quantilogram is able to capture these asymmetries and differences in directions in a visually appealing and intuitive way.

4.1.2 Example 2

Example 2 was chosen to illustrate the versatility of the methodology in the sense of what type of problems it can model, and how it can be combined with other statistical techniques.

Figure 4.3 shows how Baumöhl et al. (2022) [6] combine the CQ with a network connectedness approach to model systemic risk between financial institutions around the world, using data from 2003-2020. Figure 4.3 shows the connectedness for the entire sample in the upper left-hand corner, followed by the financial crisis in the upper right-hand corner, the European sovereign debt crisis in the lower left-hand corner, and the Covid-19 pandemic in the lower right-hand corner. Since the purpose of the paper is to quantify the systemic risk between financial institutions, they examine the joint return distributions at the 0.05th quantile ($\tau_1 = \tau_2 = 0.05$). The figure clearly captures the different severeness of the respective crisis, in particular the intense nature of the Covid-19 pandemic.

The authors find that out of all possible pairs of connections (6806), 98% were statistically significant. Their results show the strong degree of interconnectedness within the banking sector, and also why it is very important that the sector be regulated. During the global financial crisis the strongest risk spillover was from American banks, whereas during the European debt crisis the major risk spillover was from European banks, particularly SEB, Swedbank and Deutsche Bank.

In general they find that American banks are major risk transmitters, while Asian banks are major risk receivers. They assume that this is due to elements such as size, regulatory frameworks and differences in how businesses are financed.

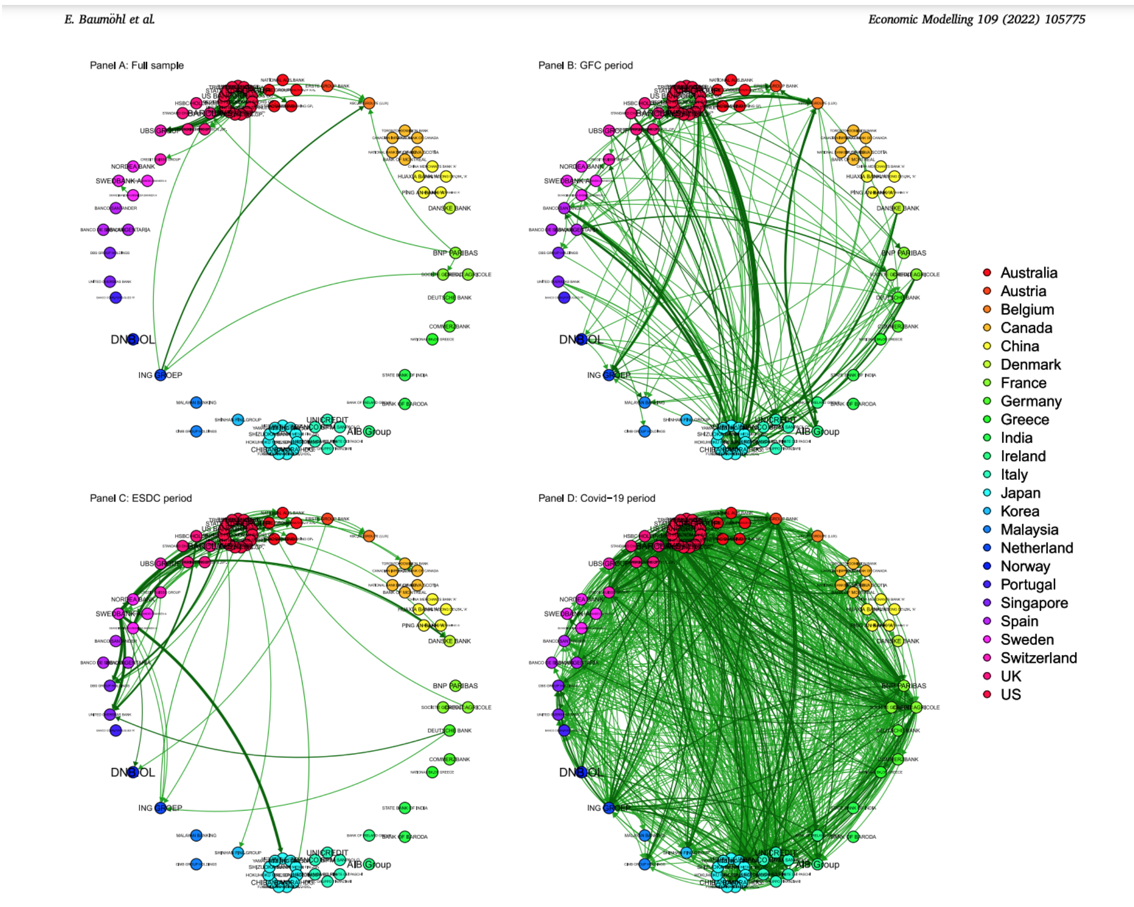

Figure 4.3: Baumöhl et al. modelling systemic risk in the global banking sector [6] using cross-quantile correlation in conjunction with a network connectedness approach.

4.1.3 Example 3

The final example from empirical finance is from the original seminal paper by Han et al. (2016) [23]. Besides developing the CQ and the PCQ, they also apply them to a real world scenario. In this case they use the technique to model systemic risk between the market and several US financial institutions (JP Morgan, Morgan Stanley and AIG). Figure 4.4 shows the cross correlation between stock market returns and volatility, when volatility (τ_2) is fixed at or below the 0.1th quantile. We see that when volatility is low, you are less likely to experience large losses, since correlation is negative in the in the first row. Similarly, we see that if volatility is low, you are also less likely to experience large gains. This is because correlation is positive in the upper quantiles on the bottom row. So if volatility is below the 0.1th quantile, returns will likely be below the 0.8th quantile and above the 0.3rd quantile. Interestingly, we also see that low volatility does not reveal anything as to whether or not returns will be above or below the median, since there are no significant estimates at 0.5th quantile.

Figure 4.5 displays the spillover effects from th e respective financial institutions to the market on the left-hand side, and vice versa on the right-hand side, when both are below the 0.05th quantile. We see that the spillover effect from JP Morgan to the market reaches its maximum at day 12 at approximately 0.15. This means that it takes around two weeks for the systemic risk from JP Morgan to the market to reach its maximum, when JP Morgan is in distress. On the right-hand side we see the individual institutions' exposure to market risk. We see that for all institutions the systemic risk from the market peaks after two days [23].

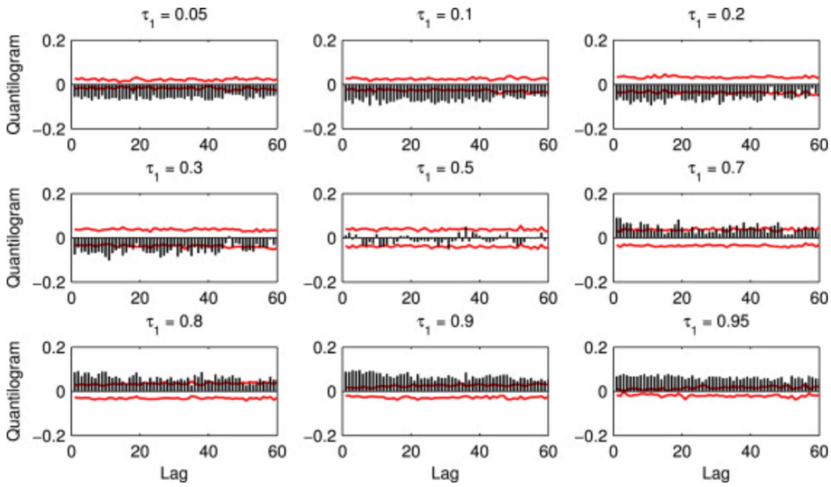

Figure 4.4: Han et al. (2016) modelling returns (τ_1) vs volatility (τ_2) where volatility is fixed at the 0.1 quantile [23]. We have sequences of different quantiles of returns (τ_1), starting at 0.05 in the upper left-hand corner and increasing until it reaches the 0.95th quantile in the lower right-hand corner. The cross-quantile correlation is on the y-axis and lags on the x-axis. The grey bars are the cross-correlation estimate and the red lines are the bootstrapped confidence intervals of no predictability. Grey bars outside the red lines represent significant results.

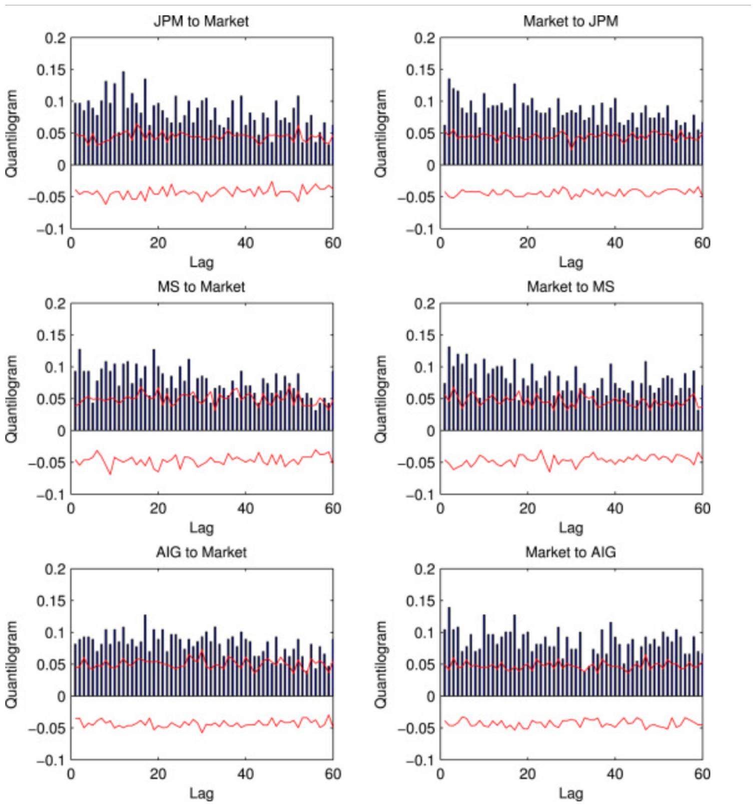

Figure 4.5: Han et al. (2016) modelling systemic risk in the US banking sector where $\tau_1 = \tau_2 = 0.05$. Grey bars represent cross-quantile correlation and red lines represent bootstrapped confidence intervals of no predictability. Grey bars outside the red lines represent significant estimates of cross-quantile correlation. Spillovers from JP Morgan, Morgan Stanley and American Insurance Group to the market to the left, and vice versa to the right. Spillovers from the market to the financial institutions can be viewed as a measure of systemic risk according to Han et al. [23].

Chapter 5

Case studies

5.1 Connectedness between OSEBX, Brent crude oil and S&P 500

"There is a widespread perception that an investment in Norway is strongly affected by the oil price" [28].

The quote belongs to Einar Johansen, portfolio manager for DNB. But you could practically ask just about "anyone" with somewhat of a relationship to investing in the stock market in Norway, and they would tell you the same, e.g. [25]. The Norwegian oil adventure started for real in 1969 with the discovery of the Ekofisk field [17]. Due to this stroke of luck, and the foresight of the politicians of the time, Norway today holds the largest sovereign wealth fund in the world. The oil industry has been a significant contributor to the evolvement of OSEBX over the years, comprising 28.8% of the index as of March 2024 [18]. Several thesis' have studied the effect of oil returns on OSEBX, but typically using statistical techniques such as linear regression. To the best of our knowledge, the directional predictability between Brent, S&P 500 and OSEBX has never been estimated using quantilograms. It would therefore be of interest for financial practitioners to gain some insight into the quantile dependence structure between OSEBX and Brent crude oil and S&P 500.

5.1.1 Data

The data used in this case study has been downloaded from Yahoo Finance. We are using daily data for the time interval March 5th 2013 − Dec 29th 2023, a total of 2589 observations.

Asset	Ticker	Description	Raw Price data	Excess returns
OSEBX	OSEBX.OL!	Oslo Stock Exchange Index	osebx	OSEBX
Brent Crude Oil	BZ=F	Brent Crude Oil Financial	brent	Brent
S&P 500	ĜSPC	S&P500 Index	sp500	SP500

Table 5.1: Variable definitions

Figure 5.1 indicates that none of the price series adhere to the assumption of stationarity. This is confirmed by an Augmented Dickey Fuller (ADF) test of the price series. Results can be found in Figure A.1 in the appendix. We have therefore transformed the data into growth rates. The daily return of a financial asset is defined as:

$$r_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}} \tag{5.1}$$

where $p_{i,t}$ is the daily closing price of the financial asset i on day t.

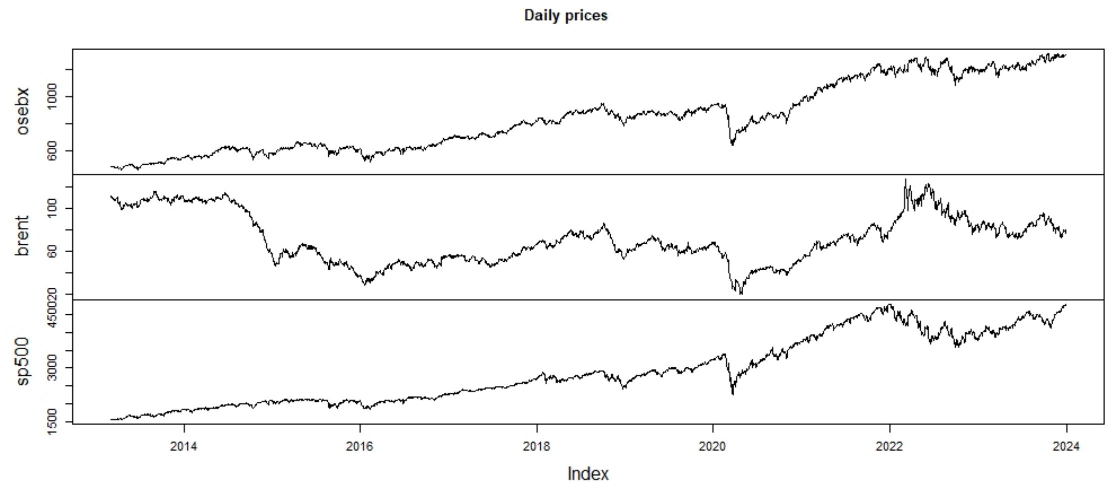

Figure 5.1: Daily prices 05.03.2013 - 29.12.2023

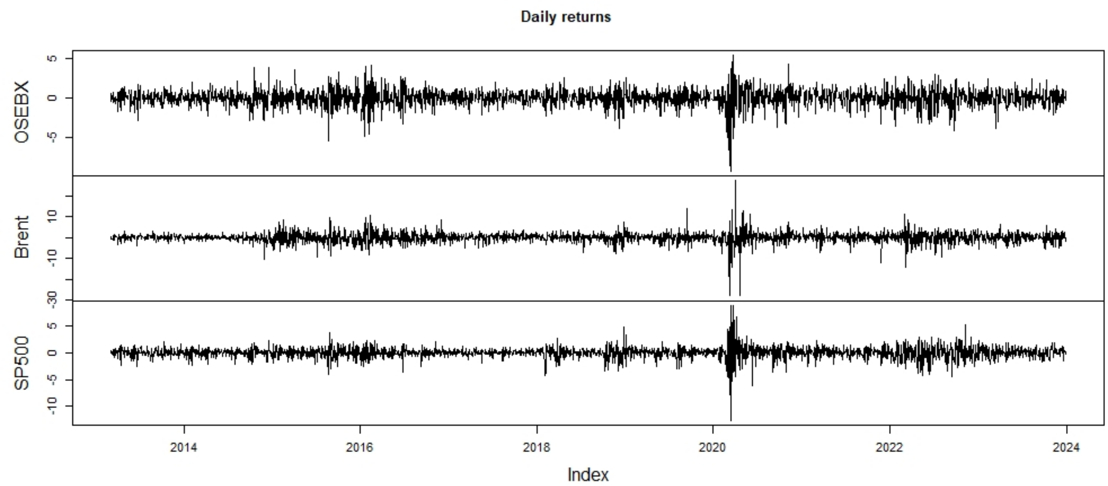

Figure 5.2: Daily returns 05.03.2013 - 29.12.2023

The series of returns are clearly more stationary than the prices, although there are still some volatility clusters, particularly during the Covid-19 pandemic, as seen in Figure 5.2. Formal testing using the Augmented Dickey Fuller test suggests that there is no convincing evidence against stationarity after transforming the data. The ADF-test was computed using default settings. All p-values were less than 0.01, rejecting H_0 (that the series has a unit root or is non-stationary). The Ljung-Box p-value reveals the we reject the null hypothesis of individually and independently distributed errors in the individual time series. There is some autocorrelation present, particularly for S&P 500, as seen in Figure 5.6. A Jarque Bera test confirms that the returns are not normally distributed, as we can also deduce from the Q-Q plots in Figure 5.3 and the histograms in Figure 5.5.

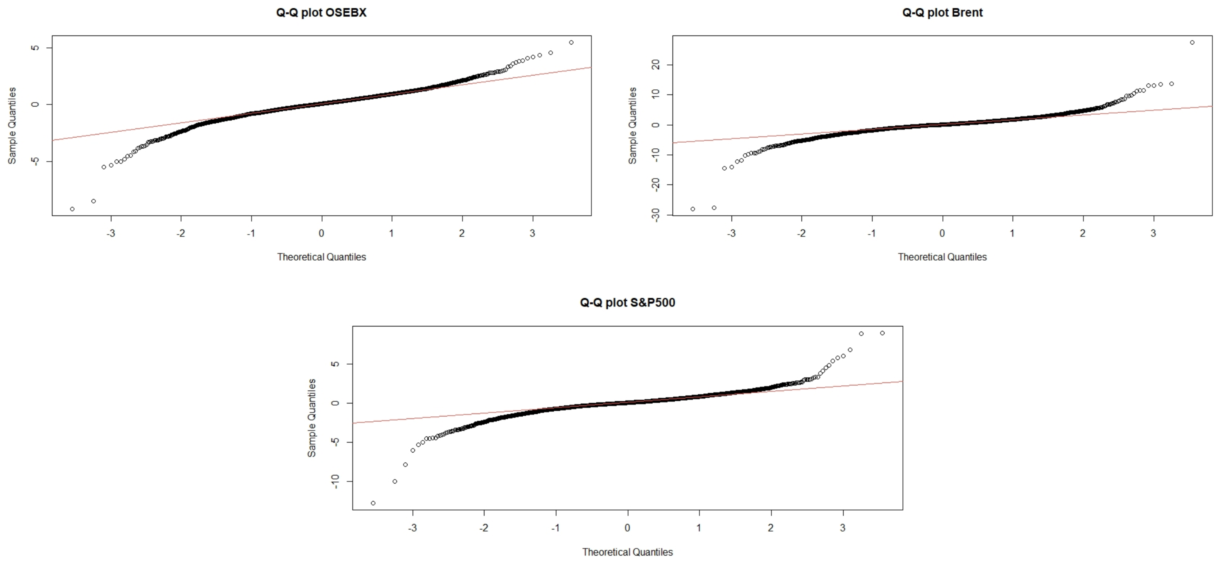

Figure 5.3: Q-Q plots for OSEBX, Brent and S&P 500

The original times series of returns for OSEBX, Brent and S&P 500 had 2681, 2690 and 2725 observations respectively, after missing values were removed. A total of 92, 101 and 136 observations respectively, have been removed from the original time series for the dataset used in this study.

	OSEBX	Brent	S&P500
# Observations	2589	2589	2589
Mean	0.04	-0.01	0.04
Median	0.07	0.04	0.06
Max	5.46	27.42	8.97
Min	-9.18	-27.98	-12.77
IQR	1.13	2.13	0.93
Std.dev	1.06	2.49	1.09
Skewness	-0.74	-0.57	-0.82
Kurtosis	8.91	23.01	19.43
ADF stat	-14.66	-13.89	-14.15
ADF p-value	0.01	0.01	0.01
Jarque Bera stat	4143.56	45044.96	30936.26
Jarque Bera p-value	0.00	0.00	0.00
Ljung-Box stat	92.82	23.88	336.55
Ljung-Box p-value	0.00	0.02	0.00

Table 5.2: Descriptive statistics for OSEBX, Brent and S&P 500 returns from 05.03.2013 to 29.12.2023

OSEBX and S&P 500 have the largest mean returns, whereas the average Brent returns are negative. Although they are all very close to zero. Brent returns are the most extreme in both directions. They have the largest interquartile range and the largest standard deviation. This makes intuitive sense since OSEBX and S&P 500 are indexes. It would therefore require much more to move them that much. OSEBX has the largest median return at 0.07%. All assets have larger medians than means, reflecting that the marginal density has negative skewness. Which in turn means that the most extreme values are found in the left-hand tail. All returns exhibit heavy tails, as seen by the excess kurtosis. This is typical of financial data, which in turn motivates the use of quantilograms.

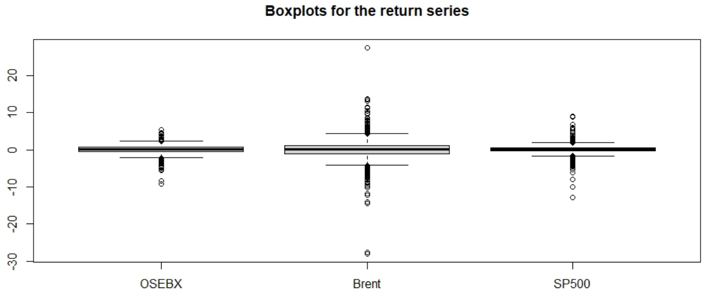

Figure 5.4: Boxplot

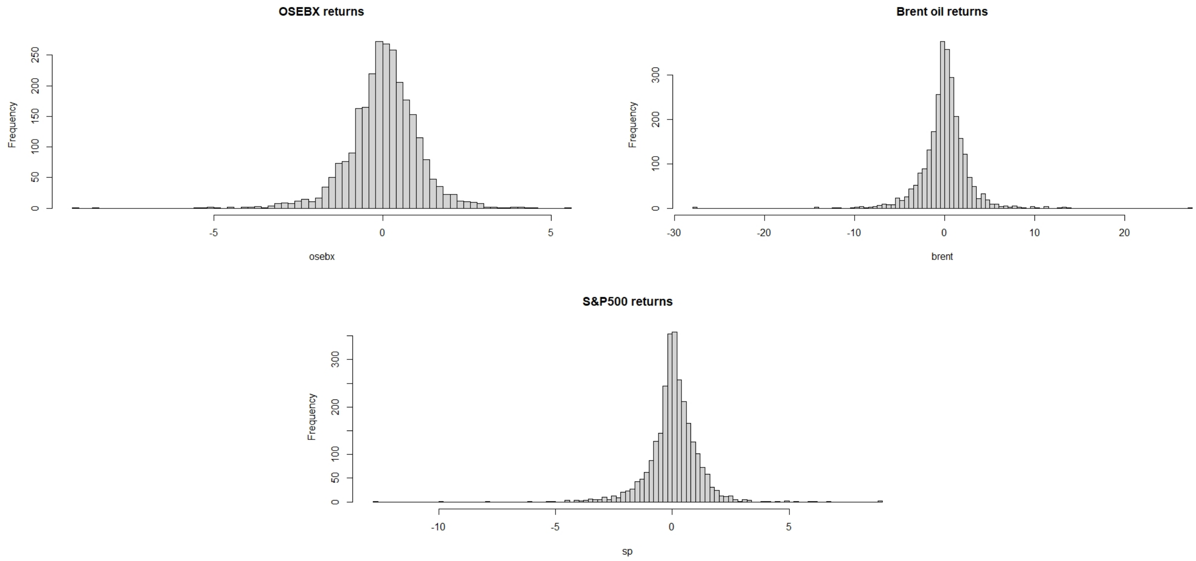

Figure 5.5: Histograms of marginal distribution of returns

The correlogram for the individual time series depicted in Figure 5.6 reveals an interesting detail. Both OSEBX and S&P 500 have negative autocorrelations at lag 1, meaning that if they are above their mean at time t-1 then they are more likely to be below the mean at time t. So the returns tend to alternate somewhat around the mean from one day to the next, although the absolute values are very small. We also see in Figure 5.6 that the standard correlation between the assets is weak to moderate. OSEBX and S&P500 have the strongest correlation of 0.45, while the correlation between OSEBX and Brent is 0.39. The correlation between Brent and S&P 500 is 0.29, implying that S&P 500 is not as influenced by oil related industries as OSEBX.

Looking at the cross-correlation matrix in Figure 5.7, we have correlations on the diagonal and cross-correlations elsewhere. In the upper right-hand corner we observe the only clearly significant cross-correlation, disregarding contemporaneous correlations. It shows a positive correlation between yesterdays return on S&P 500 and today's return on OSEBX.

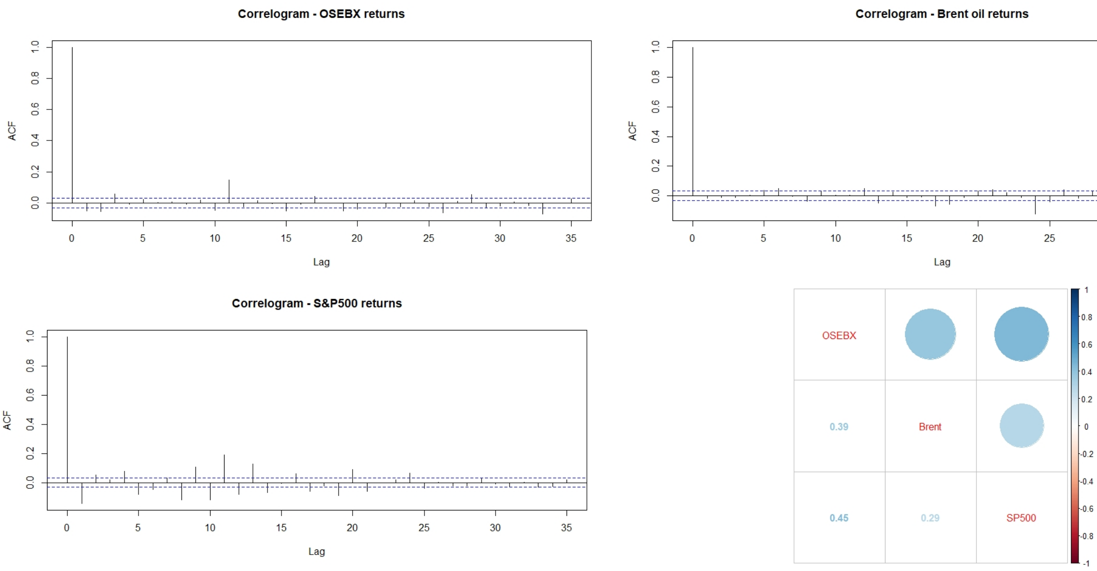

Figure 5.6: Autocorrelations and correlations

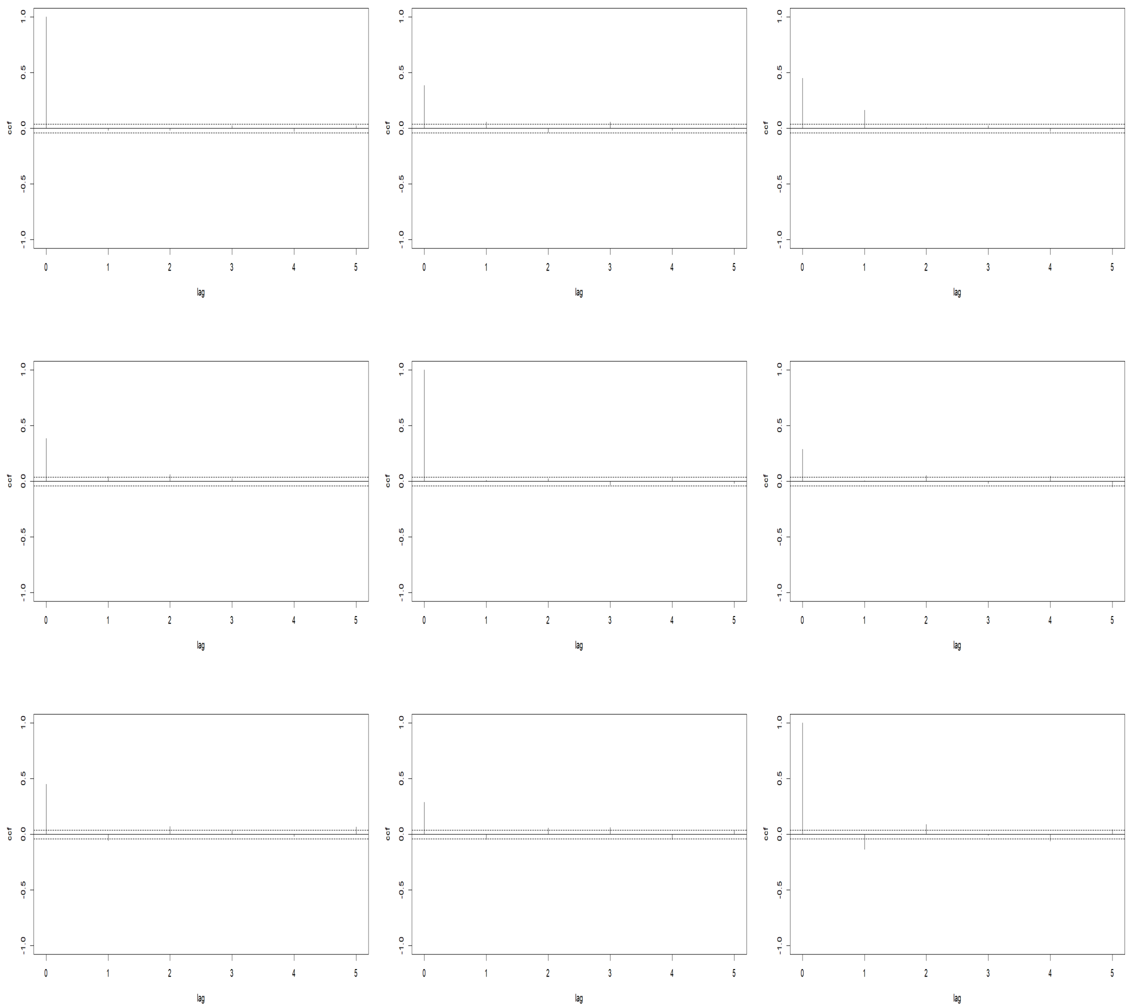

Figure 5.7: Cross-correlation matrix for up to 5 lags. OSEBX, Brent and S&P 500 respectively, from left to right, and top to bottom

5.1.2 Quantilograms

All estimations in this paper have been made using 500 bootstraps for the confidence intervals. 500 bootstraps was chosen with regards to computational time. Research papers typically used 500, 1000 or 2000 bootstraps. Certain random estimates were made using 2000 bootstraps for the confidence intervals, without any obvious implications for the outcome.

Figure 5.8 shows the quantilogram for OSEBX for various quantiles, and up to 20 lags. There are few significant results. Most are in the extreme upper or lower quantiles. We see that the correlation is positive in these extreme cases, showing that extreme losses/gains are more likely to be followed by more extreme losses/gains.

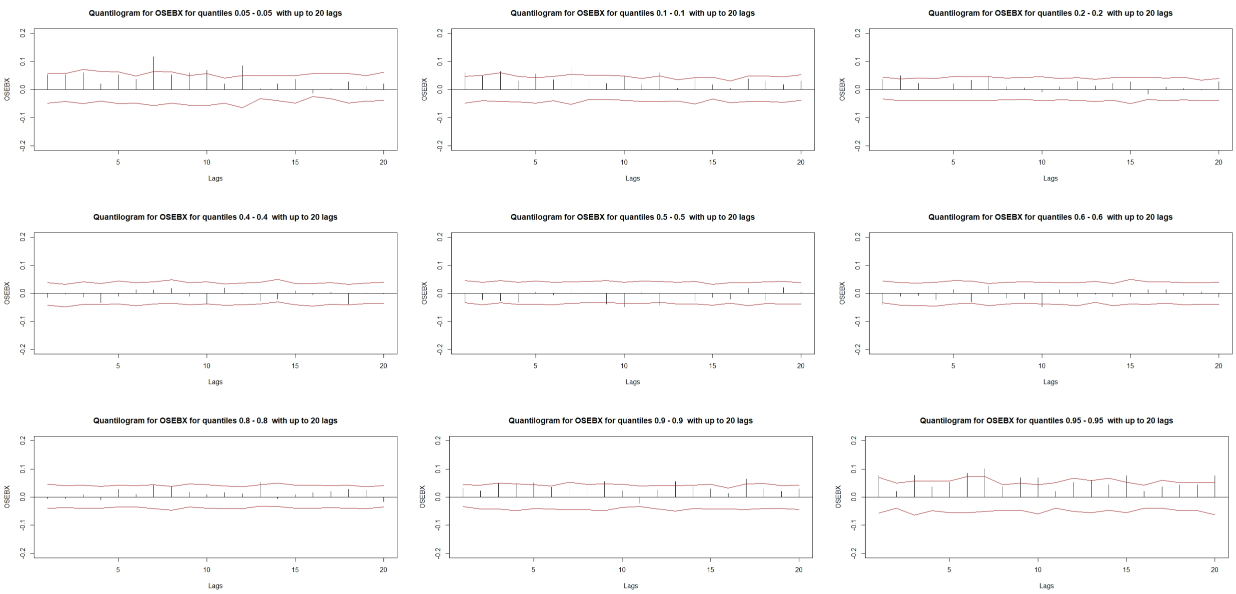

Figure 5.8: Quantilogram OSEBX for matching quantiles, up to 20 lags

Figure 5.9 shows the quantilogram for OSEBX as a heatmap with intervals from 0.05 to 0.95 for both the dependent and independent variables, in this case lagged values of itself. We see that there is positive correlation in the extreme cases where returns are around similar quantiles, i.e. when they are in the upper/upper or lower/lower quantiles. The light blue colour in the lower right-hand corner reveals that strong positive returns can also be followed by highly negative returns. This could either be a representation of the inherent volatile nature of the stock market, or it simply shows that after days of strong returns there can be days where investors decide to capitalize on those returns by realizing them. We see that the directional predictability or spillover dissipates rather quickly, except for in the most extreme quantiles.

From a diversification perspective, what you would like to see in the heatmaps in this paper is insignificant values (hedge) or negative correlation (safe haven) in the lower quantiles of both variables (lower left hand corner of the heatmaps). This means that if the independent variable is experiencing an extremely low return at time t-k, then this is insignificant as to whether or not the dependent variable will also experience extremely low returns at time t (hedge), or the dependent variable is less likely to experience extremely low returns at time t (safe haven). Of course, in the first quantilogram example this does not apply since it is the same time series. It cannot be a hedge against itself.

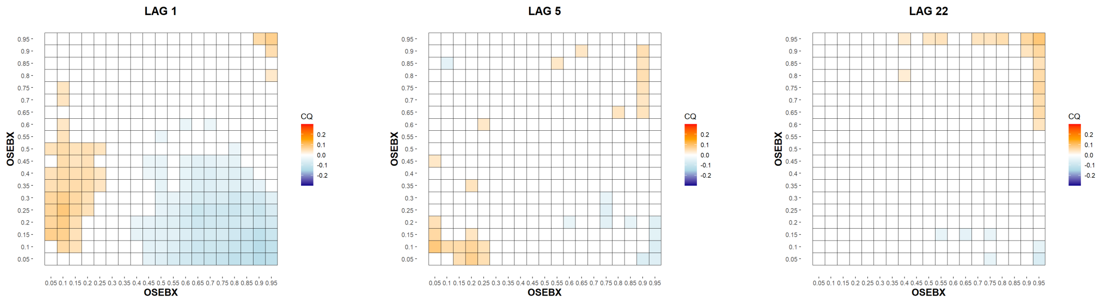

Figure 5.9: Quantilogram for OSEBX at lags 1, 5 and 22 corresponding respectively to daily, weekly and monthly time intervals. Positive values are orange, negative values are blue, and insignificant values are white. Predictability runs from the variable on the x-axis to the variable on the y-axis.

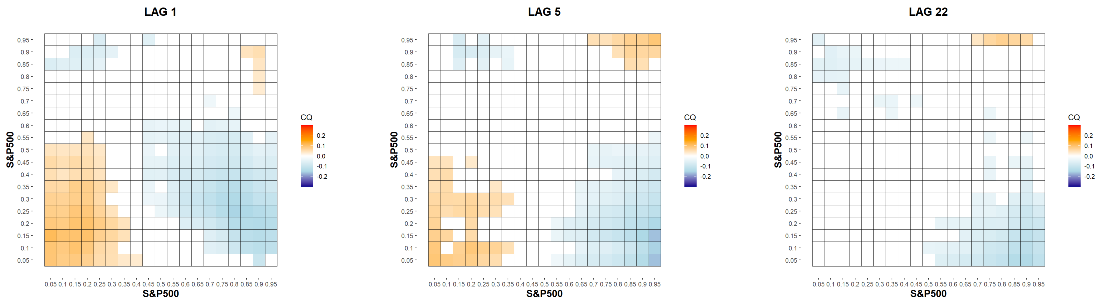

Figure 5.10: Quantilogram for S&P500 at lags 1, 5 and 22 corresponding respectively to daily, weekly and monthly time intervals. Positive values are orange, negative values are blue, and insignificant values are white. Predictability runs from the variable on the x-axis to the variable on the y-axis.

Figure 5.10 reveals that the underlying nature of the directional predictability from S&P 500 to itself is very similar to that of the OSEBX, except for the fact that the spillover effect is stronger and more persistent in the case of S&P 500, particularly for the negative values in opposite quantiles. This pattern of colour in the corners with white in the middle signifies why quantilograms are such useful tools, because the directional predictability or spillover effects lie primarily in the tails.

5.1.3 Cross-Quantilograms

Figures 5.11 and 5.12 show that the directional predictability to OSEBX is rather similar from both Brent and S&P 500. Although the magnitude of the predictability is stronger from S&P 500, except for in the lower quantiles at monthly lag. Notice how the CQ captures the asymmetric relationship and effect of time between S&P 500 and OSEBX. One day ahead there is positive cross-quantile correlation more or less across the board, but after five days the correlation is more or less gone except for in some of the most extreme quantiles. The spillover effect in opposite quantiles has even turned negative. This implies that markets are somewhat efficient and that new information transfers quickly. Five days old information is no longer particularly useful.

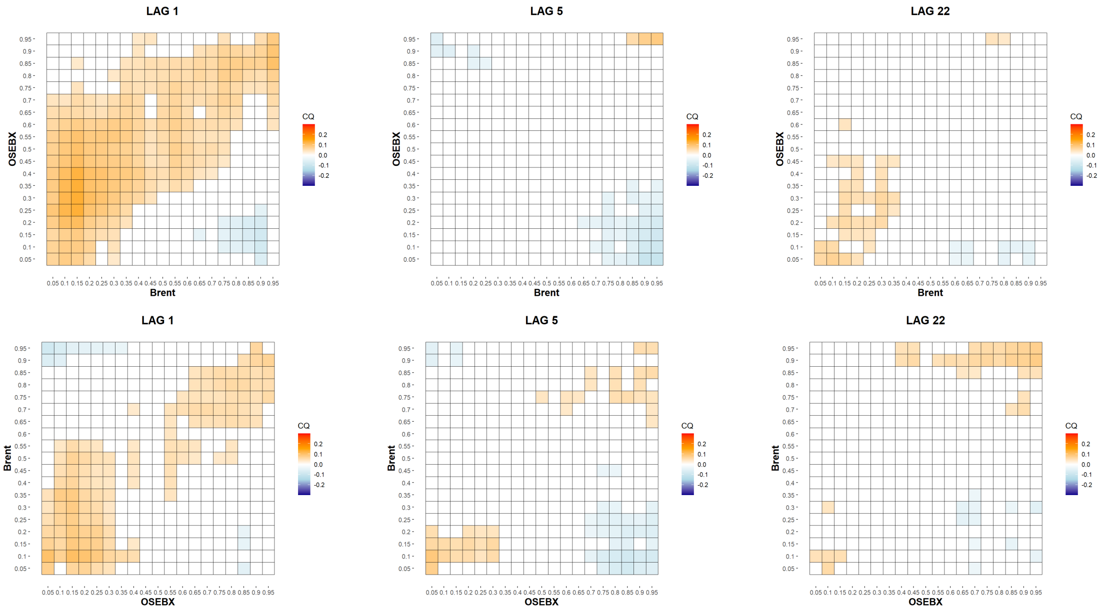

Figure 5.11: Cross-quantile correlation between Brent oil and OSEBX at lags 1, 5 and 22. Predictability runs from the variable on the x-axis to the variable on the y-axis.

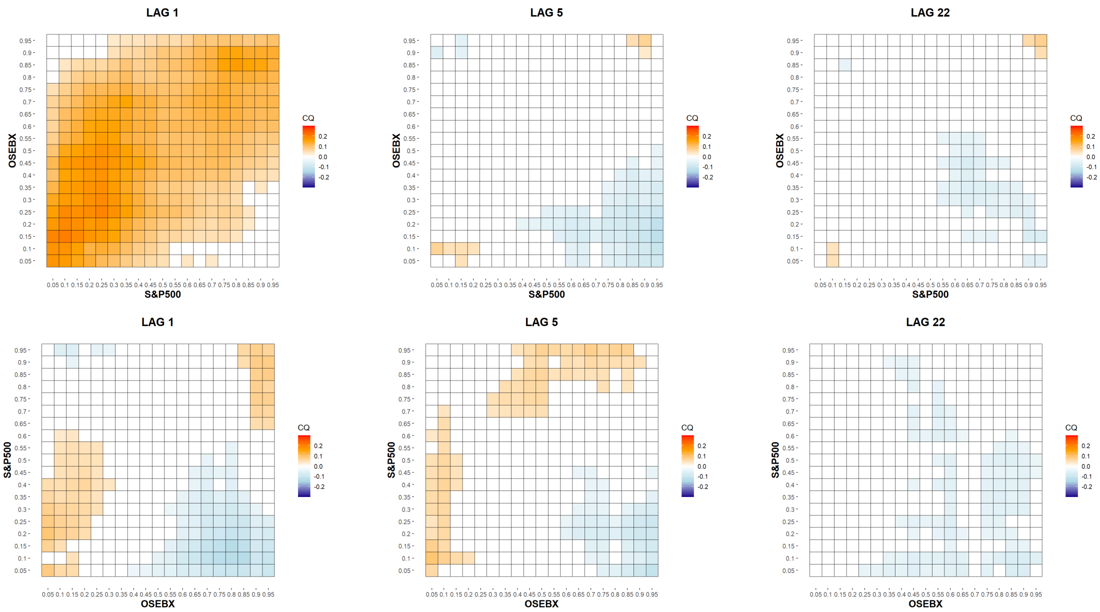

Figure 5.12: Cross-quantile correlation between S&P 500 and OSEBX at lags 1, 5 and 22. Predictability runs from the variable on the x-axis to the variable on the y-axis.

Figure 5.13 reveals that the dependence of S&P 500 from Brent is very different to that of OSEBX. Where the spillover effect from Brent to OSEBX is predominantly positive at lag 1, it is much more negative for S&P 500. This is probably due to the types of companies that make up the respective indexes. For OSEBX, which consists of roughly 29% energy related stocks, an increase in oil returns is positive. Whereas for the S&P 500, oil is much more of an input than an output for companies. Increasing oil prices therefore lead to increased production costs, which is negative for these companies and the US economy in general.

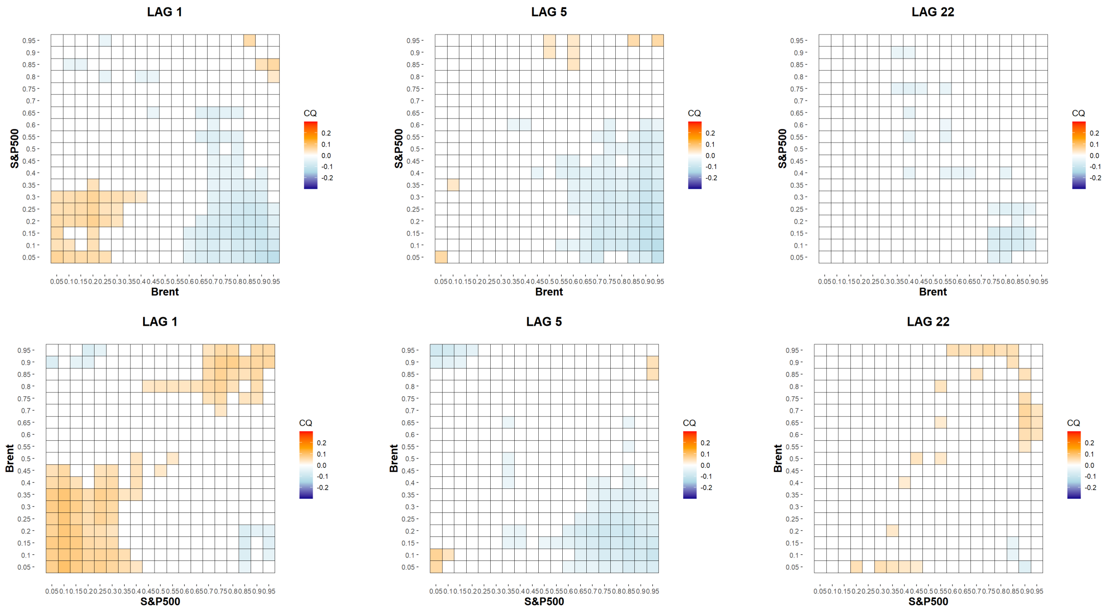

Figure 5.13: Cross-quantile correlation between Brent and S&P 500 at lags 1, 5 and 22. Predictability runs from the variable on the x-axis to the variable on the y-axis.

Figures 5.14 and 5.15 confirm that, apart from at lag 1 there is little information to be found in the normal market states around the median, 0.4th - 0.6th quantiles (the middle row). Figure 5.14 confirms what we found in Figure 5.11, that there is positive cross-quantile correlation at matching quantiles. The same is true for S&P 500. Although the first lag is significant and positive for all quantiles in Figure 5.15, the magnitude is otherwise strongest and most persistent in the lower quantiles. This shows that negative shocks have a stronger spillover effect than positive shocks.

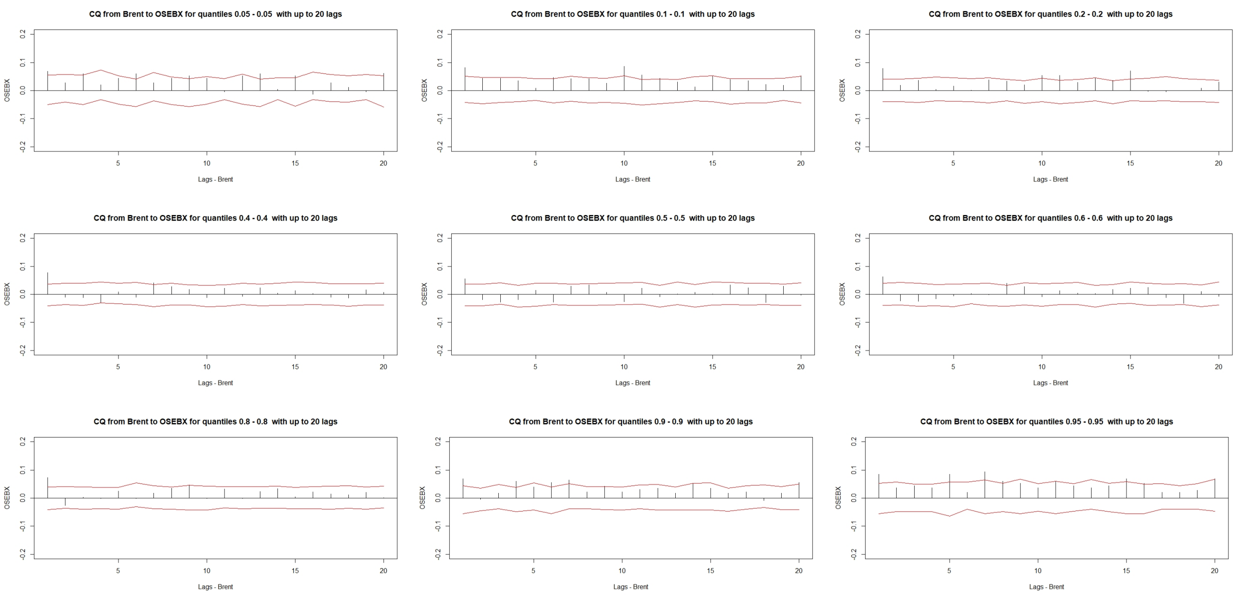

Figure 5.14: CQ from Brent to OSEBX for matching quantiles and up to 20 lags.

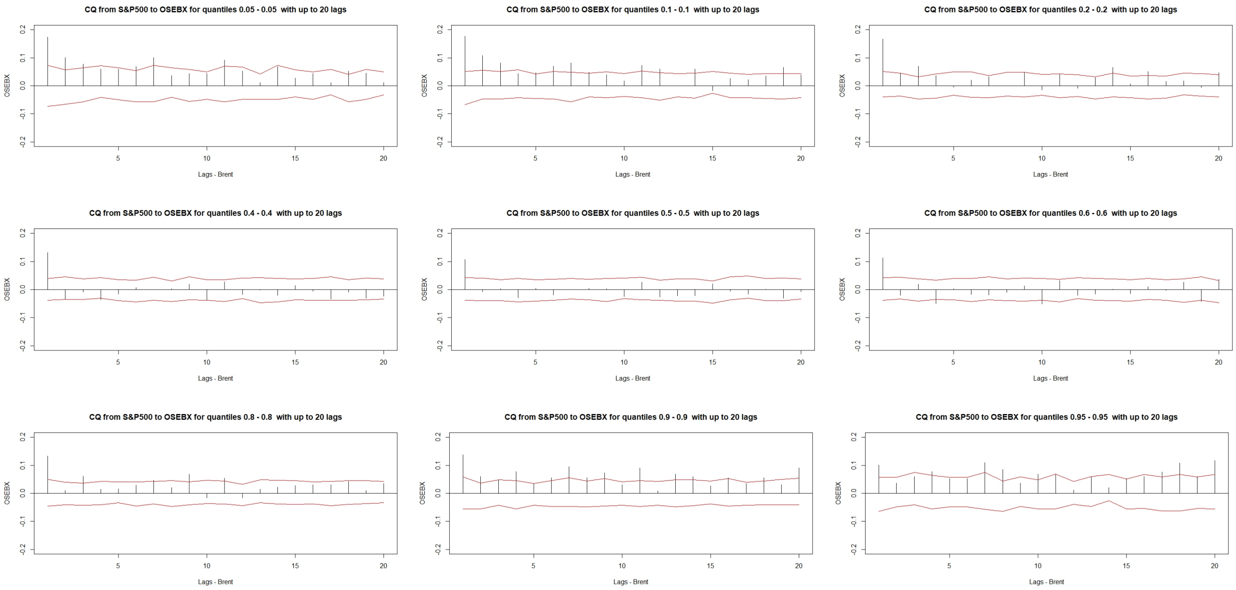

Figure 5.15: CQ from S&P 500 to OSEBX for matching quantiles and up to 20 lags.

Since both the heatmaps in Figures 5.11 and 5.12, and the cross-quantilograms for several lags in Figures 5.14 and 5.15 imply that S&P 500 is a better predictor of future returns on OSEBX, we have chosen to only include a model of the directional predictability for various market states for the connection between S&P 500 and OSEBX. We find that, discarding lag 1, most other significant estimates are in the corners of Figure 5.16, where the returns of the time series are in either the same or opposite extreme quantiles. The correlation is positive under similar market conditions, and negative for opposite conditions.

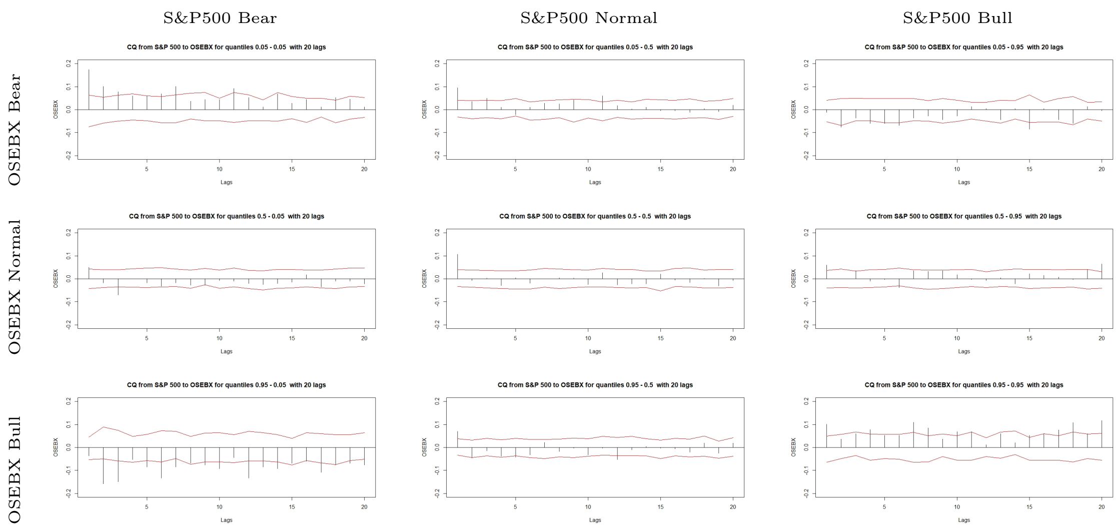

Figure 5.16: CQ from S&P 500 to OSEBX under bearish, normal and bullish market conditions, for up to 20 lags.

5.1.4 Partial Cross-Quantilograms

Figure 5.17 unveils the PCQs from Brent and S&P 500 to OSEBX, controlling for the other. Brent exhibits very little moderating effect on the directional predictability from S&P 500 to OSEBX. S&P 500 however, clearly has an intermediate, moderating effect on the directional predictability from Brent to OSEBX. These findings confirm what we already found in the cross-quantilograms, that out of the two, S&P 500 has the strongest spillover effect on OSEBX.

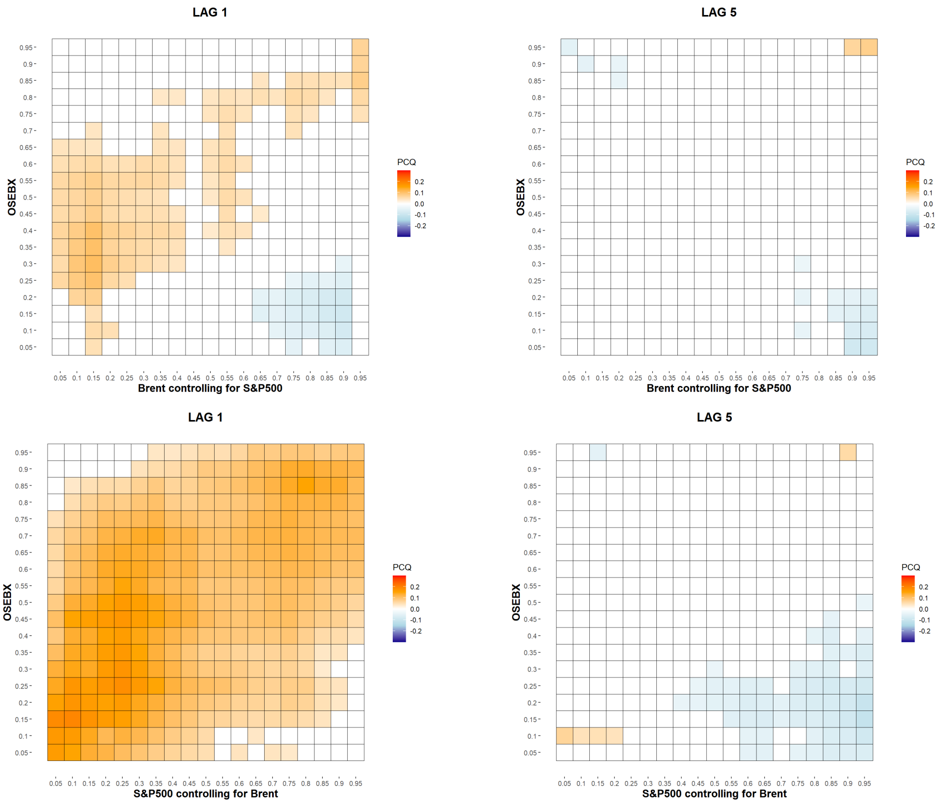

Figure 5.17: PCQs from Brent and S&P 500 to OSEBX, controlling for the other, at lags 1 and 5. Positive values are orange, negative values are blue, and insignificant values are white. Predictability runs from the variable on the x-axis to the variable on the y-axis.

Comparing Figure 5.14 to Figure 5.18, we clearly see the moderating effect from the inclusion of S&P 500 as an intermediate variable. There are still some significant values, but the absolute values are visibly smaller. There is some moderating effect from Brent on S&P 500 as well in Figure 5.19, as compared to Figure 5.15, but the effect is far less distinct.

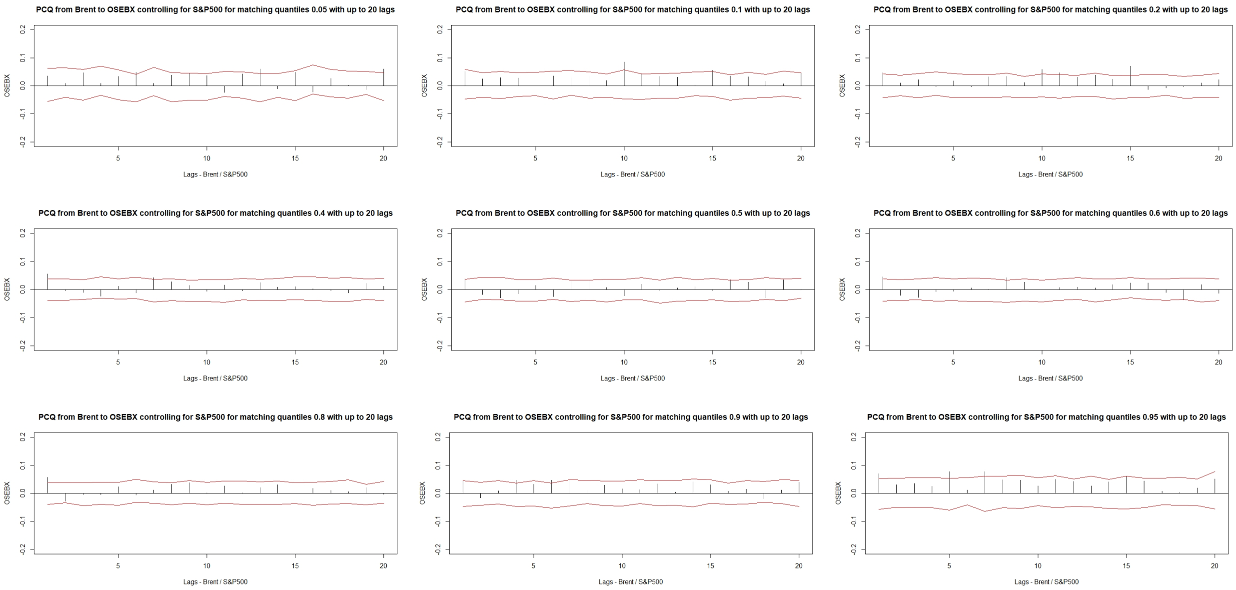

Figure 5.18: PCQ from Brent to OSEBX controlling for S&P 500, for matching quantiles and up to 20 lags.

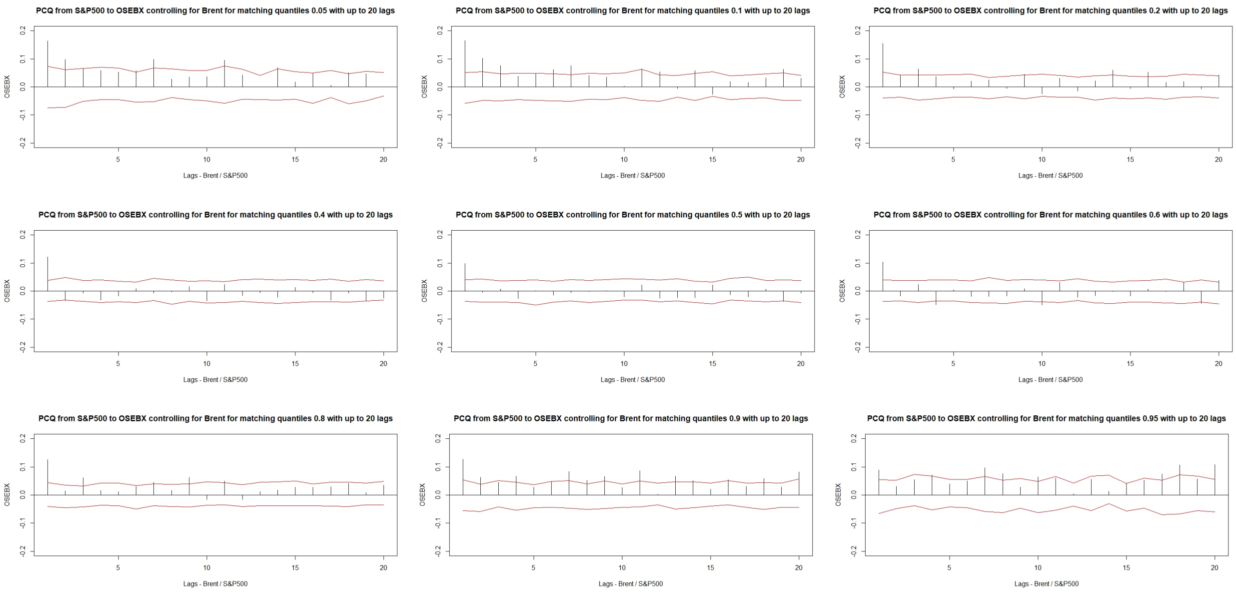

Figure 5.19: PCQ from S&P 500 to OSEBX controlling for Brent, for matching quantiles and up to 20 lags.

5.1.5 Summary/Essence of case study 1

Both Brent and S&P 500 have directional predictability for, or spillover effects to, OSEBX. The effect is not very persistent, as it has mostly dissipated after five days. There are even somewhat alternating signs, positive or insignificant directional predictability has turned negative, particularly for opposite quantiles. The spillover effect is strongest from S&P 500 to OSEBX. S&P 500 has a moderating effect on the relationship between Brent and OSEBX, whereas Brent has very little moderating effect on the relationship between S&P 500 and OSEBX.

5.2 Directional predictability between Aerospace stocks

The aerospace industry is a vast and comprehensive industry, covering everything from air transportation, to space shuttles, to weapons and warfare. We take a look at the stocks of three relatively diverse companies; Lockheed Martin, Intuitive Machines and Astrotech. Lockheed Martin produces tactical airplanes and helicopters, weapons, radars, and spacecrafts. Intuitive Machines also produces spacecrafts, cooperating with NASA to put the first American space shuttle on the moon since the Apollo program. Astrotech used to build space shuttles, but since it sold its space division to Lockheed Martin in 2014, it has developed a mass spectrometer for testing airline passengers for explosives.

5.2.1 Data

The data has been downloaded from Yahoo Finance. We are using daily data for the time interval 1.12.2021 – 25.4.2024, a total of 601 observations. No values have been removed from the time series. The excess returns have been obtained in the same way as described by Equation 5.1.1.

Company	Ticker	Raw Price data	Excess returns
Lockheed Martin	LMT	LMT	lmt
Intuitive Machines	LUNR	INTMA	intma
Astrotech	ASTC	AST	ast

Table 5.3: Variable definitions

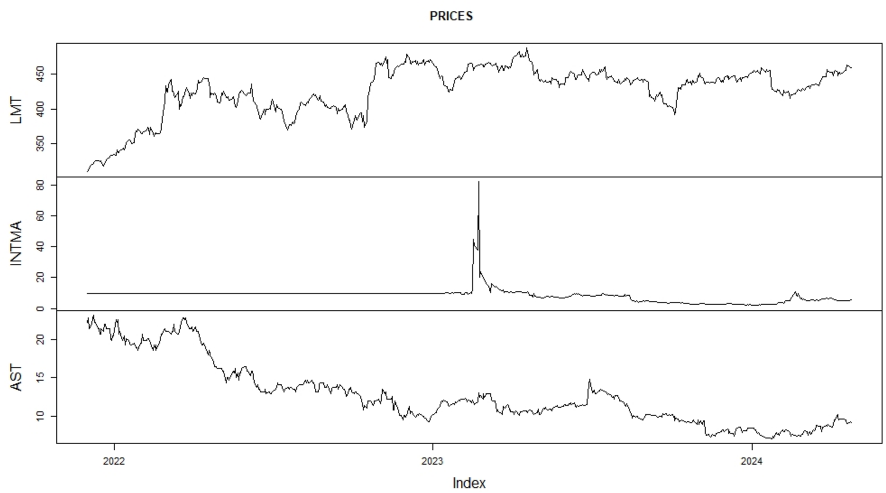

Figure 5.20: Daily prices of Lockheed Martin, Intuitive Machines and Astrotech 01.12.2021 - 25.04.2024

As seen in Figure 5.20, there are signs of non-stationarity for all price series. For LMT and AST there does not appear to be a constant mean for the entire time period, and for Intuitive Machines there is non-constant variance. An Augmented Dickey Fuller test confirms that LMT and AST are not stationary (p-values of 0.059 and 0.53 respectively, as seen in Appendix A.2). The test did not reject the null hypothesis of a unit root for INTMA despite its volatile outburst in February 2023, but since it did for the others we have transformed the data into returns.

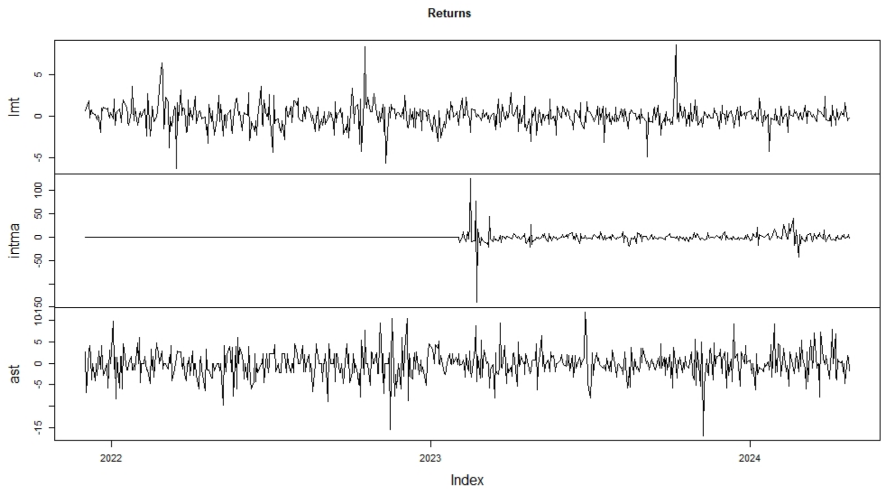

Figure 5.21: Daily returns of Lockheed Martin, Intuitive Machines and Astrotech 01.12.2021 - 25.04.2024

The series of returns are clearly closer to the ideal of stationarity. Although there are clusters of increased volatility, there appears to be a constant mean throughout the period. Formal testing using the Augmented Dickey Fuller test reveals that there is no convincing evidence against stationarity. All p-values were less than 0.01, rejecting H_0 (that the series has a unit root, or is non-stationary). The Ljung-Box p-value reveals the we reject the null hypothesis of independence in the individual time series. There is some autocorrelation present, particularly for Intuitive Machines, as seen in Figure 5.25. A Jarque Bera test confirms that the returns are not normally distributed, as we can also deduce from the Q-Q plots in Figure 5.3 and the histograms in Figure 5.5.

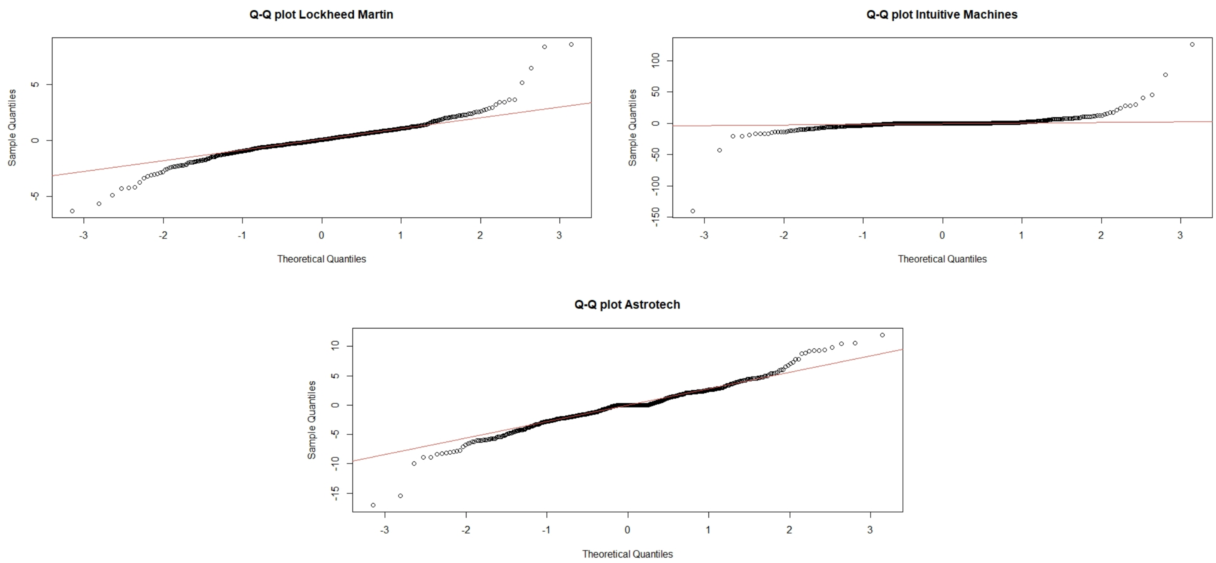

Figure 5.22: Q-Q plots for Lockheed Martin, Intuitive Machines and Astrotech

Lockheed Martin has the largest mean return. Intuitive Machines and Astrotech are averaging negative returns, although Intuitive Machines is significantly influenced by the volatile behavior of the stock on Feb 22.- 23. 2023, due to its successful landing of one of its spaceships on the moon [61]. As expected upon viewing the plots for both the prices and the returns, Intuitive Machines, by far, has the largest absolute values for maximum and minimum returns. This is also reflected in the standard deviations. Interestingly, since Intuitive Machines' volatile spur is a "one time thing", Astrotech actually has a significantly larger interquartile range.

	Lockheed Martin	Intuitive Machines	Astrotech
# Observations	601	601	601
Mean	0.07	-0.10	-0.15
Median	0.05	0.00	0.00
Max	8.56	125.68	11.91
Min	-6.28	-139.60	-16.99
IQR	1.30	1.39	3.78
Std	1.35	10.17	3.26
Skewness	0.51	-0.20	-0.18
Kurtosis	10.12	105.93	5.57
ADF stat	-8.12	-8.91	-9.15
ADF p-value	0.01	0.01	0.01
Jarque Bera stat	1296.69	265309.01	168.19
Jarque Bera p-value	0.00	0.00	0.00
Ljung-Box stat	23.75	115.30	34.90
Ljung-Box p-value	0.02	0.00	0.00

Table 5.4: Descriptive statistics for Lockheed Martin, Intuitive Machines and Astrotech returns from 01.12.2021 to 25.04.2024

It could be hard to notice from the marginal distributions in Figure 5.23, but Lockheed Martins returns have a positive marginal density (skewness), while the opposite is true for Intuitive Machines and Astrotechs. The boxplot in Figure 5.24 clearly shows that Intuitive Machines has the fattest tails. In fact, the tails of Intuitive Machines are so large that it almost makes Lockheed Martins and Astrotechs tails seem like they disappear. All of them have excess kurtosis, indicating that they are not normally distributed. This is formally confirmed by the Jarque Bera test and the Q-Q plot in Figure 5.22. This an excellent reason to apply quantilograms for analysing the quantile connectedness of the time series'.

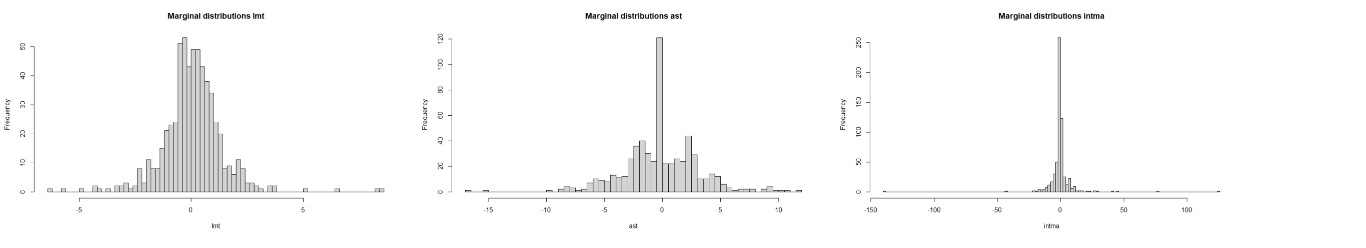

Figure 5.23: Histograms of marginal distribution of returns

The boxplot brings out the the fatter tails of Intuitive Machines' returns. Intuitive Machines is in a very risky "hit or miss" business, which is reflected in the volatile nature of their returns.

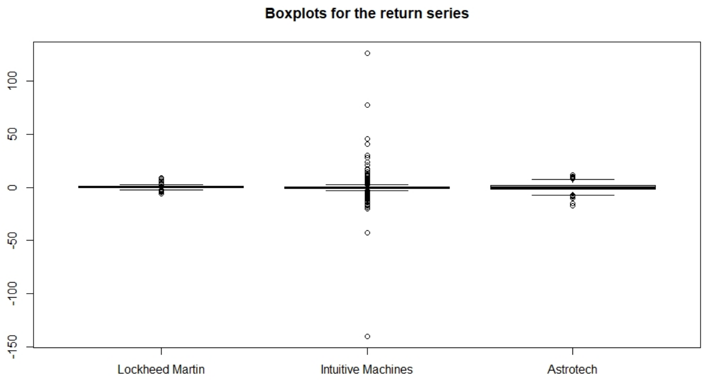

Figure 5.24: Boxplot of returns in %

Looking at the correlograms in Figure 5.25, the autocorrelation for Lockheed Martin is insignificant at most lags, whereas Intuitive Machines and Astrotech have several significant lags. For Intuitive Machines, we see that lag 1 is the most statistically significant coefficient, and it is negative. Meaning that if Intuitive Machines is above its mean at time t-1 then it is more likely to be below its mean at time t. This is why I have chosen to take a closer look at the quantilogram for Intuitive Machines at lag 1, to see if we can get a more comprehensive understanding of the relationship.

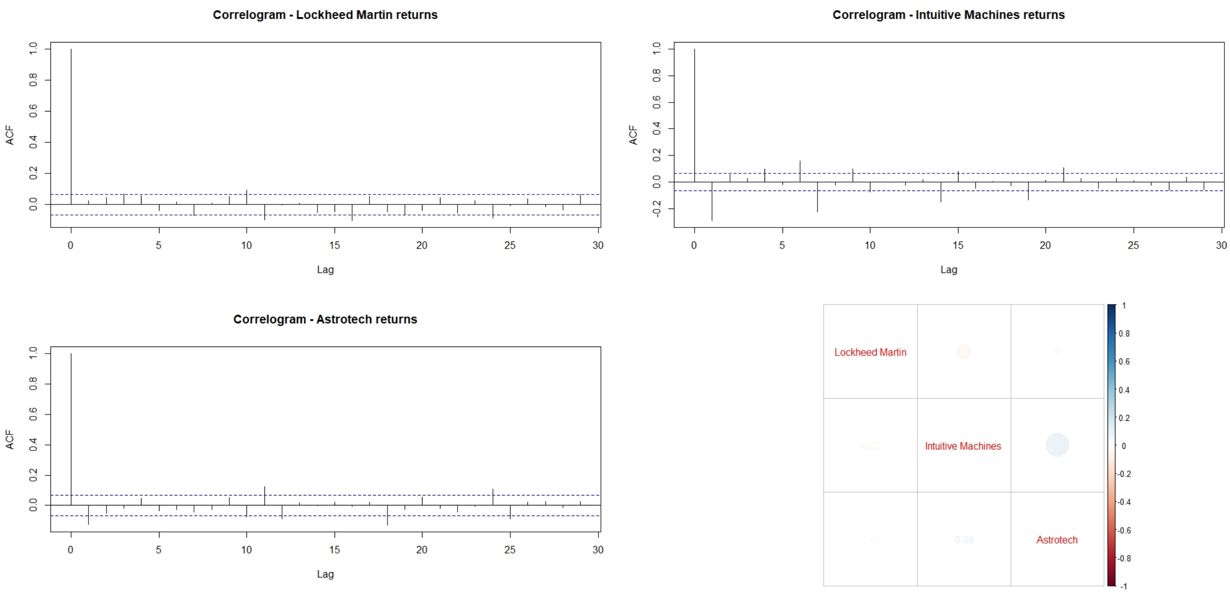

Figure 5.25: Correlograms and correlation for respective return series

We have also included an ordinary correlation matrix since we are modelling the cross-quantile dependence in this paper. As we can see, there is very weak, almost non-existing correlation between the stocks. This might seem counter-intuitive, but is probably due to the inherent differences between companies. So even if the stocks might belong to the same overall sector or index, they might still vary tremendously when it comes to business models and sectors. Since the correlogram of Intuitive Machines shows the most sign of dependency on previous information, we have chosen to take a closer look at the quantilogram of Intuitive Machines in bad, normal and good market states.

5.2.2 Quantilogram

From Figure 5.26 we see that, in the case of Intuitive Machines, most of the information evolves around the median. Even though the largest absolute value is at lag 5 in the 0.1 - 0.1 quantile, the rest of the result are mostly insignificant and taper of rather quickly. The 0.9 - 0.9 quantile has very few, and only barely significant, coefficients. For the median however, the results are more persistent. We see that if Intuitive Machines' returns are above the median, then they are more likely to also be above the median in the future.

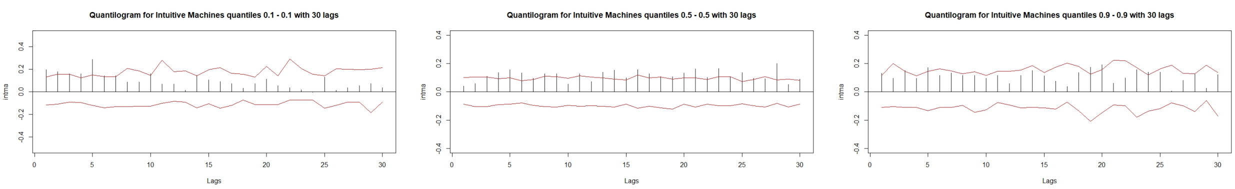

Figure 5.26: Quantilograms for Intuitive Machines in bear (0.1), normal (0.5) and bull (0.9) states

The results from lag 1 seem to conflict with the findings from the correlogram were there was negative correlation around the mean. I have only modelled certain selected quantiles, so it could be that there is more relevant information in other quantiles. For this dataset we specifically chose the quantiles 0.1 and 0.9 to model the extreme cases. The reason we chose this level instead of 0.05 and 0.95 for the extreme quantiles, was due to the limited amount of observations in the dataset.

5.2.3 Cross-quantilograms

Figures 5.27 - 5.29 showcase the cross-quantile correlations between Lockheed Martin, Intuitive Machines and Astrotech for daily (lag 1), weekly (lag 5) and monthly (lag 22) time intervals.

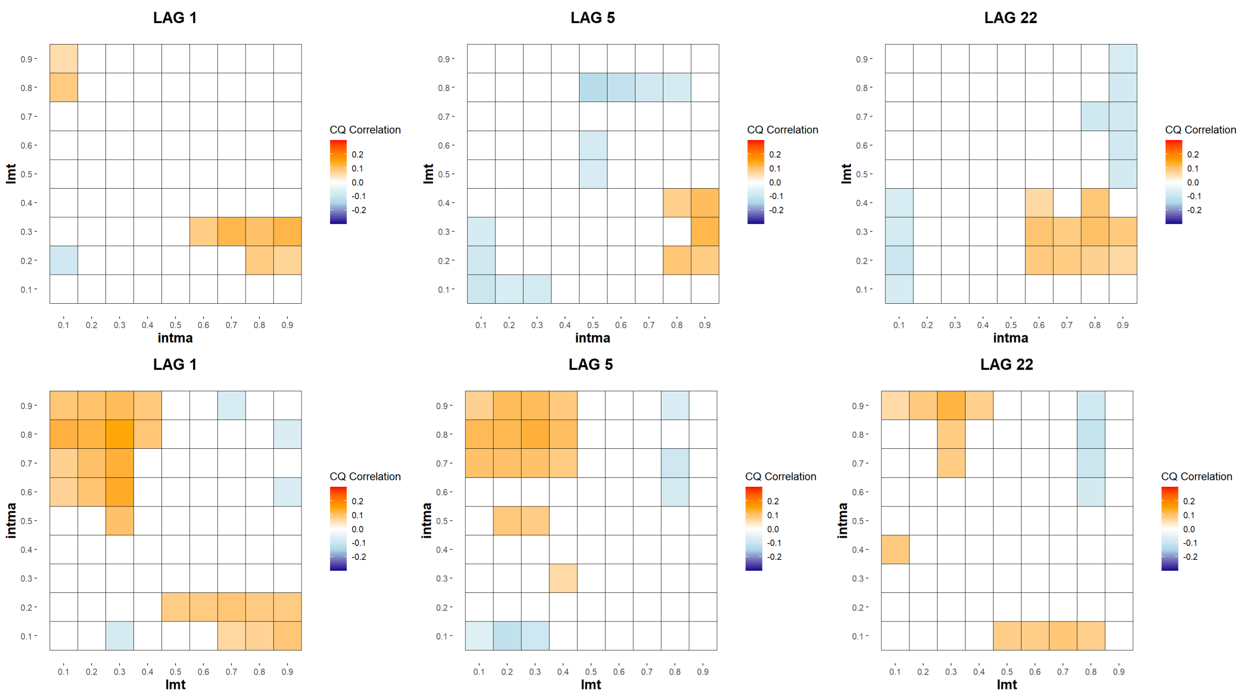

Figure 5.27: Heatmaps for lmt-intma for 1, 5 and 22 lags

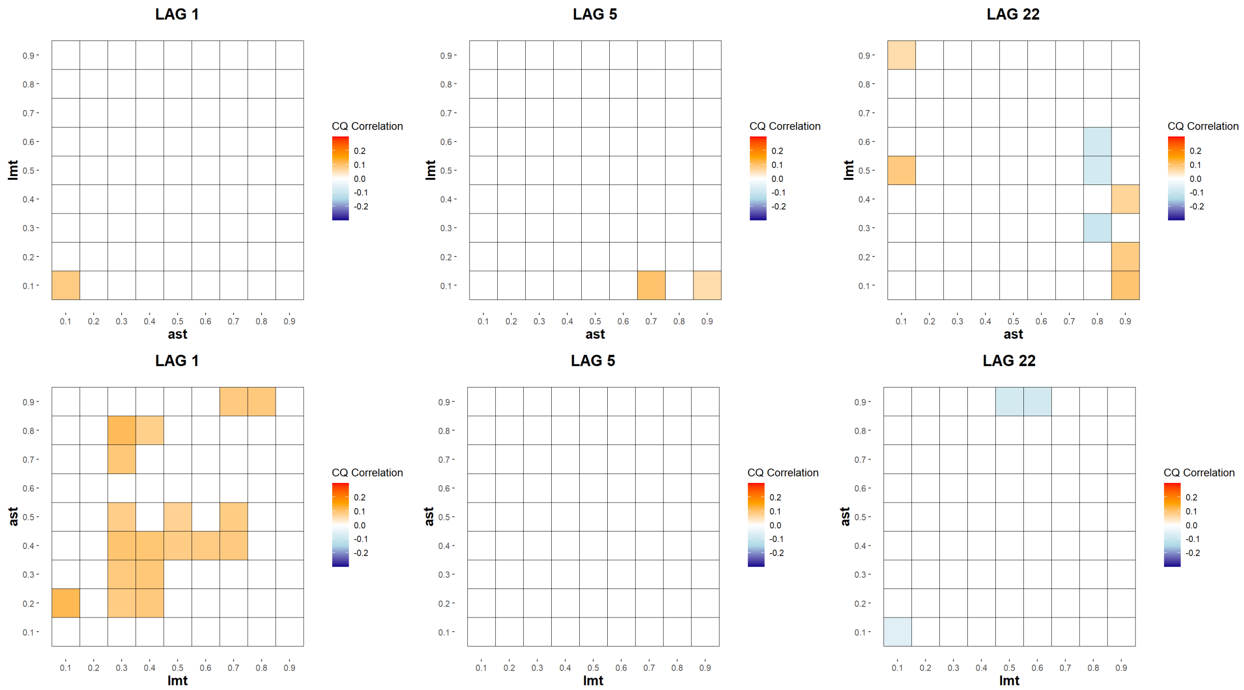

Figure 5.28: Heatmaps for lmt-ast for 1, 5 and 22 lags

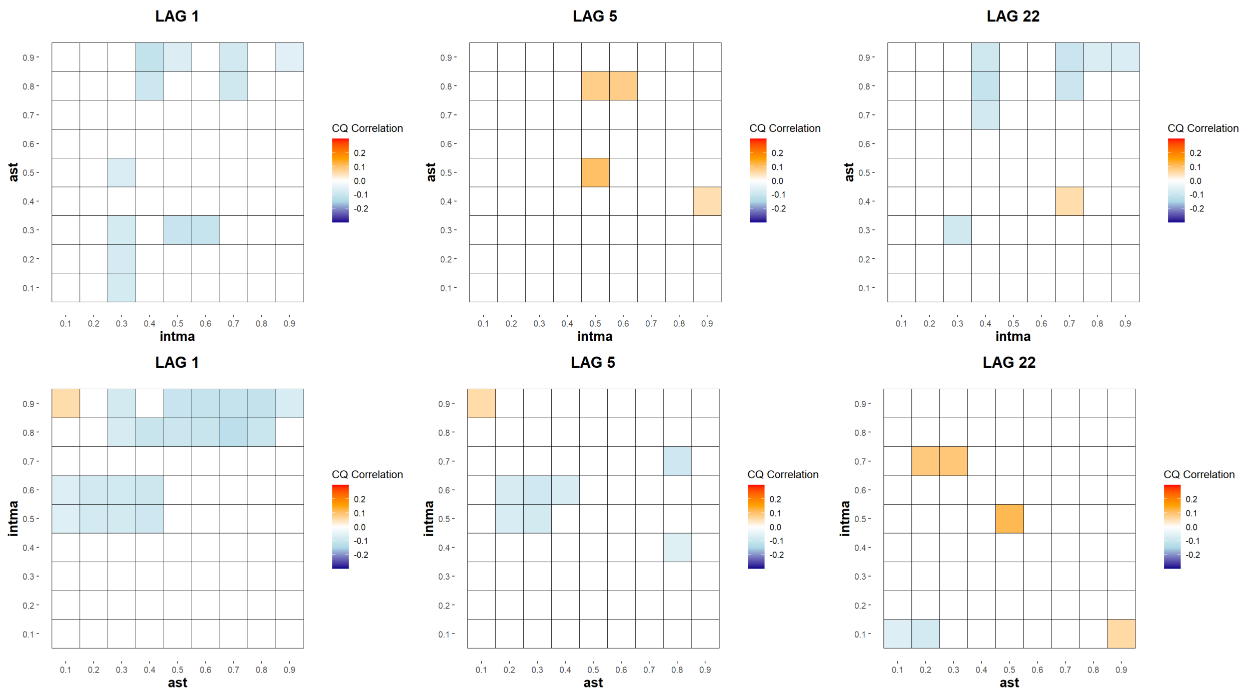

Figure 5.29: Heatmaps ast-intma for 1, 5 and 22 lags

The colour scale for the CQ estimate in Figures 5.27 - 5.29 has been set to the interval [-0.2,0.2] to make the correlations stand out a little more. Otherwise, it would be as in Figure 5.30 where the scale is set to the standard correlation interval [-1,1]. White represents insignificant correlation, meaning that knowing whether or not one time series is below (above) some quantile at time t-1 does not reveal anything about whether or not another time series will be below (above) some quantile at time t. From Figure 5.27 we see that there is positive predictability from lmt to intma in the upper left corner. This means that, e.g. if lmt is below the 0.3 quantile at t-1 then intma is also likely to be below the 0.8 quantile at time t. In other words, if lmt returns are small you should not expect large intma returns in the following days.

We can also see that at lag 1 there is absolutely no directional predictability or spillover effects from ast to lmt, ref Figure 5.28. Meaning that in the short term ast could serve as a hedge for lmt. Figure 5.29 reveals that there is no positive predictability in the medium-to-lower quantiles for ast and intma. Therefore, ast and intma could serve as hedges for each other.

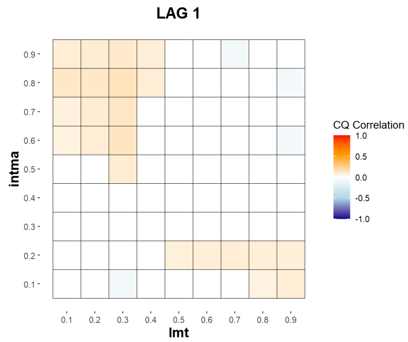

Figure 5.30: Heatmap lmt to intma lag 1 scale -1-1

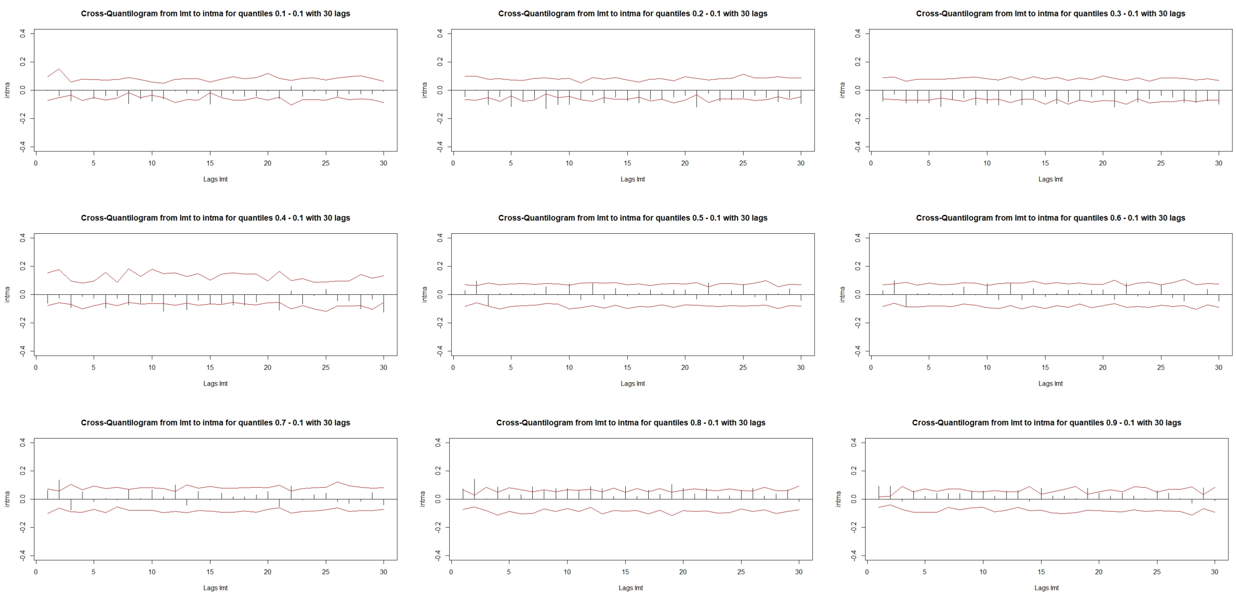

Figure 5.31: CQ from lmt to intma with lmt locked at 0.1

We see from Figure 5.31 what the cross-quantile dependence is from lmt to different quantiles of intma for various lags, when lmt is locked at the 0.1 quantile. So for lags 1 and 5 it corresponds to column 1 and rows 1 to 9 in the lower heatmaps of Figure 5.27. It does not reveal anything too interesting in this case, since we are working with returns that we already knew were very little correlated. We see that the correlation is negative for the four graphs representing the lowest quantiles, mixed in the interval 0.5-0.7, and positive for the upper quantiles of intma. Although there are very few significant values.

5.2.4 Summary/Essence of case study 2

The diversity in business models of the stocks from the aerospace industry presents itself also in the connectedness between them. The directional predictability is sparse, even negative for certain pairs, or positive only in opposite quantiles for some connections.

Astrotech and Intuitive Machines are basically short-term hedges for each other, despite being a part of the "same" industry. Instinctively this sounds peculiar. Although this does have a plausible explanation, as explained previously. Therefore, one could question whether or not they actually belong to the same industry, and perhaps Astrotech should not have been included in the dataset.

The only pairing that resembles somewhat of a relationship one would expect from two companies in similar sectors, is between Lockheed Martin and Astrotech. There is positive predictability from Lockheed Martin to Astrotech, at lag 1 on the diagonal within similar quantiles. This is what you would expect to see from the relationship between Lockheed Martin and Intuitive Machines, as they are both in the space industry. Although the space division of Lockheed Martin only makes up a small fraction of the company (18.7%). The CQ between them does not reveal such a dependency. Instead they have insignificant or negative cross-quantile dependency within similar quantiles. The positive spillover effect is contained within opposite quantiles.

Lockheed Martin appears to be the primary driver out of the three. This is probably due to the fact that they by far have the largest market capitalization of 110.60 billion USD, vs 628.15 million USD for Intuitive Machines and 16.17 million USD for Astrotech. Size matters.

Chapter 6

Discussion

In this paper we take an in-depth look at the novel statistical methods called quantilograms, cross-quantilograms and partial cross-quantilograms. We emphasize why this method is very applicable to non-normal, heavy-tailed financial data. We apply the methods to make inference about the connectedness between OSEBX, Brent crude oil and S&P500 using data from March 5th 2013 to Dec 29th 2023, and between aerospace stocks using data for the time interval 1.12.2021 − 25.4.2024.

As mentioned in the introduction to this paper, there are two main aspects to consider whenever you are making any investment decision; what return can you expect and what risk is associated with that return. There is a word of mouth saying that says that if you wish to pitch a wealthy person an investment opportunity, their main concern is not how much money they can make, but how much money they risk to lose. It is all about maximum upside potential with minimal downside risk, which Kruel & Ceretta (2022) refer to as making asymmetric bets [31].

Traditional OLS regression only estimates one measure of central tendency. Quantile regression takes it a step further, allowing for the estimation of all conditional distributions for different quantiles of a time series. This provides a broader insight into the analysis of stock market returns under different scenarios [31]. Quantilograms add even another dimension by making it possible to model the relationship at all quantiles of both the dependent and independent variables. This gives investors the opportunity to obtain a more comprehensive overview on how markets/stocks/bonds etc. are connected under different market states. Quantile dependence is at the heart of risk management.

6.1 OSEBX, Brent crude oil and S&P 500

The empirical results show that there is significant positive predictability from both Brent and S&P 500 to OSEBX at lag 1, particularly around the diagonals where they are in similar quantiles. The predictability is clearly stronger from S&P 500 to OSEBX than it is from Brent to OSEBX. From S&P 500 to OSEBX there is positive predictability across almost the entire board, except for some insignificant results in opposite extreme quantiles (upper/lower or lower/upper). Whereas from Brent to OSEBX there is some negative predictability in the lower right hand corner. The positive predictability is short-lived having more or less completely dissipated after 5 lags, except for in the most extreme quantiles. This indicates that new information is transferred quickly. The model captures the non-linearity and the asymmetries of the connections, particularly for OSEBX and S&P 500 at lag 1 in Figure 5.12. These results could not be found using OLS or standard correlation.

Figures 5.11 and 5.13 visualize the differences in the connections between Brent and the

Norwegian and US market. For OSEBX Brent has a predominantly positive spillover effect from one day to another, whereas for S&P 500 the results are much more mixed/negative. These mixed results make intuitive sense for two reasons. The first being that there are oil producers registered on both stock exchanges. So higher oil prices means higher income for them. The second being that oil or energy is a major input factor in many business models. This means that oil prices can have opposite effects on the financial results of these companies. The stronger positive predictability for OSEBX indicates a larger presence of oil related businesses making up the exchange, as opposed to the US where increased oil prices may have a more pronounced negative effect for the majority of businesses.

Our findings are in line with those of Sadorsky (1999) [52], who found that spillover effects from oil price shocks to stock market returns are negatively correlated for opposite quantiles. We found this to be particularly true for S&P 500, which is not such an energy dominated index. However, we show that there is bidirectional predictability between S&P500 and OSEBX on one side and Brent crude oil on the other side. This is in contrast with Chiou & Lee (2009) [10], Hammoudeh et al. (2004) [21] and Arouri et al. (2011) [4], who found there to be only unidirectional predictability. Reasons for this could include different time periods, oil products and statistical methodologies. Tansuchat et al. (2009) [62] found no spillover effects whatsoever. Note that all of these conflicting results are from articles written before the start of the dataset used in this article.

Kumar et al. (2021) [32] found no directional predictability from oil to stock returns in 14 emerging markets unless they controlled for geopolitical risk, then they found positive quantile dependence when both assets are in similar quantiles in the lower to middle quantiles. No directional predictability is in contrast to our findings, but then again applied to very different economical aspects. Pham (2021) [44] found that US markets are the primary drivers within green equity markets, and that they can predict movements in the European markets. We found similar results for the US stock market and the Norwegian stock markets in general. Okhrin et al. (2023) [41] also find that the S&P 500 has predictive influence on oil markets. We found this to also hold for the OSEBX.

Our results are consistent with Hovden & Batalden (2017) [25] who found four factors to have significant effect on OSEBX. Oil returns and S&P 500 were the primary drivers, and the effect was positive. Fosby & Dahl (2016) [19] also found oil returns to have significant effect on OSEBX. Heggen (2019) [24] had mixed results when examining oil returns' effect on the 25 largest companies on OSEBX. The effect was positive for energy related companies, but mixed otherwise.

6.2 Aerospace stocks

This paper finds that there is some directional predictability within the time series from the aerospace industry, but due to the inherent differences between the companies and their business models, there is a lack of tail dependence, which is what we are most interested in from a risk management point of view. The directional predictability is strongest and most persistent for the two companies with the most overlapping business models, Lockheed Martin and Intuitive Machines. Lockheed Martin, being the giant out of the three, has the most spillover effect on the others.

Bouri et al. 2024 [8] use a more complicated and comprehensive approach than this paper has the possibility to do. They found increased spillover effects from both returns and volatility under extreme market conditions. Whereas our results mainly show signs of insignificant or negative tail dependence in similar extreme quantiles.

Chapter 7

Conclusions

Quantilograms provide a visually appealing and versatile tool for analyzing financial risk spillovers under various market conditions. Quantilograms are an effective statistical model that can capture tail dependencies, asymmetry, and the time-varying nature of the relationship between two time series.

This paper contributes to the existing literature by giving a more elementary understanding of what exactly quantilograms are, and how they can be applied in empirical finance. The paper contributes to the existing literature on the effects of oil returns on the Norwegian stock market, providing a more complete picture of the connectedness between the two.

The paper examines the directional predictability from Brent crude oil and the S&P 500 to the Norwegian Stock Exchange (OSEBX). We find that both have significant predictability for OSEBX, but out of the two, S&P 500 has the strongest spillover effect. The effect is however not very persistent.

For the aerospace case study, the results reflect the size of the companies and the spread in business models. With some exceptions, there is generally little tail dependency. The directional predictability is most prevalent between Lockheed Martin and Intuitive Machines. Astrotech and Intuitive Machines can serve as hedges for each other.

Future papers could make their own summary of the existing literature on quantilograms to see if they get similar results to the one in this paper. The number of papers applying quantilograms for their research has been increasing over the last few years. Other extensions include implementing other exogenous variables that could have an intermediate effect on the underlying relationships. One could replicate the case studies in the future to see if the spillover effects have changed. Perhaps the directional predictability from Brent to OSEBX has weakened as a consequence of the transition away from fossil fuels.

Future research into the price dynamics of aerospace stocks could benefit from dividing the aerospace industry in to smaller segments that are more related to each other.

Appendix A

Datasheet A

```
                   OSEBX     BRENT        SP
ADF of prices 0.148643 0.5652867 0.2372274
```

Figure A.1: ADF p-values for price series of OSEBX, Brent and S&P 500

```
                      LMT INTMA       AST
ADF of prices 0.05912746  0.01 0.529873
```

Figure A.2: ADF p-values for price series of aerospace stocks

```
[1] "Covariance matrix:"
      OSEBX Brent SP500
OSEBX 1.137  1.03 0.526
Brent 1.033  6.31 0.800
SP500 0.526  0.80 1.214
CCM at lag:  0
      [,1]  [,2]  [,3]
[1,] 1.000 0.386 0.448
[2,] 0.386 1.000 0.289
[3,] 0.448 0.289 1.000
Simplified matrix:
CCM at lag:  1
. + +
+ . .
- - -
Correlations:
        [,1]     [,2]     [,3]
[1,] -0.0177  0.05581  0.16302
[2,]  0.0426  0.00817  0.00332
[3,] -0.0550 -0.04714 -0.13183
CCM at lag:  2
. . .
+ . +
+ + +
Correlations:
        [,1]    [,2]    [,3]
[1,] -0.0197 -0.0374 0.00361
[2,]  0.0605  0.0227 0.05210
[3,]  0.0677  0.0543 0.09086
CCM at lag:  3
. + .
. . .
. + .
Correlations:
       [,1]    [,2]     [,3]
[1,] 0.0230  0.0548  0.02361
[2,] 0.0258 -0.0308 -0.01919
[3,] 0.0301  0.0593 -0.00976
CCM at lag:  4
. . .
. . +
. - -
Correlations:
          [,1]    [,2]    [,3]
[1,] -0.026888 -0.0198 -0.0255
[2,] -0.000149  0.0281  0.0453
[3,] -0.015734 -0.0449 -0.0587
CCM at lag:  5
. . .
. . -
+ . +
Correlations:
        [,1]     [,2]     [,3]
[1,] 0.02553  0.00538 -0.00245
[2,] 0.00274 -0.01986 -0.04953
[3,] 0.06607  0.03679  0.04376
```

Figure A.3: Cross-correlation matrix values for up to 5 lags

Appendix B

Reflection note

International

First of all, I would like to point out that I think this reflection note is a juvenile, "high-schoolish" requirement. It underpins my general perception of the university as a second-tier university. My impression after 5 years at this institution is that the institution is more preoccupied with getting as many students as possible "through the mill", than it is with delivering high quality education that requires high standards of its students. In the future I would recommend less micro-management. That being said, I am thankful for the opportunity to attend the Analytical Finance direction of the master program. The courses specific to this program have been of high quality, and something the university should invest in going forward to meet industry needs in the future.

Master Thesis

Quantilograms: Concept and use in empirical finance.

Case study including OSEBX, Brent Crude Oil and S&P 500.

The master thesis is about a novel statistical method called the quantilogram. It was developed by Linton and Whang in 2006 [35], to model quantile predictability and spillover effects in a univariate setting, in other words between lagged versions of the same time series. The method was later extended by Han et al. in 2017 [23] to a bivariate version called the cross-quantilogram, modelling the lead-lag dependence between two different time series. The quantilogram is now a special case of the cross-quantilogram where the two time series are set to the same time series. They also introduced a multivariate version called the partial cross-quantilogram, which models the lead-lag dependence between two time series while controlling for exogenous, intermediate effects. The partial cross-quantilogram can for instance model the directional predictability from energy prices to stock indexes, controlling for e.g the VIX index.

The methods are based on a quantile hit process, defined as whether or not a realization of a time series is below or above some predefined arbitrary quantile. The cross-quantilogram is the correlogram of this quantile hit process. The method is practical to use and visually appealing. It can measure non-linear dependence for arbitrary lags and does not really on moments. It is therefore very useful in modelling financial time series which often do not have finite fourth moments (kurtosis). There is only one strict requirement to be able to apply quantilograms, and that is that the time series are stationary. The quantilograms are excellent for modelling tail dependence or correlation in different market states, be it bear, normal or bullish markets.

Internationally connected markets

Today, almost all markets have some sort of global connection in one way or another. Either products being produced and sold are internationally renowned trademarks, or the products are produced in Asia, Southern Europe or Central America and then imported to the west. Most domestic industries are reliant on foreign inputs in their production process in one way or another, either through input factors or through production machinery being produced abroad. Perhaps the most prominent example today is microchips from Taiwan Semiconductor (TSMC). They are so important that a war is hypothetically at risk between China and the US in this unique case. China regards Taiwan as a part of China, but Taiwan claims independence (actually they claim that China is a part of Taiwan). The US supports Taiwan because they and their multi-national corporations (Magnificent 7) are completely reliant on TSMCs microchips for their business models to expand with regards to the AI industry. Abakah et al. (2023) [1] have examined the dynamic effect of Bitcoin, fintech and artificial intelligence stocks on eco-friendly assets, Islamic stocks, and traditional financial markets. It does not get more international and up to date than that. They found amongst others that Islamic stocks are a good hedge for Bitcoin, and that S&P Treasury Bond and S&P Green Bond were perfect hedges for fintech. This article includes both state of the art technology, modern trading techniques, contemporary "money" (Bitcoin), a green aspect, and traditional financial assets stemming from different continents and religions. It has it all

Internationally connected markets generally benefit everyone. Free trade and free movement of labor and capital allows for resources to be used in a more efficient socio-economic way. It means that countries can produce whatever they have a comparative advantage in, and then trade between themselves, raising the standard of living in both countries [43]. But it also means that the countries or economies become more integrated and that risks and spillover effects transfer across borders, which they do faster and faster in today's highly digitalized technological world. This inter-connectedness amongst markets also means that the magnitude of crisis has a tendency to increase, as displayed in Baumöhl et al. (2022).

Systemic risk in the global banking sector

Baumöhl et al. (2022) [6] model systemic risk in the global banking sector using a cross-quantilogram in combination with a network connectedness approach. Their present the systemic risk for the entire sample, the global financial crisis, the European sovereign debt crisis and the Covid-19 pandemic. The systemic risk is without a doubt greatest during the latter. One could argue though that the Covid-19 pandemic was a crisis of a different nature, being that it was a health emergency and not a financial crisis per se. The claim still stands though that economic crisis are becoming ever more frequent and more severe. A local crisis anywhere in the world in the 19th century was very unlikely to have any noticeable global impact. Whereas today a small bank in trouble in Silicon Valley could shake up the market.

Risk transmission between currencies

Shazhad et al. (2018) [56] performed a similar exercise modelling the connectedness and risk transmission between the currencies of 35 countries, split between developed economies, Asia, the Middle East and North-Africa (excluding the USD). They show how the connectedness was almost non-existent before Covid, but that the connectedness increased dramatically during the crisis, and that it has even stabilized on a higher level. This suggests that the Covid-19 pandemic could have changed risk transmission and connectedness in global currency markets indefinitely. Their main findings were that Australian and Canadian dollars were the largest risk transmitters (disregarding US dollars) and that the Korean won, Swedish kronor and Mexican peso are strong spillover receivers, although this varies under different market conditions. In general, currencies from developed markets act as risk transmitters whereas less significant currencies act as risk receivers. This is something to keep in mind for corporations doing business abroad who may have income and expenses in different currencies.

Inflation and interest rates

The "hottest topic" in the Norwegian financial press, and mainstream press for that sake, during the last couple of years has been inflation and the seemingly never-ending increases in interest rates. Inflation has reached levels not seen in decades, due to the massive printing of money during the Covid pandemic. Governments were frightened of how the pandemic would affect the economy. Fearing an economic meltdown, they went for a better safe than sorry strategy, injecting large amounts of liquidity into the economy. When the pandemic passed and everyone returned to their normal lives, people found themselves with lots of excess cash. This cash has found its way back into the economy, driving up inflation. The problem seen from Norway's point of view is that the seemingly endless increases in interest rates is starting to take its toll on the economy. People are having to cut down on unnecessary expenses, and businesses are starting to cut back on their work force. Some have already had to file for bankruptcy. One of the largest housing manufacturers in Norway, Boligpartner, is already bankrupt. The dilemma for the Norwegian Central Bank is that while interest rates have reached levels where they are having a contracting effect on the economy, the Norwegian krone keeps depreciating. This in turn keeps imported inflation high, which then again leads to higher claims in the annual salary negotiations, which in turn fuels the economy which necessitates higher interest rates for longer, and so on. Due to this conundrum, the central bank cannot reduce interest rates before the American Central Bank does, otherwise the Norwegian krone will depreciate even more. This demonstrates how a minor currency like the Norwegian krone is completely interconnected with, and dependent on, foreign exchange markets and interest rates in the US and European Union.

Climate crisis

Certain challenges are of the nature of a prisoner's dilemma, where there is no Nash equilibrium [40]. The ongoing climate crisis being, without comparison, the most important of all time. Without drastic action we risk pushing the environment into a new steady state in unknown territory [53]. A state that we do not know even know if will be habitable for mankind. This is an extremely difficult challenge to solve, but also one that can only be solved together. The difficulty lies in that for every individual country it is in their own best interest that everyone else cuts their emissions, while this one country can continue with business as usual. Also, there are challenges with respect to where in the world emissions are the greatest, typically in developed western countries and large producers in Asia such as India and China. While other less evolved countries, particularly in Africa and South America, struggle with poverty and hunger, and need industrial evolution to lift more people to a higher standard of living.

Cross-quantilograms are used to model risk transmitters and receivers in renewable energy markets, spillover effects from oil and gas, and precious metals amongst others. This is of global concern if the climate crisis is going to be solved by switching from fossil fuels to renewable energy. The quantilograms offer insights into the connectedness of these markets, offering regulators such as governments valuable knowledge they can apply when enforcing regulations, subsidizing green technology and carbon emission etc.

Other examples

Other examples of international topics of relevance that the cross-quantilogram and partial cross-quantilogram have been applied to are international tourism demand(), global impact of the Euro [34], energy security risk [30], if geopolitical events transmit opportunities or threats to green markets [60], international oil volatility and its directional predictability for stock returns in BRICS countries (Brazil, Russia, India, China and South Africa) [71], if geopolitical risk improves the directional predictability from oil to stock returns in oil-exporting and oil-importing countries [32], if the US market plays a major role in extreme dependence and spillovers between uncertainty indices and stock markets [37], and directional predictability in foreign exchange rates of emerging markets [51]. The quantilogram /cross-quantilogram/ partial cross-quantilogram is a highly applicable statistical technique that can model a broad range of topics.

Master thesis

The master thesis first and foremost makes the quantilogram methodology accessible to a wider audience. It summarizes the existing literature, which currently consists only of research papers, highlighting which attributes and properties of the technique the aforementioned papers have expressed as their main motivations for applying this specific method to their research questions. As the methodology has become better known, more and more research papers are written using cross-quantilograms.

The master thesis finds that both Brent crude oil and the S&P 500 are useful in predicting the next days' returns on Oslo Stock Exchange (OSEBX). The S&P 500 has the strongest 1 day lagged predictability for OSEBX, with significantly positive values almost across the entire spectrum of quantiles. Using a partial cross-quantilogram the thesis also reveals that the S&P 500 has a moderating effect on the directional predictability from Brent to OSEBX. Whereas Brent also has a moderating effect on the spillovers from S&P 500 to OSEBX, this effect is minuscule. This confirms that out of the two, S&P 500 has the strongest predictive power for Oslo Stock Exchange. The effect dissipates rather quickly though, and after 5 days it is more or less gone, except for in the most extreme quantiles. The paper also reveals a large difference in predictability from Brent to OSEBX and S&P 500. Where the returns on Brent have a predominantly positive effect on OSEBX, it has a much weaker, and also interchanging between positive and negative effect, depending on which quantile is examined. This probably relates to the difference in structure between the two indexes. OSEBX is heavily comprised by fossil fuel companies, whereas S&P 500 consist mostly of other types of businesses. For those businesses an increase in oil prices would probably have a negative effect.

To summarize, the universe of the international applicability of the cross-quantilogram seems endless. Whatever time series' one wishes to investigate, quantilograms can provide a thorough and comprehensive overview of the correlation between them for any arbitrary quantiles and lags. Due to the fact that the method does not require normality in the joint distributions, the results hold in cases where other statistical methods may have to take precautionary measures with regards to the validity of their findings.

Appendix C

R-script

```
rm(list=ls(all=TRUE))

setwd("C:/Users/stian/Documents/RScript/MASTER")
library(xtable)
library(zoo)
library(tseries)
library(quantmod)
library(ggplot2)
library(tidyverse)
library(ggsci)
library(moments)
library(xtable)
library(zoo)
library(boot)
library(np)
library(Quandl)
library(xts)
library(readxl)
library(MTS)
library(xtable)
library(quantilogram)
library(data.table)
library(egg)
library(reshape2)
library(corrplot)
library(astsa)
library(investr)
library(stringr)

source("master functions.r")


Sys.setlocale("LC_TIME", "English")


# ------------------------------------------------------------------------------

# Data
```

```
brent.price = get.hist.quote(instrument= 'BZ=F',
                             start = "2013-03-05",
                             end = "2023-12-31",
                             quote="AdjClose",
                             provider = "yahoo",
                             compression = "d",
                             retclass="zoo")

oslobors.price = get.hist.quote(instrument= 'OSEBX.OL',
                                start = "2013-03-05",
                                end = "2023-12-31",
                                quote="AdjClose",
                                provider = "yahoo",
                                compression = "d",
                                retclass="zoo")

sp500.price = get.hist.quote(instrument= '^GSPC',
                                start = "2013-03-05",
                                end = "2023-12-31",
                                quote="AdjClose",
                                provider = "yahoo",
                                compression = "d",
                                retclass="zoo")




osebx <- (diff(log(oslobors.price)))*100
brent <- (diff(log(brent.price)))*100
sp <- (diff(log(sp500.price)))*100
length(osebx)
length(brent)
length(sp)


brent <- na.omit(brent)
osebx <- na.omit(osebx)
sp <- na.omit(sp)
length(brent.price)
length(oslobors.price)
length(sp500.price)


BRENT <- na.omit(brent.price)
OSEBX <- na.omit(oslobors.price)
SP <- na.omit(sp500.price)

adf.BRENT <-adf.test(BRENT, alternative="stationary")
adf.OSEBX <-adf.test(OSEBX, alternative="stationary")
adf.SP <-adf.test(SP, alternative="stationary")
adf.PRICES <- cbind(adf.OSEBX$p.value, adf.BRENT$p.value, adf.SP$p.value)
adf.PRICES <- as.data.frame(adf.PRICES, "ADF of prices", digits=3)
colnames(adf.PRICES) <- c("OSEBX", "BRENT", "SP")
```

```
adf.PRICES


plot(osebx.price)
plot(brent.price)
plot(sp500.price)
prices <- cbind(oslobors.price, brent.price, sp500.price)
colnames(prices) <- c("osebx", "brent", "sp500")
plot(prices, main="Daily prices")
prices <- na.omit(prices)
length(prices[,3])




returns <- cbind(osebx, brent, sp)
colnames(returns) <- c("OSEBX", "Brent", "SP500")
plot(returns, main="Daily returns")
returns <- na.omit(returns)
length(returns[,1])

qqnorm(returns[,1], main="Q-Q plot OSEBX")
qqline(returns[,1], distribution = function(p) qnorm(p,0,1), prob = c(0.25, 0.75), co
qqnorm(returns[,2], main="Q-Q plot Brent")
qqline(returns[,2], distribution = function(p) qnorm(p,0,1), prob = c(0.25, 0.75), co
qqnorm(returns[,3], main="Q-Q plot S&P500")
qqline(returns[,3], distribution = function(p) qnorm(p,0,1), prob = c(0.25, 0.75), co

#---------------------------------------------------------------------------------------

# DESCRIPTIVE STATISTICS

hist(osebx, breaks = 100, main="OSEBX returns")
hist(brent, breaks = 100, main="Brent oil returns")
hist(sp, breaks = 100, main="S&P500 returns")


cor(osebx, brent, na.rm = TRUE)
cor(osebx, sp, use ="complete.obs")


nobs <- cbind(length(returns[,1]), length(returns[,1]), length(returns[,1]))
max <- cbind(max(osebx), max(brent), max(sp))
min <- cbind(min(osebx), min(brent), min(sp))
means <- cbind(mean(osebx), mean(brent), mean(sp))
medians <- cbind(median(osebx), median(brent), median(sp))
stddev <- cbind(sd(osebx), sd(brent), sd(sp))
skew <- cbind(skewness(osebx), skewness(brent), skewness(sp))
kurt <- cbind(kurtosis(osebx), kurtosis(brent), kurtosis(sp))
iqr <- c(IQR(osebx), IQR(brent), IQR(sp))

lbstat <- cbind(Box.test(osebx, lag=12, type="Ljung-Box", fitdf=0)$statistic,
                Box.test(brent, lag=12, type="Ljung-Box", fitdf=0)$statistic,
                Box.test(sp, lag=12, type="Ljung-Box", fitdf=0)$statistic)
```

```
lbpval <- cbind(Box.test(osebx, lag=12, type="Ljung-Box", fitdf=0)$p.value,
                Box.test(brent, lag=12, type="Ljung-Box", fitdf=0)$p.value,
                Box.test(sp, lag=12, type="Ljung-Box", fitdf=0)$p.value)

jbstat <- cbind(jarque.bera.test(osebx)$statistic,
                jarque.bera.test(brent)$statistic,
                jarque.bera.test(sp)$statistic)
jbpval <- cbind(jarque.bera.test(osebx)$p.value,
                jarque.bera.test(brent)$p.value,
                jarque.bera.test(sp)$p.value)

adfstat <- cbind(adf.test(osebx, alternative="stationary")$statistic,
                 adf.test(brent, alternative="stationary")$statistic,
                 adf.test(sp, alternative="stationary")$statistic)
adfpval <- cbind(adf.test(osebx, alternative="stationary")$p.value,
                 adf.test(brent, alternative="stationary")$p.value,
                 adf.test(sp, alternative="stationary")$p.value)



df.desc <- rbind(nobs, means, medians, max, min, stddev, skew, kurt, iqr, lbstat, lbp
colnames(df.desc) <- c("OSEBX", "Brent", "S&P500")
rownames(df.desc) <-c("Obs", "Mean", "Median", "Max", "Min", "Std.dev", "Skewness", "

xtable(df.desc, digits=2)


# BOXPLOT
boxplot(prices, main="Boxplots for the return series")


# AUTOCORRELATIONS
acf.osebx<-acf(osebx, na.action=na.pass, main="Correlogram - OSEBX returns")
acf.brent<-acf(brent, na.action=na.pass, main="Correlogram - Brent oil returns")
acf.sp<-acf(sp, na.action=na.pass, main="Correlogram - S&P500 returns")


# PARTIAL AUTOCORRELATIONS
pacf.osebx<-pacf(osebx, na.action=na.pass, main="Partial acf - OSEBX returns")
pacf.brent<-pacf(brent, na.action=na.pass, main="Partial acf - Brent returns")
pacf.sp<-pacf(sp, na.action=na.pass, main="Partial acf - S&P500 returns")


# CROSS_CORRELATION MATRIX
returns.ccm <- na.exclude(returns)
ccm.data <- ccm(returns.ccm, lags=5, level=TRUE)
ccf.osebx.brent <- ccf(as.numeric(brent), as.numeric(osebx), 12, na.action = na.pass)
ccf.osebx.sp <- ccf(as.numeric(sp), as.numeric(osebx), 12, na.action = na.pass)


# Correlation Lagged
sp.ccf <- as.numeric(sp)
```

```
sp.ccf <- na.exclude(sp.ccf)
brent.ccf <- as.numeric(brent)
brent.ccf <- na.exclude(brent.ccf)
osebx.ccf <- as.numeric(osebx)
osebx.ccf <- na.exclude(osebx.ccf)
ccf(brent.ccf, osebx.ccf, lag.max = 12)
ccf(sp.ccf, osebx.ccf, lag.max = 12)


R <- na.exclude(returns)
corr.R <- cor(R)
corrplot.mixed(corr.R)



#--------------------------------------------------------------------------------

# Quantilogram/CQ

Q <- cbind(returns[,2], returns[,3]) # S&P to Brent
# Q <- cbind(returns[,1], returns[,3]) # S&P to OSEBX
# Q <- cbind(returns[,1], returns[,2]) # Brent to OSEBX
# Q <- cbind(returns[,3], returns[,2]) # Brent to S&P
# Q <- cbind(returns[,2], returns[,1]) # OSEBX to Brent
# Q <- cbind(returns[,3], returns[,1]) # OSEBX to S&P
# Lagged values of the second variable in data
Q <- na.exclude(Q)

quantiles1 <- c(0.1,0.1)
quantiles2 <- c(0.5,0.5)
quantiles3 <- c(0.9,0.9)

crossq(Q, quantiles, 1)

n <- 20
lags <- seq(1:20)
q.sb <- rep(NA, n)
q.sb.confint.low <- rep(NA, n)
q.sb.confint.high <- rep(NA, n)
q.sb.computed <- rep(NA, n)

quantiles <- c(0.95, 0.95)

for (i in 1:n){
      q.sb <- crossq.sb.opt(Q, quantiles, lags[i], 500, 0.05)
      # Lagged values of the second variable in data
      q.sb.confint.low[i] <- q.sb$vecCV[1]
      q.sb.confint.high[i] <- q.sb$vecCV[2]
      q.sb.computed[i] <- q.sb$vCRQ
      }

q.lag <- data.frame("q.estimate" = q.sb.computed,
                    "High" = q.sb.confint.high,
```

```
                    "Low" = q.sb.confint.low)


plot(q.lag$q.estimate, type ="h", ylim = c(-0.2, 0.2), main = str_glue("CQ from S&P50
lines(q.lag$High,col="red")
lines(q.lag$Low,col="red")
abline(h = 0)




#---------------------------------------------------------------------------------

# Cross-Quantilogram without bootstrap but with estimates

prob1 <- seq(0.05,0.95,0.05)
prob2 <- seq(0.05,0.95,0.05)


c <- length(prob1)
d <- length(prob2)
cq.lag <- 1
# cq.lag <- 5
# cq.lag <- 22


Q <- cbind(returns[,2], returns[,3]) # S&P to Brent
# Q <- cbind(returns[,1], returns[,3]) # S&P to OSEBX
# Q <- cbind(returns[,1], returns[,2]) # Brent to OSEBX
# Q <- cbind(returns[,3], returns[,2]) # Brent to S&P
# Q <- cbind(returns[,2], returns[,1]) # OSEBX to Brent
# Q <- cbind(returns[,3], returns[,1]) # OSEBX to S&P
data <- Q
data <- na.exclude(data)
cq <- matrix(NA, nrow=c, ncol=d)
for (i in 1:c){
  for (j in 1:d){
    cq[i,j] <- crossq(data, c(prob1[i], prob2[j]), cq.lag)
  }
}


probs.data <- as.data.frame(cq)

colnames(probs.data)[1:19] <- seq(0.05,0.95,0.05)
rownames(probs.data)[1:19] <- seq(0.05,0.95,0.05)
probs.data.vector <- as.vector(cq)
names(probs.data.vector) <- NULL

probs.df <- data.frame(expand.grid(c(seq(0.05,0.95,0.05)),c(seq(0.05,0.95,0.05))))
probs.df$cg <- probs.data.vector


cols <- c("darkblue", "lightblue", "white", "orange", "red" )
```

```
ggheatmap <- ggplot(probs.df,aes(x = Var1,y = Var2, fill = cg)) +
  geom_tile(color = "black") +
  labs(y= "Brent",
       x = "S&P 500",
       title = str_glue("LAG {cq.lag}")) +
  geom_text(aes(label = round(probs.data.vector, 3)), color = "black", size = 2)+
  scale_fill_gradientn(name="CQ",
                       colors=cols,
                       limits=c(-0.3,0.3))+
  theme(panel.background = element_blank(),
        axis.title=element_text(size=14,face="bold"),
        plot.title = element_text(hjust = 0.5, size = 16, face="bold")) +
  scale_x_continuous(breaks=seq(0.05,0.95,0.05), labels=seq(0.05,0.95,0.05)) +
  scale_y_continuous(breaks=seq(0.05,0.95,0.05), labels=seq(0.05,0.95,0.05)) +
  coord_fixed()

print(ggheatmap)


#--------------------------------------------------------------------------------

# Cross-Quantilogram with bootstrapped confidence intervals

prob1 <- seq(0.05,0.95,0.05)
prob2 <- seq(0.05,0.95,0.05)
c <- length(prob1)
d <- length(prob2)


Q <- cbind(returns[,2], returns[,3]) # S&P to Brent
# Q <- cbind(returns[,1], returns[,3]) # S&P to OSEBX
# Q <- cbind(returns[,1], returns[,2]) # Brent to OSEBX
# Q <- cbind(returns[,3], returns[,2]) # Brent to S&P
# Q <- cbind(returns[,2], returns[,1]) # OSEBX to Brent
# Q <- cbind(returns[,3], returns[,1]) # OSEBX to S&P

data <- Q
data <- na.exclude(data)

cq.lag <- 1
# cq.lag <- 5
# cq.lag <- 22

cq.sb <- matrix(NA, nrow=c, ncol=d)
cq.sb.confint.low <- matrix(NA, nrow=c, ncol=d)
cq.sb.confint.high <- matrix(NA, nrow=c, ncol=d)
cq.sb.computed <- matrix(NA, nrow=c, ncol=d)
cq.sb.corrected <- matrix(NA, nrow=c, ncol=d)

for (i in 1:c){
  for (j in 1:d){
    cq.sb <- crossq.sb.opt(data, c(prob1[i], prob2[j]), cq.lag, 500, 0.05)
```

```
    # Lagged values of the second variable in data
    cq.sb.confint.low[i,j] <- cq.sb$vecCV[1]
    cq.sb.confint.high[i,j] <- cq.sb$vecCV[2]
    cq.sb.computed[i,j] <- cq.sb$vCRQ
    cq.sb.corrected[i,j] <- ifelse(cq.sb.computed[i,j] > cq.sb.confint.low[i,j]  && c
  }
}

cq.sb.computed.vec <- as.vector(cq.sb.computed)
cq.sb.corrected.vec <- as.vector(cq.sb.corrected)
cq.sb.confint.low.vec <- as.vector(cq.sb.confint.low)
cq.sb.confint.high.vec <- as.vector(cq.sb.confint.high)
cq.data <- cbind(cq.sb.computed.vec, cq.sb.corrected.vec, cq.sb.confint.low.vec, cq.s

names(cq.sb.corrected.vec) <- NULL
probs.df.boot <- data.frame(expand.grid(c(seq(0.05,0.95,0.05)),c(seq(0.05,0.95,0.05))
probs.df.boot$cq.corr <- cq.sb.corrected.vec
probs.df.boot$cq.computed <- cq.sb.computed.vec


cols <- c("darkblue", "lightblue", "white", "orange", "red" )

ggheatmap2 <- ggplot(probs.df.boot,aes(x = Var1,y = Var2, fill = cq.sb.corrected.vec)
  geom_tile(color = "black") +
  labs(y= "Brent",
       x = "S&P500",
       title = str_glue("LAG {cq.lag}")) +
  scale_fill_gradientn(name="CQ",
                       colors=cols,
                       limits=c(-0.3,0.3))+
  theme(panel.background = element_blank(),
        axis.title=element_text(size=14,face="bold"),
        plot.title = element_text(hjust = 0.5, size = 16, face="bold")) +
  scale_x_continuous(breaks=seq(0.05,0.95,0.05), labels=seq(0.05,0.95,0.05)) +
  scale_y_continuous(breaks=seq(0.05,0.95,0.05), labels=seq(0.05,0.95,0.05)) +
  coord_fixed()

print(ggheatmap2)


--------------------------------------------------------------------------------


# PCQ with bootstrapped confidence intervals

  pcq.returns <- cbind(osebx, sp, brent) # From S&P500 to OSEBX controlling for Brent
# pcq.returns <- cbind(osebx, brent, sp) # From Brent to OSEBX controlling for S&P500

data.pcq <- as.matrix(pcq.returns)
data.pcq <- na.exclude(data.pcq)

probs.match <- cbind(seq(0.05,0.95,0.05),seq(0.05,0.95,0.05),seq(0.05,0.95,0.05))
prob1 <- seq(0.05,0.95,0.05)
```

```
prob2 <- seq(0.05,0.95,0.05)
c <- length(prob1)
d <- length(prob2)
cq.lag <- 1
# cq.lag <- 5
# cq.lag <- 22


pcq.sb <- matrix(NA, nrow=c, ncol=d)
pcq.sb.confint.low <- matrix(NA, nrow=c, ncol=d)
pcq.sb.confint.high <- matrix(NA, nrow=c, ncol=d)
pcq.sb.computed <- matrix(NA, nrow=c, ncol=d)
pcq.sb.corrected <- matrix(NA, nrow=c, ncol=d)

for (i in 1:c){
  for (j in 1:d){
    pcq.sb <- crossq.partial.sb.opt(data.pcq, c(prob1[i], prob2[j], prob2[j]), cq.lag
    # Lagged values of the second variable in data
    pcq.sb.confint.low[i,j] <- pcq.sb$vecCV[1]
    pcq.sb.confint.high[i,j] <- pcq.sb$vecCV[2]
    pcq.sb.computed[i,j] <- pcq.sb$vParCRQ
    pcq.sb.corrected[i,j] <- ifelse(pcq.sb.computed[i,j] > pcq.sb.confint.low[i,j]  &
  }
}

pcq.sb.computed.vec <- as.vector(pcq.sb.computed)
pcq.sb.corrected.vec <- as.vector(pcq.sb.corrected)
pcq.sb.confint.low.vec <- as.vector(pcq.sb.confint.low)
pcq.sb.confint.high.vec <- as.vector(pcq.sb.confint.high)
pcq.data <- cbind(pcq.sb.computed.vec, pcq.sb.corrected.vec, pcq.sb.confint.low.vec, 

names(pcq.sb.corrected.vec) <- NULL
probs.df.boot <- data.frame(expand.grid(c(seq(0.05,0.95,0.05)),c(seq(0.05,0.95,0.05))
probs.df.boot$cq.corr <- pcq.sb.corrected.vec
probs.df.boot$cq.computed <- pcq.sb.computed.vec

cols <- c("darkblue", "lightblue", "white", "orange", "red" )

ggheatmap2 <- ggplot(probs.df.boot,aes(x = Var1,y = Var2, fill = pcq.sb.corrected.vec
  geom_tile(color = "black") +
  labs(y= "OSEBX",
       x = "S&P500 controlling for Brent",
       title = str_glue("LAG {cq.lag}")) +
  scale_fill_gradientn(name="PCQ",
                       colors=cols,
                       limits=c(-0.3,0.3))+
  theme(panel.background = element_blank(),
        axis.title=element_text(size=14,face="bold"),
        plot.title = element_text(hjust = 0.5, size = 16, face="bold")) +
  scale_x_continuous(breaks=seq(0.05,0.95,0.05), labels=seq(0.05,0.95,0.05)) +
  scale_y_continuous(breaks=seq(0.05,0.95,0.05), labels=seq(0.05,0.95,0.05)) +
  coord_fixed()
```

```
print(ggheatmap2)



# -------------------------------------------------------------------------------

# PCQ with bootstrap and lags

pcq.returns <- cbind(osebx, sp, brent) # From S&P500 to OSEBX controlling for Brent
# pcq.returns <- cbind(osebx, brent, sp) # From Brent to OSEBX controlling for S&P500

data.pcq <- as.matrix(pcq.returns)
data.pcq <- na.exclude(data.pcq)

prob1 <- seq(0.05,0.05,0.05)
prob2 <- seq(0.05,0.05,0.05)
c <- length(prob1)
d <- length(prob2)


n <- 20
lags <- seq(1:20)
q.sb <- rep(NA, n)
q.sb.confint.low <- rep(NA, n)
q.sb.confint.high <- rep(NA, n)
q.sb.computed <- rep(NA, n)


quantiles.pcq <- c(rep(0.95,3))


for (i in 1:n){
  q.sb <- crossq.partial.sb.opt(data.pcq, quantiles.pcq, lags[i], 500, 0.05)
  # Lagged values of the second variable in data
  q.sb.confint.low[i] <- q.sb$vecCV[1]
  q.sb.confint.high[i] <- q.sb$vecCV[2]
  q.sb.computed[i] <- q.sb$vParCRQ
}

pcq.lag <- data.frame("q.estimate" = q.sb.computed,
                      "High" = q.sb.confint.high,
                      "Low" = q.sb.confint.low)


plot(pcq.lag$q.estimate, type ="h", ylim = c(-0.2, 0.2), main = str_glue("PCQ from S&
lines(pcq.lag$High,col="red")
lines(pcq.lag$Low,col="red")
abline(h = 0)
```

```
# ===================================================================

# AEROSPACE

LMT = get.hist.quote(instrument= 'LMT',
                     start = "2021-12-01",
                     end = "2024-04-25",
                     quote="AdjClose",
                     provider = "yahoo",
                     compression = "d",
                     retclass="zoo")

INTMA = get.hist.quote(instrument= 'LUNR',
                       start = "2021-12-01",
                       end = "2024-04-25",
                       quote="AdjClose",
                       provider = "yahoo",
                       compression = "d",
                       retclass="zoo")

AST = get.hist.quote(instrument= 'ASTC',
                     start = "2021-12-01",
                     end = "2024-04-25",
                     quote="AdjClose",
                     provider = "yahoo",
                     compression = "d",
                     retclass="zoo")

plot(LMT)
plot(INTMA)
plot(AST)
PRICES <- cbind(LMT, INTMA, AST)
colnames(PRICES) <- c("LMT", "INTMA", "AST")
plot(PRICES)

adf.LMT <-adf.test(LMT, alternative="stationary")
adf.INTMA <-adf.test(INTMA, alternative="stationary")
adf.AST <-adf.test(AST, alternative="stationary")
adf.prices <- cbind(adf.LMT$p.value, adf.INTMA$p.value, adf.AST$p.value)
adf.prices <- as.data.frame(adf.prices, "ADF of prices", digits=3)
colnames(adf.prices) <- c("LMT", "INTMA", "AST")
adf.prices


lmt <- diff(log(LMT))
intma <- diff(log(INTMA))
ast <- diff(log(AST))
length(lmt)
length(intma)
length(ast)
```

```
lmt <- lmt*100
intma <- intma*100
ast <- ast*100
plot(lmt)
plot(intma)
plot(ast)

returns <- cbind(lmt, intma, ast)
colnames(returns) <- c("lmt", "intma", "ast")
plot(returns, main="Returns")


data.ts <- cbind(lmt, intma, ast)
colnames(data.ts) <- c("Lockheed Martin", "Intuitive Machines", "Astrotech")
plot(data.ts, main="Daily returns")



# Descriptive statistics -------------------------------------------------------

means <- c(mean(data.ts[,1]), mean(data.ts[,2]),  mean(data.ts[,3]))
medians <- c(median(data.ts[,1]), median(data.ts[,2]),  median(data.ts[,3]))
stddevs <- c(sqrt(var(data.ts[,1])), sqrt(var(data.ts[,2])), sqrt(var(data.ts[,3])))
skew <- skewness(data.ts)
kurt <- kurtosis(data.ts)
iqr <- c(IQR(data.ts[,1]), IQR(data.ts[,2]), IQR(data.ts[,3]))
lengths <- c(length(data.ts[,1]), length(data.ts[,2]), length(data.ts[,3]))
max.values <- c(max(data.ts[,1]), max(data.ts[,2]), max(data.ts[,3]))
min.values <- c(min(data.ts[,1]), min(data.ts[,2]), min(data.ts[,3]))


boxplot(data.ts, main="Boxplots for the return series")
hist(lmt, breaks = 100, main="Marginal distributions lmt")
hist(intma, breaks = 100, main="Marginal distributions intma")
hist(ast, breaks = 100, main="Marginal distributions ast")

qqnorm(returns[,1], main="Q-Q plot Lockheed Martin")
qqline(returns[,1], distribution = function(p) qnorm(p,0,1), prob = c(0.25, 0.75), co
qqnorm(returns[,2], main="Q-Q plot Intuitive Machines")
qqline(returns[,2], distribution = function(p) qnorm(p,0,1), prob = c(0.25, 0.75), co
qqnorm(returns[,3], main="Q-Q plot Astrotech")
qqline(returns[,3], distribution = function(p) qnorm(p,0,1), prob = c(0.25, 0.75), co




# Augmented Dickey Fuller test for stationarity
lmt.ADF<-adf.test(lmt, alternative="stationary")
intma.mADF<-adf.test(intma, alternative="stationary")
ast.ADF<-adf.test(ast, alternative="stationary")
adf <- c(lmt.ADF$p.value, intma.mADF$p.value, ast.ADF$p.value)
adf.stat <- c(adf.test(lmt, alternative="stationary")$statistic,
```

```
              adf.test(intma, alternative="stationary")$statistic,
              adf.test(ast, alternative="stationary")$statistic)
lmt.ADF
intma.mADF
ast.ADF


# Jarque Bera test for normality
lmt.jb <-jarque.bera.test(lmt)
intma.jb <-jarque.bera.test(intma)
ast.jb <-jarque.bera.test(ast)
jb <- c(lmt.jb$p.value, intma.jb$p.value, ast.jb$p.value)
jb.stat <- c(jarque.bera.test(lmt)$statistic,
             jarque.bera.test(intma)$statistic,
             jarque.bera.test(ast)$statistic)


# Ljung-Box test
Box.test(ind.ts[,1], lag=10, type="Ljung-Box", fitdf=0)
lb.stat <- c(Box.test(lmt, lag=12, type="Ljung-Box", fitdf=0)$statistic,
             Box.test(intma, lag=12, type="Ljung-Box", fitdf=0)$statistic,
             Box.test(ast, lag=12, type="Ljung-Box", fitdf=0)$statistic)
lb.pval <- c(Box.test(lmt, lag=12, type="Ljung-Box", fitdf=0)$p.value,
             Box.test(intma, lag=12, type="Ljung-Box", fitdf=0)$p.value,
             Box.test(ast, lag=12, type="Ljung-Box", fitdf=0)$p.value)


df <- data.frame(lengths, means, medians, max.values, min.values, iqr, stddevs, skew,
colnames(df) <- c("# Observations","Mean", "Median", "Max", "Min",  "IQR", "Std", "Sk
rownames(df) <- c("Lockheed Martin", "Intuitive Machines", "Astrotech")
print(df)

df <- t(df)
xtab <- xtable(df, digits=2)
print(xtab)


R <- na.exclude(data.ts)
corr.R <- cor(R)
corrplot.mixed(corr.R)



# Autocorrelations
acf.lmt<-acf(lmt, na.action = na.pass, main="Correlogram - Lockheed Martin returns")
acf.intma<-acf(intma, na.action = na.pass, main="Correlogram - Intuitive Machines ret
acf.ast<-acf(ast, na.action = na.pass, main="Correlogram - Astrotech returns")


# Partial autocorrelations
pacf.lmt<-pacf(lmt, na.action = na.pass, main="Partial acf - Lockheed Martin")
pacf.intma<-pacf(intma, na.action = na.pass, main="Partial acf - Intuitive Machines r
pacf.ast<-pacf(ast, na.action = na.pass, main="Partial acf - Astrotech returns return
```

```
# Cross Correlation Matric (CCM)
ccm.data <- ccm(data.ts, lags=12, level=TRUE)


#--------------------------------------------------------------------------------

#Quantilogram with bootstrapped confidence intervals


quantiles1 <- c(0.1,0.1)
quantiles2 <- c(0.5,0.5)
quantiles3 <- c(0.9,0.9)
quantiles <- c(0.1,0.1)


n <- 30
lags <- seq(1:30)
q.sb <- rep(NA, n)
q.sb.confint.low <- rep(NA, n)
q.sb.confint.high <- rep(NA, n)
q.sb.computed <- rep(NA, n)

Q <- cbind(intma, lmt) # Predictability from lmt to intma
# Q <- cbind(intma, ast) # Predictability from ast to intma
# Q <- cbind(ast, lmt) # Predictability from lmt to ast
# Q <- cbind(ast, intma) # Predictability from intma to ast
# Q <- cbind(lmt, intma) # Predictability from intma to lmt
# Q <- cbind(lmt, ast) # Predictability from ast to lmt
# Predictability from lagged values of the second variable to the first variable


for (i in 1:n){
  q.sb <- crossq.sb.opt(Q, quantiles, lags[i], 500, 0.05)
  q.sb.confint.low[i] <- q.sb$vecCV[1]
  q.sb.confint.high[i] <- q.sb$vecCV[2]
  q.sb.computed[i] <- q.sb$vCRQ
}

q.lag <- data.frame("q.estimate" = q.sb.computed,
                    "High" = q.sb.confint.high,
                    "Low" = q.sb.confint.low)


plot(q.lag$q.estimate, type ="h", ylim = c(-0.4, 0.4), main = str_glue("Cross-Quantil
lines(q.lag$High,col="red")
lines(q.lag$Low,col="red")
abline(h = 0)



# Cross-Quantilogram ---------------------------------------------------------------
```

```
prob1 <- c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9)
prob2 <- c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9)

c <- length(prob1)
d <- length(prob2)

cq.lag <- 1
# cq.lag <- 5
# cq.lag <- 22

a <- 2
b <- 1
data.cq <- cbind(returns[,a], returns[,b])
colnames(data.cq) <- c(colnames(returns)[a], colnames(returns)[b])
names.cq <- cbind(colnames(returns)[a], colnames(returns)[b])
data.cq <- na.exclude(data.cq)


cq.sb <- matrix(NA, nrow=c, ncol=d)
cq.sb.confint.low <- matrix(NA, nrow=c, ncol=d)
cq.sb.confint.high <- matrix(NA, nrow=c, ncol=d)
cq.sb.computed <- matrix(NA, nrow=c, ncol=d)
cq.sb.corrected <- matrix(NA, nrow=c, ncol=d)


for (i in 1:c){
  for (j in 1:d){
    cq.sb <- crossq.sb.opt(data.cq, c(prob1[i], prob2[j]), cq.lag, 500, 0.05)
    # Lagged values of the second variable in data
    cq.sb.confint.low[i,j] <- cq.sb$vecCV[1]
    cq.sb.confint.high[i,j] <- cq.sb$vecCV[2]
    cq.sb.computed[i,j] <- cq.sb$vCRQ
    cq.sb.corrected[i,j] <- ifelse(cq.sb.computed[i,j] > cq.sb.confint.low[i,j]  && c
  }
}

cq.sb.computed.vec <- as.vector(cq.sb.computed)
cq.sb.corrected.vec <- as.vector(cq.sb.corrected)
cq.sb.confint.low.vec <- as.vector(cq.sb.confint.low)
cq.sb.confint.high.vec <- as.vector(cq.sb.confint.high)
cq.data <- cbind(cq.sb.computed.vec, cq.sb.corrected.vec, cq.sb.confint.low.vec, cq.s

names(cq.sb.corrected.vec) <- NULL
probs.df.boot <- data.frame(expand.grid(c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9),c(0.1,
probs.df.boot$cq.corr <- cq.sb.corrected.vec


cols <- c("darkblue", "lightblue", "white", "orange", "red" )

ggheatmap2 <- ggplot(probs.df.boot,aes(x = Var1,y = Var2, fill = cq.sb.corrected.vec)
  geom_tile(color = "black") +
  labs(
```

```
    x = str_glue("{names.cq[2]}"),
    y = str_glue("{names.cq[1]}"),
    title = str_glue("LAG {cq.lag}")) +
  scale_fill_gradientn(name="CQ Correlation",
                       colors=cols,
                       limits=c(-0.3,0.3))+
  theme(panel.background = element_blank(),
        axis.title=element_text(size=14,face="bold"),
        plot.title = element_text(hjust = 0.5, size = 16, face="bold")) +
  scale_x_continuous(breaks=seq(0,0.9,0.1), labels=seq(0,0.9,0.1)) +
  scale_y_continuous(breaks=seq(0,0.9,0.1), labels=seq(0,0.9,0.1))
coord_fixed()

print(ggheatmap2)
```

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