Systemic Risk in the Scandinavian Banking Sector

Gazi Salah Uddin
Department of Management and Engineering,
Linköping University, Linköping, Sweden
E-mail: gazi.salah.uddin@liu.se

Md Lutfur Rahman
Newcastle Business School,
The University of Newcastle, Australia
Email: Mdlutfur.Rahman@newcastle.edu.au

Axel Hedström
Department of Management and Engineering,
Linköping University, Linköping, Sweden
E-mail: axel.hedstrom@liu.se

Bo Sjö
Department of Management and Engineering,
Linköping University, Linköping, Sweden
E-mail: bo.sjo@liu.se

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Abstract:

The banking sectors in the Nordic countries are quite concentrated and have suffered from banking crises following international shocks in combination with undercapitalization. This paper analyses the systemic risk in the Scandinavian banking sector (Denmark, Norway and Sweden). We look at risks spreading from individual banks to the whole sector by using, partly in a new way, conditional cross-quantilograms. We find that the cross-quantilograms are positive and statistically significant in the low and high quantiles. This indicates that the Scandinavian banks are systemically linked and show a tendency to boom and crush along with the market. These results hold even after controlling for equity market volatility and economic policy uncertainty. We further observe that the systemic risk was insignificant from the early-2000 to the outbreak of the global financial crisis (GFC). After the GFC and the euro zone crises it has increased substantially. Finally, we find that bank size has a positive relationship with systemic risk while return on assets and the loan-to-deposit ratio exhibit a negative influence. Further, these relationships are asymmetric across quantiles.

Keywords: Systemic risk, tail dependence, cross-quantilogram, Scandinavian banking sector

JEL classifications : C53, G20, G21, G32

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1. Introduction

The 2007–2008 global financial crisis (GFC) provides ample evidence that simultaneous losses of several financial institutions can adversely affect other industries and impose an externality on the overall macro-economy. Spillovers from an individual financial institution-in-distress can led to systemetic risk, which is the danger that the entire financial system will fail due to its interlinkages.[1] These links can be attributed directly to contractual links across institutions and a high level of counterparty credit risk, and indirectly to price and liquidity shocks (Adrian & Brunnermeier, 2016). These spillovers can lead to a heightened co-movement between institutions, which depend on undercapitalization and asymmetric information. Understanding systemic risk and contagion effects in the banking sector is not only an academic concern; it has important significance to the banking sector's regulator and policy makers for formulating new finance/banking regulations[2].

This paper examines the time-varying systemic risk in the Scandinavian[3] banking sector using the Han et al. (2016) conditional cross-quantilogram (CQ). While the CQ is particularly designed to measure directional predictability across quantiles, our approach essentially involves measuring directional tail dependence between equity returns of an individual financial institution and the overall banking system. While the previous studies examine idiosyncratic bank characteristics as determinants of systemic risk, we explore both

[1] See The Systemic Risk Centre (SRC) at London School of Economics, http://www.systemicrisk.ac.uk/.

[2] For example, Obama administration proposed a "crisis responsibility fee"(White House press release, 14 January 2010), the International Monetary Fund advocated a systemic risk levy (IMF 2010), Basel III requires a capital surcharge on systemically important bank (BCBS, 2012, 2013), a pigouvian tax has been proposed for systemically important financial institutions (Acharya et al., 2011, 2017), the Dodd-Frank Act emphasizes for more stringent regulation for firms vulnerable to systemic risk (Richardson, 2011). These regulations aim to reduce the exposure of financial institutions to crisis as well as enhance their ability to internalize the cost of crisis.

[3] The Scandinavian region is represented by Denmark, Norway, and Sweden. The other Nordic countries, Finland and Iceland, are excluded due to insufficient data.

bank-specific and market-wide variables' asymmetric explanatory power for dependence across quantiles

Examining systemic risk in the Scandinavian banking sector is motivated by the fact that they have experienced severe banking crises. And, first, compared to the banking system in other European countries, the Scandinavian banking system is highly concentrated and interconnected (Markevicius, 2015). Second, Scandinavian banks exhibit similar characteristics in terms of their exposure to non-bank assets, borrower portfolios, and high dependence on consumer lending[4]. Third, Scandinavian banks typically have small capital base and their loan to deposit ratio is higher than their European counterparts (FactSet Fundamentals & Euro area statistics, 2018). All these factors are likely to magnify the Scandinavian banks' sensitiveness to systemic risk factors. More specifically, in the case of a strong macro-financial shock, these features can lead to an intensification of losses in banking sector that ultimately can affect the real economy. Brunnermeier (2009) argue that large and interconnected financial institutions rapidly propagate negative risk to others. Moreover, our initial analysis (discussed in section 3) shows that Scandinavian banks have learnt lessons from earlier financial crises and taken precaution in terms of creating capital cushions and they have increased their liquidity to cover loan losses. These aspects may have caused a change in the Scandinavian banks' sensitivity to systemic risk exposure.

We use daily returns of individual banks and aggregate banking sector from three Scandinavian countries. Four banks from Sweden, three banks from Denmark and one bank from Norway are considered in this study. These banks are the largest in the respective countries. We first estimate the CQ from individual banks to the corresponding market for each country. Any significant dependence in the low quantiles would indicate the impact of individual bank, when it is in distress, on the aggregate banking sector. We also estimate the

[4] The Scandinavian banks are highly dominated by borrowers from Scandinavian countries and a large portion of their lending constitutes residential mortgage loan (in the other European countries, residential mortgage loans are typically provided by specialized housing financing companies) (Berglund & Mäkinen, 2019).

CQ from aggregate banking sector to individual bank to reveal individual bank's exposure to aggregate banking sector when the overall sector is in distress.

Due to the importance of systemic risk in banking operations, a wide range of systemic risk measure has been proposed in the literature. For instance, the systemic expected shortfall (SES) of Acharya et al. (2017), the conditional value-at-risk (CoVaR) of Adrian and Brunnermeier (2016), the systemicness of Greenwood, Landier, and Thesmar (2015), the distressed insurance premium (DIP) of Huang, Zhou, and Zhu (2012), and the SRISK index of Brownlees and Engle (2012). These systemic risk measures are commonly based on the magnitude of losses experienced by the overall financial system when many financial institutions are simultaneously distressed. Although the above-mentioned systemic risk measures are widely used in the literature, they have few limitations. First, in general, the measures (i.e., CoVaR and SES) are highly dependent on extreme losses. Therefore, they show a high degree of correlation as connectedness tend to be higher during and after a systemic shock. Moreover, the CoVaR-based methodology is based on an explicit assumption that shocks to individual institutions exhibit the same symmetric linear and proportional responses to the whole system. However, there are strong arguments that systemic responses to idiosyncratic negative shocks are likely to be more intense compared to that of positive shocks (López-Espinosa, Moreno, Rubia, & Valderrama, 2015).[5] Therefore, we expect an asymmetric dependence between equity returns of aggregate banking sector and individual financial institution in the lower and upper quantiles which has largely been ignored in the literature. Second, time-varying systemic risk in different lag structures was generally beyond the scope of the previous studies. The conditional cross-quatilograms can be used to extend the literature in this front. Third, a large part of the literature examines the market-wide impact of individual financial institution in distress, overlooking individual financial

[5] Theoretically, risk averse investors are more concerned about large downside losses compared to upside gains, therefore they show more sensitiveness to a shock that lead to reduction of their financial wealth.

institution's sensitiveness to market-wide distress condition. Fourth, current systemic risk measures' reliability may be questionable due to model misspecification (Hansen, 2013) and estimation risk associated with them (Danielsson, James, Valenzuela, & Zer, 2016). Finally, although systemic risk in the US (Adrian & Brunnermeier, 2016; Weiß et al., 2014; Girardi & Ergün, 2013; López-Espinosa et al., 2015) and European banking sector has been examined in the literature (Karimalis & Nomikos, 2018; Drakos & Kouretas, 2015; Bernal et al., 2014), the Scandinavian banking sector has received less attention. The studies of Black et al. (2016), Laeven et al. (2016), Varotto and Zhao (2018) and Weiß et al. (2014), among others, include Scandinavian banks in their systemic risk studies. While Black et al. (2016) and Laeven et al. (2016) estimate country-specific and bank-specific systemic risk without a special concentration on Scandinavian banks, Varotto and Zhao (2018) and Weiß et al. (2014) do not provide a segregated analysis for systemic risk in the Scandinavian banking sector.

The first contribution of this paper is to address systemic risk challenge both methodologically and empirically. In terms of methodology, we use an econometric framework (CQ) that allows for complex tail risk-based measures of systematic risk which has become particularly important aftermath of the GFC. The CQ is designed to measure co-dependence between tails of two time series. This approach has a number of advantages over the competing approaches. For example, while the commonly used measures of systemic risk consider distressed condition of a financial institution when it is exactly at its value-at-risk (VaR) (bottom 5%) or at most at its VaR, the CQ approach enables us to capture asymmetric dependence across quantiles. The CQ method can measure both an individual financial institution's contribution to systemic risk and an individual financial institution's exposure to distress condition in the aggregate financial sector. Additionally, the CQ approach provides a simple measure to detect changes in the association between two variables as lag structure increases.[6] Furthermore, the CQ approach is a correlation-based model-free measure, therefore it does not depend on any underlying ex-ante modelling.[7]

The second contribution of this paper is to estimate the partial cross-quantilogram (PCQ) to explore the nature of systemic risk in the Scandinavian banking sector after controlling for different economic state variables. The PCQ allows us to specify different quantiles of the state variables enabling us to examine systemic risk in different states of the uncertainty variables. This type of analysis has largely been ignored in the previous literature on systemic risks in the Scandinavian banking sector. We consider the Chicago Board of Exchange Volatility Index (VIX) and economic policy uncertainty index (EPU) as economic state variables.

The third contribution of this paper is to estimate time-varying cross-quantile correlation (particularly in the case of extreme quantiles). We do so by estimating CQ in recursive samples for different lag structures. Since this analysis aims to capture any paradigm shift in the cross-quantile correlation structure between individual financial institution and aggregate banking sector, this provides new insights into a possible time-varying tail risk dependence.

The fourth contribution is to modelling the cross-quantile dependence in terms bank-specific and market-wide variables. While the previous studies examine idiosyncratic bank characteristics as determinants of systemic risk, we explore both bank-specific and market-wide variables' asymmetric explanatory power for dependence across quantiles.

Finally, this paper makes an empirical contribution through examining systemic risk in the banking sector of the three Scandinavian countries. This work is worthwhile as it

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[6] For instance, in order to examine tail dependence for large lag order within the multivariate and multiquantile framework, White, Kim, and Manganelli (2015) rely on an additional impulse response function.

[7] For example, Brownlees and Engle's (2012) systemic risk measure is based on standard multivariate GARCH modelling. Moreover, their systemic risk measure depends on modelling characteristics of the entire multivariate distribution. Adrian and Brunnermeier's (2016) CoVaR estimate is based on quantile regression framework.

contributes to the international banking policy arrangement (for example, the Basel regulatory framework) and in the context that European banks appeared to be source of risk for the global financial markets particularly after the sovereign debt crisis.

This paper presents several key findings. The cross-quantilograms are found to be positive and statistically significant in the low quantiles (for example, 0.05:0.05 quantile). This result indicates that Scandinavian banks are systemically important, that is, they create significant impact on the aggregate banking sector when they are in distress and they show significant exposure to the distressed condition of the entire financial system. Overall, Scandinavian banks show a tendency to boom and crush along with the market. As we incorporate two uncertainty measures (VIX and EPU) as control variable, we still find statistically significant cross-quantilograms indicating that systemic risk in the Scandinavian banking sector is not driven by the uncertainty measures rather individual banks and aggregate banking sector’s endogenous interrelationship may be the main driver of the systemic risk. The recursive sample analysis reveals that systemic risk (when both individual bank and aggregate banking return are in the 5% quantile) was insignificant from the late-1990s to the outbreak of the GFC. However, the systemic risk has increased substantially and become significant during and after the GFC and Eurozone crisis. Finally, we find that size has a positive relationship with systemic risk while return on asset and loan to deposit ratio exhibit a negative influence. This relationship, however, is asymmetric across quantiles.

The rest of the paper proceeds as follows: section 2 provides a brief review of the approaches to modelling systemic risk and the relevant literature; section 3 presents highlights of the Scandinavian banking sector; methodological aspects are described in section 4; section 5 presents data and descriptive statistics; empirical results and discussion are in section 6; section 7 concludes by providing a summary of the paper.

2. Common methods for modelling systemic risk and the related literature:

Although systemic risk has been a concern particularly since the start of the new millennium, the GFC has established renewed interest on the importance of assessing, monitoring and controlling systemic risk for achieving macroeconomic stability. While the regulators across the globe are considering the ways to reduce the exposure to systemic crises, it is also an academic concern to identify the nature of systemic risk, particularly in the financial market. Accordingly, a large literature has emerged proposing measures of systemic risk and utilizing them in the financial sector.

2.1 Approaches to modelling systemic risk

The systemic risk literature essentially concentrates on risk spillover, contagion and probability of joint crashes in banking sector in particular. The extant literature estimates simple correlation, ARCH models generated correlation, and extreme/tail dependence between returns of individual financial institution and aggregate financial system. The studies of Lehar (2005), Gray, Merton, and Bodie (2008), among others, use a structural approach of measuring systemic risk based on an analysis of contingent claims of financial institution's assets. This approach, however, is based on a strong assumption with regard to liability structure of the financial institutions. Alternatively, researchers use market data to explore systemic risk. For instance, Choudhry and Jayasekera (2014) use bivariate GARCH-GJR model (Glosten, Jagannathan, & Runkle, 1993) to examine return, volatility, and leverage spillover in the European banking sector. Huang, Zhou, and Zhu (2009) and Segoviano and Goodhart (2009) use credit default swap (CDS) data to measure systemic risk. Huang et al. (2009) estimate correlations between financial firms' CDS and their stock returns to find out if expected credit losses of a financial institution is higher than a given share of its total liabilities.

The literature concentrating on extreme dependence attempts to explore the response of individual financial institution's stock price toward a major market downturn and the contribution of individual financial institution towards the downturn. This strand of literature uses approaches to examine the co-dependence between financial institutions in the case of distressed events. Acharya, Engle, and Richardson (2012) and Acharya et al. (2017) provide theoretical foundations of this approach. Acharya et al. (2017) present a model of systemic risk where financial sector's undercapitalization is assumed to depress the real economy. The authors show that systemic risk can be measured by systemic expected shortfall (SES) which is the propensity of an individual institution to be undercapitalized when the whole system is undercapitalized. Achary et al. (2012) propose a measure, expected capital shortfall (ECS), which indicates the capital shortage/requirement of a financial firm in the case of a financial crisis.

Adrian and Brunnermeier (2016) propose a novel measure of systemic risk, ΔCoVaR, which aims to capture cross-sectional tail dependence between a particular financial institution and the whole financial system. ΔCoVaR is the difference between the CoVaR conditional on the *i*th institution being in distress and the CoVaR conditional on the *i*th institution being on the median state. López-Espinosa et al. (2015) and Girardi and Ergün (2013) propose extensions to CoVaR methodology respectively to capture asymmetries in tail dependence and more distressed events. The ΔCoVaR approach is also used by Bernal, Gnabo, and Guilmin (2014), Drakos and Kouretas (2015), Karimalis and Nomikos (2018), Laeven et al. (2016), among others. Giesecke and Kim (2011) measure dynamic systemic risk of the financial sector as a whole. This measure, firstly, estimates the conditional probability of failure of a large proportion of financial institutions, and secondly, attributes the systemic distress to financial institutions' correlated failure to satisfy obligations towards creditors, customers, and other trading partners. Billio, Getmansky, Lo, and Pelizzon (2012) estimate unconditional correlation using Granger-causality-network and principal component analysis which is used to assess the magnitude of connectedness between individual financial institution and the overall financial system. Brownlees and Engle (2012) develop SRISK index to measure systemic risk which is a function of size, leverage and marginal expected shortfall and manifestation of expected capital shortage of a bank in response to a substantial decline in the market.

More recently, tail dependence as a measure of systemic risk has been examined using alternative methodologies such as cross-quantilogram (CQ) and frequency-based measure of systemic risk. Han et al. (2016) propose the CQ to measure quantile dependence. This approach is particularly suitable for heavy-tailed series and it does not depend on any underlying moment condition. The CQ approach has recently been widely used to examine the quantile dependence between financial time-series.[8] Baruník and Křehlík (2018) propose a frequency-based measure of systemic risk which is built on spectral representation of variance decomposition. This approach can measure financial variables' connectedness that is linked to asymmetric response to shocks across frequencies. Teply and Kvapilikova (2017) also use a frequency-based approach to measure short-, medium-, and long-term connectedness between financial institutions. Their approach essentially measures individual financial institution's contribution to overall systemic risk based on a wavelet framework that analyses stock returns in a time-frequency domain.

2.2 What do we know about systemic risk in the global banking sector?

Although systemic risk in the US and European banking sector has been examined, Scandinavian banking sector has received less attention from researchers. For instance, examining all publicly traded US commercial banks, Adrian and Brunnermeier (2016) find that larger banks with higher leverage, higher maturity mismatch, and higher asset valuations

[8] For example, Shahzad, Naifar, Hammoudeh, and Roubaud (2017) examine the quantile dependence between crude oil and sovereign credit default swap spread market of major oil-exporting countries; Jiang, Su, Todorova, and Roca (2016) focus on tail dependence of the US and Chines commodity futures market, Todorova (2017) concentrates on overnight and intraday returns of the ten largest stocks in the Australian market, and Labidi, Rahman, Hedström, Uddin, and Bekiros (2018) measure tail dependence between emerging and developed equity markets. While the CQ measures quantile dependence between financial time-series, the quantilogram and extremogram are the measures of dependence between different parts of a distribution. The quantilogram, developed by Linton and Whang (2007) is a test based on a comparison of cumulated squared autocorrelations and corresponding critical value while extremogram (Davis & Mikosch, 2009) a quantilogram of exteme events.

exhibit high systemic risk. Similar result is found by Laeven, Ratnovski, and Tong (2016) and Varotto and Zhao (2018), among others, for both US and European banks. On the other hand, Weiß et al. (2014) show that instead of bank-specific variables, regulatory regime is the main driver of systemic risk. In other US-based studies, Girardi and Ergün (2013) report that among the four groups of financial institutions (depository institutions, insurance companies, broker-dealers and other non-depository institutions), depository institutions are the largest contributors to systemic risk. Drakos and Kouretas (2015) find that although both the US and non-US banks contribute to systemic risk, the US banks are the major contributor. Giesecke and Kim (2011) document that systemic risk increased significantly in the US in the second half of 2008. López-Espinosa et al. (2015) find the evidence of asymmetric pattern associated with individual banks' marginal contribution to total system particularly with respect to positive and negative shocks. Examining systemic risk of three major financial institutions (JP Morgan, Morgan Stanley, and AIG), Han et al. (2016) show that the CQs from individual institutions to market are positive and generally significant in the case of large lags. Baruník and Křehlík (2018) show that US financial institutions' connectedness in low and high frequency is asymmetric with regard to stock market condition and persistence of shocks.

In the European context, Karimalis and Nomikos (2018) show that French and Spanish financial institutions are the most systemic while Portuguese, Irish and Greek financial institutions are the least systemic. Black et al. (2016) report that systemic risk exhibits a time-varying nature as they find that the UK and Germans banks were systemically important before the GFC, however, their systemic importance decline after the GFC. On the other hand, Italian and Spanish banks played insignificant role with regard to systemic risk in the pre-crisis period while during the heightened systemic risk in Europe in 2011, these banks were the largest contributors. Drakos and Kouretas (2015) show that in the UK, banking industry is the largest contributor to systemic risk during the periods of distress, compared to insurance and other financial service industry; however, Bernal et al. (2014) report that in the

Eurozone, other financial industry is the larger contributor to systemic risk compared to banking and insurance industry. Choudhry and Jayasekera (2014) find an increase in spillover between major and stressed European economies from the pre-crisis to post-crisis period.

As indicated earlier, we have come across a very few studies examining systemic risk in the Scandinavian banking sector. For instance, Black et al. (2016) show that in the European banking sector, Scandinavian banks are systemically less important compared to the British, German, Spanish, and Italian banks which is attributed to relatively smaller size of the Scandinavian banks compared to other competing European counterparts. Laeven et al. (2016) examine systemic risk of 412 depository financial institutions of 56 countries including Scandinavian banks. One Swedish bank (Skandinaviska Enskilda Banken) is reported to be one of the top ten largest contributor of systemic risk during the GFC. Karimalis and Nomikos (2018) show that among the European banks, the Swedish banks exhibit high systemic risk when tail dependence is estimated either by country or by individual banks. Although Varotto and Zhao (2018) and Weiß et al. (2014), among others, include Scandinavian banks in their international systemic risk studies, they do not provide a segregated analysis for systemic risk in the Scandinavian banks.

Reviewing the previous literature, we find few gaps. For instance, the typical systemic risk measures (i. e, CoVaR and SES) are conditional on extreme losses only, therefore, they generally show high degree of correlation as connectedness tend to be higher during and after a huge systemic shock. Similarly, although Han et al. (2016) use the CQ approach, the authors assume that a financial institution is in a distressed condition when its stock return is in the 5% quantile. Therefore, the authors fail to capture asymmetries in the cross-quantile relationship. Moreover, examining time-varying systemic risk in different lag structures is generally ignored by the previous studies. We aim to fill up these gaps.

3. The Scandinavian banking sector

This section provides a brief overview of the Scandinavian banking sector in terms of its structure, vulnerabilities as well as development of key financial ratios. First, the Scandinavian banking sector characterizes by the dominance of small number of large banks (Mahlanen & Fransén Eklund, 2015) which may indicate that the Scandinavian banks are systemically important, and they make significant contribution to vulnerability of the aggregate banking sector. The Scandinavian banks include Nordea bank, Skandinaviska Enskilda Banken SEB, Svenska Handelsbanken SHB, Swedbank, Danske Bank, Jyske Bank, SydBank, and DNB. The first four banks' headquarters are in Sweden while the next three and the last one have their headquarters in Denmark and Norway respectively. These banks together hold more than ninety percent of the assets of all publicly traded commercial banks operating in the Scandinavian region (Mahlanen & Fransén Eklund, 2015). The size of the asset of these banks is about double of the Scandinavian GDP which may manifest potential of sovereigns' large contingent liabilities.

Second, the Scandinavian banks, in general, lend mainly to Scandinavian borrowers and, to a lesser extent, borrower from Baltic countries. For instance, almost 75% of Nordea's lending is to borrowers from outside Sweden and predominantly to Scandinavian borrowers. Danske and DNB respectively are the leading banks of Denmark and Norway, and about 30% of their lending are in their home market (Mahlanen & Fransén Eklund, 2015). This characteristic has important implications for systemic risk. Since the Scandinavian banks have significant cross-border operations and they operate as regional banks, they are vulnerable to risk spillover. For instance, credit loss in any of these markets may lead to pressure for deleverage and reduced lending in these countries which may ultimately have a negative impact on real economies.

Third, the Scandinavian banks' loan-to-deposit ratios are almost double of the average loan-to-deposit ratios of other European banks (Berglund & Mäkinen, 2019) indicating that these banks are heavily reliant on wholesale funding. This phenomenon may have increased the Scandinavian banks vulnerability. Additionally, a high household/private sector debt is a common characteristic of the Scandinavian economies which may be attributed to the fact that the Scandinavian banks are the main supplier of residential mortgage loans while residential mortgage lending is typically performed by special housing finance institution in other European countries (Berglund & Mäkinen, 2019). It may also increase vulnerability arising from the banking sector. While households' main assets are real estate and pension fund holdings, they suffer from illiquidity and fluctuations in asset valuation. Therefore, in the case of a decline in real estate prices, deleveraging pressure can lead to a negative feedback loop in the aggregate banking industry.

Figure 1 plots four key financial variables of the Scandinavian banks over time. The ratios considered are return on equity (ROE), price/earnings ratio (P/E), capital adequacy ratio (CAR), and (invested assets + loans)/deposit ratio (LDR). These ratios respectively indicate the Scandinavian banks' profitability, valuation, capital adequacy, and liquidity. Although the sample period used for our empirical analysis ranges from 1st January 1996 to 29th of June 2018, the financial variables are available only for December 2003 to September 2018.[9] We observe that average ROE for the Scandinavian banks was mostly between 15% - 20% from 2003 to the outbreak of the GFC. The Danish banks' ROE declined most during the GFC and Eurozone crisis compared to that of Sweden and Norway. Profitability of the Norwegian banks was least affected by the crises indicating that the business model followed by these banks were more resilient to the negative effect of the financial crises. We further observe that P/E ratio of the Scandinavian banks were around 10 before the crises started. At the height of the GFC, P/E ratio of the Swedish and Danish banks increased up to as high as 30. P/E ratio of the Danish banks skyrocketed to more than 60 during the Eurozone crisis. This high P/E ratio can be attributed to low EPS generated by the respective banks during the crises. Nonetheless, the Norwegian bank's P/E ratio remained mostly unaffected to the consequences

[9] The data on financial variables are obtained from FactSet database.

of financial crises. This result is logical as DNB is the largest Norwegian bank, it has a dominant operation in home market and unlike the other Scandinavian banks it has not been expanded its operation to Baltic countries (Mahlanen & Fransén Eklund, 2015). These factors may have contributed to strong performance of the bank even at the height of the crises. CAR shows an increasing trend for all the three countries since early-2000 to the end of the sample period in 2018 indicating that the Scandinavian banks significantly strengthened their capital cushions since the GFC. The increase in CAR of the Swedish and Danish banks was higher compared to the Norwegian banks while the Swedish banks' CAR was markedly higher compared to those of the other two countries since 2013 until the end of the sample period. Overall, these results indicate that the Scandinavian banks learned from the crises and took precaution in terms of robust capital cushion to fight against future financial crisis. This strategy is most evident in the case of Swedish banks. Finally, LDR of the Swedish banks was found to be significantly higher compared to other two banks from 2003 – 2010. This result implies that the Swedish banks' ability to cover loan losses was lower and probability of loan default was higher compared to the banks in the other two Scandinavian countries However, in the post-GFC period, the Swedish banks gradually declined their LDR which is consistent in terms of their safety measure taken against financial crisis.

[INSERT FIGURE 1 ABOUT HERE]

4. Methodology

The CQ method is based on Linton and Whang's (2007) quantilogram approach which is a univariate tool to examine predictability in different parts of a distribution. The quantilogram examines if past information set of a stationary time-series $\{x_t\}$ can predict if x_t will be different (above or below) from the unconditional quantile. The univariate quantilogram is extended in a bivariate setting by Han et al. (2016) to detect if any quantile of a distribution can predict any quantile of another distribution when both distributions are stationary stochastic processes. It is a simple-to-interpret and conceptually-attractive model-free measure. The CQ method is particularly suitable for heavy-tailed series as it is based on quantile hits and it does not require any moment condition. This approach can also adjust exogenous shocks by incorporating different economic state variables.

Let, two time-series stochastic process be defined as $[\{x_{i,t}, t \epsilon Z\}$, i = 1, 2] where $x_{1,t}$ and $x_{2,t}$ interchangeably represent daily returns of individual bank and corresponding banking sector index. Further assume that $F_i(\cdot)$ represent the cumulative distribution function and $f_i(\cdot)$ manifest the cumulative density function of the series $x_{i,t}$. The cumulative density function is obtained through differentiation of the cumulative distribution function. The conditional distribution function and quantiles of the distributions $x_{i,t}$ can be represented as $F_{x_1|x_2}(\cdot\, |x_{2t})$ and $q_i(\propto_i) = inf\{v: F_i(v) \geq \alpha_i\}$, for $\alpha_i \epsilon$ [0,1]. Each $q(\propto)$ is a representation of cross-quantiles $(q_1(\propto_1) q_2(\propto_2))^\tau$ where α ≡$(\propto_1, \propto_2)^\tau$. The cross-quantilogram for α-quantile and k-lag can be presented in the following manner:

$$\rho_\alpha(k) = \frac{E[\Psi_{\alpha 1}(x_{1,t} - q_1(\alpha_1))\Psi_{\alpha 2}(x_{2,t-k} - q_2(\alpha_2))]}{\sqrt{E[\Psi^2_{\alpha 1}(x_{1,t} - q_1(\alpha_1))]}\sqrt{E[\Psi^2_{\alpha 2}(x_{2,t} - q_2(\alpha_2))]}} \qquad (1)$$

where k is the number of lags to time t and $\Psi_a(\mu) \equiv 1[\mu < 0]$. $1[x_{i,t} \leq\ q_i(\alpha_i)]$ represent the quantile hit process or the quantile exceedance process where 1[·] is an indicator function.

The CQ captures serial dependence and directional predictability across return quantiles. More specifically, the CQ function $[\rho_\alpha(1)]$ indicates whether returns of banking index below or above a quantile $q_{banking\ index}(\alpha_{banking\ index})$ at time t show a dependence on returns of individual bank being above or below the quantile $q_{individual\ bank}(\alpha_{individual\ bank})$ at time t-1. We also examine whether individual bank returns show a cross-quantile dependence on banking index returns. As we hypothesize that there is no directional predictability or spillover between individual bank and banking index returns, we fail to reject the null hypothesis in the case $\rho_\alpha(1)$ is not statistically different from zero [$\rho_\alpha(1) = 0$] which indicates that individual bank returns below or above a quantile $q_{individual\ bank}(\alpha_{individual\ bank})$ at time *t-1*, do not have the ability to predict whether the corresponding aggregate banking returns will be lower or higher than the quantile $q_{banking\ index}(\alpha_{banking\ index})$ at time *t*. On the other hand, we reject the null hypothesis of no-directional predictability between individual bank and banking index returns in the case $\rho_\alpha(1)$ is statistically different from zero [$\rho_\alpha(1) \neq 0$] which suggests that individual bank return quantiles have significant ability to predict banking index return quantiles. Similar inference can be drawn in relation to banking index returns' ability to predict individual bank returns.

The CQ presented in equation (1) is a bivariate quantilogram of two variables' arbitrary quantiles for a positive value of *k*. For an unconditional cross-quantile, the CQ's sample counterpart can be derived as follows:

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{T} \Psi_{\alpha 1}(x_{1,t} - q_1(\alpha_1))\Psi_{\alpha 2}(x_{2,t-k} - \hat{q}_2(\alpha_2))}{\sqrt{\sum_{t=k+1}^{T} \Psi_{\alpha 1}^2(x_{1,t} - \hat{q}_1(\alpha_1))}\sqrt{\sum_{t=k+1}^{T} \Psi_{\alpha 2}^2(x_{2,t-k} - \hat{q}_2(\alpha_2))}} \quad (2)$$

where $\hat{q}_\mathrm{i}(\alpha_\mathrm{i})$ is the unconditional sample counterpart of $q_i(\alpha_\mathrm{i})$ of the return series $x_{\mathrm{i},t}$. In order to derive statistical inference, the Ljung-Box-Pierce statistic's[10] quantile version is used to test the null hypothesis $H_0: \rho_\alpha(k) = 0$, against an alternative hypothesis $H_1: \rho_\alpha(k) \neq 0$ where *k* takes the value of 1, …, *p*. The test statistic is calculated in the following manner:

$$\hat{Q}_\alpha^{(p)} = \frac{T(T+2)\sum_{k=1}^{p} \hat{\rho}_\alpha^2(k)}{T-k}$$

(3)

where $\hat{Q}_\alpha^{(p)}$ is the test statistic of a portmanteau-type test of the presence of directional predictability or serial dependence between individual bank and banking index returns. We

[10] The use of this test statistic is consistent with the literature [see for example, Han et al. (2016)].

conduct the test for lag orders 1, 5, and 10. Since it is argued that the asymptotic null distribution of CQ relies on nuisance parameters (Han et al., 2016), the stationary bootstrap (SB) procedure (Politis and Romano, 1994) is used for the purpose of approximating the null distribution and deriving critical values. The SB approach is a block bootstrap method which unlike conventional bootstrapping, derives a block of observations at a time instead of one observation at a time. This feature enables us to preserve the underlying autocorrelation structure in the data. Additionally, the resampling technique under the SB method is strictly stationary. [11]

In order to examine the effect of different uncertainty measures on the cross-quantile dependence structure between individual bank and banking index returns, we also estimate the partial cross-quntilogram (PCQ) model of Han et al. (2016). While the CQ detects serial dependence between $x_{1t} \leq q_{1,t}(\tau_1)$ and $x_{2,t-k} \leq q_{2,t-k}(\tau_2)$, the PCQ model incorporates control variables as intermediate events between t and $t - k$. The PCQ model, therefore, captures asymmetric dependence structure between two point-of-interest variables for different quantiles of a control variable. Let, z_t is a vector $\{z_t \equiv [\psi\left(\mathrm{x}_{\tau_3}\left(x_{3t} - q_{3,t}(\tau_3)\right), \dots, \psi\left(x_{lt} - q_{l,t}(\tau_l)\right)\right]^{\intercal}\}$, that comprises lagged predictor variables and economic state variables as control variables. Assuming $\bar{x}_{1,t} = \left[x_{1,1t}, \dots, x_{1,lt}\right]^{\intercal}$ and $\bar{x}_{2,t} = \left[x_{2,1t}, \dots, x_{2,lt}\right]^{\intercal}$, the following equation shows the relationship between the hit processes' correlation matrix and their corresponding inverse matrix,

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[11] Let $B_{K_i,\mathrm{L}_i} = \{(x_{1,t}x_{2,t-k})\}_{t=k_i}^{L_i-1}$, which denotes the sequence of i-th block. The length of the blocks ranging between K_i to L_i. L_i and K_i respectively represent an *iid* series with scalar parameter P_r (L_i = s) = $\gamma(1 - \gamma)^{s-1}$, s = 1,2,…, for $\gamma \in (0,1)$, and an *iid* sequence derived from a discrete uniform distribution $\{1,2, \dots T\}$. The SB procedure generates bootstrap samples $\{(x_{1,t}^{*}\ x^{*}{}_{2,t-k})\}_{t=k+1}^{T}$ using $(T - k)$ observations. If t exceeds T, the pair $(x_{1,j}x_{2,j-k})$ replaces the pair $(x_{1,t}x_{2,t-k})$ where $j = k + (t \bmod (T-k))$ and *mod* is a modulo operator. The purpose of this exercise is to properly draw the sequence of random blocks in the case the upper limit of $B_{ki,Li} > T$. Finally, a confidence interval for each CQ statistic is constructed by SB procedure relying on random blocks' sequences.

$$R_{\bar{\tau}}^{-1} = E[h_t(\bar{\tau})h(\bar{\tau})^{\intercal}]^{-1} = P_{\bar{\tau}} \tag{4}$$

where $h_t(\bar{\tau})$ denotes the vector of quantile hit process and it can be written as $h_t(\bar{\tau}) = \left[\psi\left(x_{1t} - q_{1,t}(\tau_1)\right), \ldots, \psi_{\tau l}\left(x_{lt} - q_{l,t}(\tau_l)\right)\right]^{\intercal}$. Given this condition, the PCQ model can be defined as follows:

$$\rho_{\bar{\tau}|z} = -p_{\bar{\tau},12}/\sqrt{p_{\bar{\tau},11}p_{\bar{\tau},22}} \tag{5}$$

where the PCQ $\rho_{\bar{\tau}|z}$ alternatively can be expressed as $\rho_{\bar{\tau}|z} = \delta\sqrt{\frac{\tau_1(1-\tau_1)}{\tau_2(1-\tau_2}}$. The scalar parameter δ is defined based on the following equation,

$$\psi\left(x_{1t} - q_{1,t}(\tau_1)\right) = \delta\psi_{\tau 2}\left(x_{2t} - q_{2,t}(\tau_2)\right) + \gamma^{\intercal}z_t + u_t$$

Using the PCQ, we test the null hypothesis $\rho_{\bar{\tau}|z} = 0$ against an alternate of $\rho_{\bar{\tau}|z}\# 0$. Hence, we examine the presence of serial dependence and directional predictability between quantile hits of two variables assuming that quantile hits are conditional on the information set embedded in the vector z_t. This test is in line with testing causal relationship between two variables proposed by Granger (1969).

We present the results pertaining to the CQ analysis in a graphical way. In the heatmaps, the *x*- and *y*-axes represent the quantile hits of the return distribution for individual bank and banking index returns and each cell in the graph is a quantile combination of the variables. We use color scale to denote the positive and negative dependence. If the CQ coefficient is statistically insignificant for any quantile combination, it is set to zero.

5. Data

This study concentrates on the banking sectors of three Scandinavian countries, namely Denmark, Norway and Sweden. We consider three banks from Denmark (Danske Bank, Jyske Bank, and SydBank), one bank from Norway (DNB), and four banks from Sweden (Nordea bank, Skandinaviska Enskilda Banken SEB, Svenska Handelsbanken SHB, and Swedbank). These are the major banks in the respective country and they are publicly traded. Our sample does not include banks that are not publicly traded as we use a stock return-based measure of systemic risk. DataStream banks sectoral index is used to represent aggregate banking index of the respective countries. We use daily data for a sample period of 1st January 1996 to 29th of June 2018. All data of the individual banks and aggregate banking index are collected from Thomson Reuters DataStream (DS). DS codes of the data series are presented in Table 1. The VIX index data is obtained from Chicago Board of Exchange's website (http://www.cboe.com/vix/), and the US EPU index data is collected from EPU index webpage (http://www.policyuncertainty.com/).

Figure 2 presents time-trends of the variables. While Panel A and Panel B respectively display daily equity prices (log) of the individual banks and aggregate banking index, Panel C plots uncertainty indices. From Panel A, we observe that the equity prices of individual banks exhibit a huge decline during the GFC. The banking stocks also appear to suffer at the time of the Eurozone crisis of 2012 and the China stock slowdown in 2015. However, the magnitude of the stock price decline during the GFC was the highest. The stock prices of Nordea, SEB, SHB, Danske and DNB also show a decline during the dot-com burst in the early 2000s. The equity prices, however, regain sharply after the crises. Panel B shows that as expected, the banking indices follow a trend similar to that of the individual banks described earlier. This result may indicate the presence of systemic risk and possibility of a co-movement between individual bank and the aggregate banking sector particularly during the extreme conditions. With regard to the uncertainty variables (Panel C), VIX index indicates increase in equity market volatility during the periods of stock market crises around 2001, 2008, 2012, and 2015. However, in general, VIX index appears to decline in the post-crises period. The EPU index show some spikes during the period going from 2008 – 2012 which may coincide with the GFC and Eurozone crises.

[INSERT FIGURE 2 ABOUT HERE]

Table 1 presents descriptive statistics of the daily equity returns of individual banks and aggregate banking indices and first difference of the uncertainty measures. The Scandinavian banks (both individual and the banking sector as a whole) exhibit mean positive returns over the sample period indicating that positive returns are well enough to offset negative returns generated during the crises periods. We find that daily returns of the Danish and Norwegian banks are typically higher compared to that of the Swedish banks. For example, daily equity returns of the Danish banks ranges between 0.023% to 0.043% whereas the Swedish banks' daily stock returns ranges between 0.013% to 0.022%. Equity returns of the Danish banks are found to be less volatile compared to that of the Swedish banks indicated by standard deviation. The skewness of most the Swedish bank returns are positive indicating that they tend to have more extreme positive returns without corresponding extreme negative returns. This result may indicate that the Swedish banks were not severely affected the GFC and Eurozone crisis. Furthermore, a contingent real estate boom particularly in Sweden may have had a positive impact on banks' profitability and stock prices. High kurtosis for all the return distribution indicates that the distributions are leptokurtic, and the presence of extreme returns compared to the extreme returns that we can expect from a normally distributed return series. The aggregate banking indices show a result similar to that of the individual banks. For instance, positive mean returns, positive skewness and high kurtosis are found for all the three indices. The null hypothesis of normality is rejected at the conventional significance level by the Jarque-Bera test in the case of all the return distributions. Since the key requirement for implementing the cross-quantilogram approach is that the variables have to be stationary stochastic process, to test for stationarity, we use both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test with time trend. Result reveals that the null hypothesis of a unit root is rejected at the 1% significance level by both the unit root tests indicating firstly, that they reject any integrated process higher than the first order, and secondly that the return series are stationary stochastic process. This result holds for all the return series.

[INSERT TABLE 1 ABOUT HERE]

6. Empirical results

This section consists of four subsections. In the first subsection, we present results pertaining to cross-quantile dependence between individual banks and aggregate banking indices. In the second subsection, we examine if the dependence structure is sensitive to the inclusion of two uncertainty measures, namely equity market volatility and economic policy uncertainty. The time-varying cross-quantile relationship between individual banks and aggregate banking sector in the recursive samples is presented in the third subsection. Finally, in the fourth subsection, the degree of systemic risk is explained in terms of idiosyncratic bank characteristics and market-wide variables by estimating a panel regression.

6.1 Cross-quantile correlation between individual banks and banking index

In Figure 3, we present cross-quantile correlation (CQC) going from individual banks to their respective banking index. Panel A, B and C respectively show results relating to the Swedish, Danish and Norwegian banks. We use the Box-Ljung test to derive statistical significance of any directional predictability and statistically insignificant correlations are set to zero.

From Panel A, we observe that cross-quantilograms are positive and statistically significant in the low quantiles ranging from 0.05:0.05 to 0.25:0.25. This result reveals that the Swedish banks are systemically important and when these banks are in distress, they create impact on the aggregate banking sector. This result holds from lag 1 to lag 10 indicating that in the distressed condition of these banks, systemic risk persists even up to two weeks (10 days). Overall, low tail dependence may be attributed to increased risk premia due to increased probability of default and increased solvency risk when a financial institution is in distress. This result can further be attributed to deterioration of investor sentiment. We further observe aggregate banking index returns' positive dependence on individual banks when they are in high quantiles ranging from 0.85:0.85 to 0.95:0.95 indicating a co-movement between them. Overall, these results imply that individual banks show a tendency to boom and crush along with the market. Among the four Swedish banks, Swedbank appears to be systemically less important as this bank exhibits less incidences of statistically significant positive correlation.

We find strikingly similar result in the cases of Danish (Panel B) and Norwegian (Panel C) banks in relation to the Swedish banks. In general, the Danish banks are more systemically important compared to the other Scandinavian banks as we find greater evidence of positive dependence of the aggregate banking returns on individual bank returns. Among the three Danish banks, Danske and Jyske show a positive and statistically significant influence on the aggregate banking returns when the return series are in the low, medium or high quantiles indicating that these banks influence the aggregate banking sector, not only when these banks are in distress, but also when these bank returns are in the normal and booming states. These banks are also systemically more important compared to Sydbank.

Our finding of the presence of systemic risk in the Scandinavian banking sector is consistent with Karimalis and Nomikos (2018) and Laeven et al. (2016), among others. However, the novelty of our finding is that while Adrian and Brunnermeier (2016) and Girardi and Ergün (2013) respectively show the presence of systemic risk when a financial institution is exactly at its VaR (5% quantile) and at most at its VaR, we show that the Scandinavian banking sector is subject to a co-movement when individual banks' stock return ranges between 0.05 to 0.25 quantiles. Moreover, unlike the previous studies that concentrate on downside risk spillover (systemic risk), we show significant evidence of upside risk spillover between individual bank and aggregate banking index returns. However, upside risk spillover appears to be less intense compared to downside risk spillover. This result may be attributed to asymmetric capital flows in an extreme distressed and rising condition in the banking returns. (Reboredo, Rivera-Castro, & Ugolini, 2016). In the case of an extreme distressed condition, investors' overreaction may lead them to withdraw their investment from the banking sector causing a further decline in banking stock returns. However, similar overreaction and capital inflow to the banking sector may not be exhibited during a booming condition in the banking company stocks.

[INSERT FIGURE 3 ABOUT HERE]

Figure 4 presents cross-quantile correlation going from aggregate banking index to individual banks. This analysis reveals individual bank's response to sector-wise distress, and it is somewhat similar to the typical stress test conducted by individual banks. Similar to the CQC reported in Figure 3, we observe that individual banks exhibit a positive dependence on the aggregate banking sector when the return series are in low (ranging from 0.05:0.05 to 0.25:0.25) and high (ranging from 0.85:0.85 to 0.95:0.95) quantiles.

Overall, this result indicates individual bank's co-movement with the aggregate banking sector when the sector is either bearish (represented by low quantiles) or bullish (represented by high quantiles). However, the co-movement disappears in the normal market condition. This result holds for all the Scandinavian banks. Although the extreme quantile positive dependence between individual banks and aggregate banking index observed in lag 1, 5, and 10, the magnitude of the dependence slightly weakens in lag 5 and lag 10 compared to that in lag 1.

[INSERT FIGURE 4 ABOUT HERE]

6.2 Cross-quantile correlation after incorporating uncertainty measures

In this subsection, we examine the CQC after controlling for two uncertainty measures. This analysis aims to capture any change in the interdependence between individual banks and aggregate banking index due to underlying risk associated with the change in the uncertainty measures. In fact, we estimate the partial cross-quantilogram (PCQ) adopting VIX and EPU as the economic state/control variables. The measurement of EPU is based on the frequency of publication of a group of words linked to economic policy uncertainty (uncertainties with regard to who will take the policy decision, what will be the policy decision and what economic effect the policy decision will have) in leading newspapers. On the other hand, VIX is an indication of investors' perception with respect to equity market's implied volatility associated with the S&P 500 index options in the next 30 days. The choice of the control variables is consistent with the literature (see Adrian, & Brunnermeier, 2016; Han et al., 2016; Karimalis & Nomikos, 2018).

Theoretically, in the premise of a discounted cash flow model of stock prices, since equity market and economic policy uncertainties can affect estimated cash flows and discount rate, they can ultimately affect equity prices. More specifically, rational investors typically make a downward (upward) adjustment of cash flows (discount rates) in response to heightened uncertainty. Therefore, a higher value of EPU or VIX is a manifestation of higher economic policy or equity market uncertainty which may depress stock market prices. Consistent with this argument, Chang, Chen, Gupta and Nguyen (2015) and Arouri, Estay, Rault and Roubaud (2016), among others, show a negative relationship between EPU and stock returns. Additionally, while VIX and stock returns are found to have a negative contemporaneous relationship (Whaley, 2009), equity market uncertainty appears to negatively affect cross-market stock prices (Connolly, Stivers, & Sun, 2005). Based on the theoretical argument and empirical evidences presented above, we hypothesize that the uncertainty measures can moderate the tail dependence between individual bank and the aggregate banking index returns particularly during the extreme events.

Since the uncertainty measures exhibit high persistence and they can be modelled as integrated process, instead of using the index level, the first difference of the indices is used as the control variables. In estimating the PCQ, the quantile hit process for the control variables are allowed to reach up to 90% quantile. The justification for this choice is two-fold. First, the low quantile stock return generally exhibits an association with high-level of uncertainty (Han et al., 2016). Second, this exercise aims to reveal the impact of increased risk or higher level of uncertainties on the cross-quantile dependence between individual banks and aggregate banking index.

Figure 5 and Figure 6 respectively present the CQC between individual banks and aggregate banking index after controlling for VIX and EPU. In the case of both the figures, the first two columns present the quantile dependence running from individual banks to aggregate banking index while the last two columns display the quantile dependence running from aggregate banking index to individual banks. Although our analysis in subsection 5.1 was based on three different lags (lag 1, 5, and 10), in this subsection, we only consider lag 1 and 5 to conserve space.

A qualitative comparison of Figures 5 and 6 with Figures 3 and 4 indicates that the cross-quantilograms remain almost unchanged after incorporating VIX and EPU as control variables as we find positive and statistically significant cross-quantilograms in the low and high quantiles. This result reflects that the uncertainty measures do not carry any material information with regard to the cross-quantile relationship between the individual banks and aggregate banking index in the Scandinavian countries. This finding supports Han et al. (2016). Our result may reveal that systemic risk in the Scandinavian banking sector is not driven by these uncertainty measures, rather bank specific variables and individual banks and aggregate banking sector's endogenous interrelationship may be the main driver of the systemic risk in the banking sector of these three countries.[12] For instance, Adrian and Brunnermeier (2016) find that larger banks with higher leverage, higher maturity mismatch, and higher asset valuations tend to exhibit higher systemic risk. Supporting this finding,

[12] Bank-specific and market-wide variables' ability to explain the cross-sectional and time series variation in systemic risk is explored in subsection 6.4.

Girardi and Ergün (2013) show that financial institutions' size, leverage and beta are the important determinants of their contributions to systemic risk.

[INSERT FIGURE 5 AND 6 ABOUT HERE]

6.3 Cross-quantile correlation in the recursive subsamples

In the recent years, Euro-area financial markets have experienced an unprecedented increase in volatility and European banking system has struggled coping with sovereign stress (Weiß et al., 2014). IMF has reported that European banks' balance sheets have been shrunk by as much as USD 2,900 billion through the end of 2013 (IMF, 2013). Additionally, the global economic system has witnessed consolidation of industries, substantial upsurge in capital mobility, and liberalization of cross-border lending impediments in the last decade (Bartram et al., 2007). These phenomena may have increased systemic risk in the banking sector. On the other hand, financial innovations (for example, rapid increase in number and fund-under-management in exchange traded funds, development of credit derivative markets etc.) and burgeoning non-bank financial intermediary activities (for example, reinsurance) may have lessened the financial distress being spilled over from one financial institution to the entire financial system. Moreover, Basel II capital allocation rule has increased financial institutions' ability to measure and manage risk associated with credit crisis without spreading the risk to other financial institutions. Therefore, it may be interesting to examine the time-varying dependence structure between individual bank and aggregate banking index.

In the previous two subsections, the cross-quantile dependence between individual banks and aggregate banking index as a measure of systemic risk has been presented for the whole sample period. Since this analysis is time-static, a potential shift in the interdependence over time cannot be captured by the quantile hit process in this setting. In this subsection, we examine the time-varying nature of systemic risk by estimating the CQC in recursive subsamples. The recent literature commonly uses recursive sample approach in order to examine time-variation in the relationship between financial variables (see for example, Basher & Sadorsky, 2016; Broadstock, Cao, & Zhang, 2012; Shahzad, Naifar, Hammoudeh, & Roubaud, 2017). The justification for using recursive sample analysis is intuitive. In the case of any structural break or regime shift in the relationship between two variables, a linear model firstly, may be unable to capture such structural break and secondly, may suffer from parameter instability. Under this circumstance, a recursive sample estimation may better reflect the time-variation in the relationship between two variables (Shahzad et al., 2017).

In recursive sample estimation, a two-year window length is considered. More specifically, the CQC is first estimated for the first window period, which has a length of 504-days. Then the window length is increased by one day and the CQC is re-estimated. This process, which is continued until the last observation of the sample period is used, generates 5366 recursive samples. Figure 7a presents cross-quantilogram running from individual banks to aggregate banking index for lag 1 while similar analysis up to 10 lags is displayed in Figure 7b. In both the graphs, Panel A, B and C respectively shows results associated with the Swedish, Danish and Norwegian banks. The first and second columns respectively present the time-varying CQC when the return distributions are in low (0.05:0.05) and high (0.95:0.95) quantiles. In the figure 7a, the green and red lines represent 95% confidence level for the null hypothesis of no directional predictability while the blue line indicates time-varying dependence structure.

We first concentrate on Figure 7a. From the first column (when both the return distributions are at 5% quantile), we observe insignificant cross-quantilograms running from individual banks to aggregate banking index since the start of the sample period in the late 1990s until the outbreak of the GFC in 2007-2008. This result is indicated by the blue line mostly within the 95% confidence level. This finding is consistent with Bartram, Brown, and Hund (2007) and Weiß et al. (2014), among others, who show that 1997-Asian crisis, 1998-

Long-term capital management (LTCM) crisis, and 2001-burst of dot-com bubble did not lead to an increase in systemic risk. However, during the GFC and Eurozone crises and in the post-crises period, the low quantile dependence, a measure of systemic risk, appears to increase and becomes statistically significant revealed by the blue line out of the 95% confidence level. While this finding is observed for almost all the Scandinavian banks, it is more obvious in the case of Danish and Norwegian banks compared to the Swedish banks, which is also consistent with our previous remark that the Danish banks are systemically more important compared to the Swedish banks. This result may be at odds with Karimalis and Nomikos (2018) and Laeven et al. (2016) who show that in the European context, the Swedish banks are among the top contributor to systemic risk. However, while we examine individual bank's systemic risk contribution to aggregate banking sector of respective country, Karimalis and Nomikos (2018) and Laeven et al. (2016) investigate individual bank's contribution to aggregate European banking sector. Among the four Swedish banks, Nordea and SEB exhibit increased systemic risk during and after the financial crisis while such result for SHB and Swedbank is less obvious. [13]

As we move to the second column, (when both the return distributions are in 95% quantile), we find that the blue line is mostly with the 95% confidence level indicating statistically insignificant cross-quantile correlation over the sample period except the case of Danske bank. With regard to Danske bank, we observe positive and statistically significant correlation over the sample period. This result implies that along with the low quantile co-movement, this bank also exhibits a high quantile co-movement with the market.

[13] Although not reported in Table 7a, as we estimate time-varying CQC in median quantiles (when both the return distributions are at 50% quantile), we find that the blue line is mostly with the 95% confidence level indicating statistically insignificant cross-quantile correlation and absence of a mean-to-mean dependence between aggregate banking index and individual banks. This result firstly is consistent with our previous finding derived from a time-static whole-sample analysis and secondly, holds for most of the Scandinavian banks except for two Danish banks (Jyske and Sydbank). In the cases of these two banks, the CQC is found to be positive and statistically significant from 2005 to the rest of the sample period indicating a statistically significant dependence structure even when the individual banks and the aggregate banking index are in normal state.

While Figure 7a presents the CQC from individual bank to aggregate banking index in recursive sample, it only focuses on the first lag order which does not capture any richer information regarding the lag structure in the data series. Hence, we extend the analysis by estimating CQC in recursive sample for up to 10 lags and present them in a surface plot (Figure 7b).

We find several interesting findings from this analysis. First, from panel A, we observe that the Swedish banking index show a statistically positive and significant dependence on individual banks during the 2008 – 2009 crisis period indicating systemic risk contribution of individual Swedish bank to overall banking system. However, this dependence is not prevalent in lag 1 rather the dependence is dominated in the 4 – 8 days or roughly one-week lag. We find a very similar result for the Danish (Panel B) and Norwegian banks (Panel C). This result implies that it takes about one-week period for systemic risk to reach from individual bank to the aggregate banking index which may be due to the fact that information contained in individual bank's stock price takes one-week period to be diffused in aggregate banking index. The higher CQC in the 4 – 8 days lag can be explained in terms of gradual information diffusion hypothesis of Hong and Stein (1999) and Hong et al. (2007). The authors argue that price-sensitive information can be diffused gradually as investors underreact to that information due to their limited information processing capacity (bounded rationality). Investors may take time to assess the impact of a bank-in-distress to the overall banking sector resulting persistence in systemic risk.

Second, we find that the lower tail CQC spillover is mostly confined during the crisis period while in the opposite right tail (95:95), CQC spillover in the longer daily lags is found scattered over the sample period. This result implies that systemic risk in the Scandinavian banking sector is intensified during the crisis period while the upper tail co-movement in longer lags is observed in both crisis and non-crisis period without any secular trend.

However, CQC in the right tail (95:95) is generally smaller than that of the left tails indicating an asymmetric response in low and high quantiles.

Third, although lower tail dependence is mostly observed during the GFC, in the case of Swedish banks, we also observe the evidence of significant spillover in the post-GFC period. For instance, significant CQC is found between 2010 – 2015 in 8 – 9 days lag for most banks. This result may be attributed to these banks' larger investment in the less stable and emerging Baltic states. This finding implies that banks with more unstable business and balance sheets with more uncertain assets are larger contributor to systemic risk. However, some peaks (significant CQC) seem to be bank specific. For instance, in the case of SEB, strong CQC is found in early 2000 in the 8-10 days lag. We also find evidence of significant CQC in the recent years which may be due to (i) decline in real estates (condominium) prices that affect banks' lending strategies and profitability; (ii) the increase in geopolitical uncertainty with Brexit as focal point; and (iii) overall slowdown of the economic activity in 2018.

[INSERT FIGURE 7a AND 7b ABOUT HERE]

As we look at Figure 8a and 8b, we find that the CQC running from aggregate banking index to individual bank measured in lag 1 (Figure 8a) and in 1 – 10 lags (Figure 8b) are very much similar to that of the CQC running from individual bank to aggregate banking index. For instance, in the lower tails, CQC is mostly insignificant from early 2000s to the inception of the GFC while the CQC is positive and statistically significant during and the post-crisis period. In the case of upper tails, for the Danish banks, cross-quantile correlation is mostly positive and statistically significant from 2009 onwards indicating that quantile relationship in the bullish market has been strengthened in the post-crisis period. While this result is weakly evident for the Norwegian bank, the high-quantile relationship for the Swedish banks is mostly insignificant.

[INSERT FIGURE 8a AND 8b ABOUT HERE]

Overall, our recursive sample analysis reveals that the systemic risk (low-quantile dependence) in the Scandinavian banking sector has substantially increased from the inception of the global financial crisis indicating that systemic risk was mainly driven by risk premia and contagion concerns spreading from one individual bank to the aggregate banking sector.

6.4 Determinants of systemic risk

In order to identify the main driver of systematic risk, in this subsection, we model the CQC (running from individual banks to the aggregate banking sector) as a function of several bank-specific and market-wide variables. With regard to bank-specific variables, we consider bank size (the natural log of the book value assets), bank valuation (the ratio of book-to-market value of the assets), asset growth (percentage change in risk weighted assets), profitability (the return on assets), liquidity (the cash and liquid securities to invested assets ratio, the loan to deposit ratio, invested assets to deposit ratio), and capital ratio (the risk-based capital ratio). We hypothesize that systemic risk has a positive relationship with bank size and asset growth as larger banks with high asset growth are expected to be systemically more important. On the other hand, systemic risk is expected to be negatively related to profitability, liquidity, and capital adequacy as they typically indicate banks' resilience to different economic and financial shocks. To incorporate market-wide factors, we include housing index, the term spread (difference between the 10-year government bond yield and 3-month T-bill rate or equivalence), the policy rate or repo rates for the central banks, and the percentage change in GDP to gross domestic income ratio.

To analyse the impact of bank-specific and market-wide variables on systemic risk, we estimate the following panel regression model:

$$\overline{CQC}_{it} = \alpha + +\beta_1 size_{it} + \beta_2 MV_{it} + \beta_3 \% \Delta RWA_{it} + \beta_4 ROA_{it} + \beta_5 \frac{Cash}{IA}_{it} + \beta_6 \frac{Loan}{Dep}_{it} + \beta_7 \frac{IA}{Dep}_{it} + \beta_8 RCAR_{it} + \beta_9 HOX_{it} + \beta_{10} TS_{it} + \beta_{11} PR_{it} + \beta_{12} \frac{\Delta \%GDP}{\ln GDI}_{it} + \epsilon_t \qquad (6)$$

Where $\overline{CQC}_t$ is the quarterly average of the CQC estimates from the rolling sample estimation of the cross-quantilogram model (see section 6.3), $Size$ is the natural log of the book value of assets, MV is the book-to-market value of the assets, $\%\Delta RWA$ is the percentage change in risk weighted assets, ROA is the return on assets, $\frac{Cash}{IA}$ is the cash and liquid securities to invested assets ratio, $\frac{Loan}{Dep}$ is the loan to deposit ratio, $\frac{IA}{Dep}$ is the invested assets to deposit ratio, $RCAR$ is the risk-based capital ratio, HOX is the housing index, TS is the term spread, PR is the policy rate or repo rates for the central banks and $\frac{\Delta\%GDP}{\ln GDI}$ is the percentage change in GDP to gross domestic income ratio. Before estimating the regression, all the variables (except for $Size$ and HOX) are transformed using $\ln(\frac{x}{100} + 1)$ for the ease of interpretation and comparison. The regression model is estimated for the low (0.05), median (0.50), and high (0.95) quantiles. For each of the quantiles, two separate regression models are estimated. The first one incorporates only bank-specific factors as explanatory variables while the second one incorporates both the bank-specific and market-wide factors. Bank fixed effect is included in the estimation process.

In table 2, we present the regression results from the panel estimation. We observe that *Size* has a statistically significant impact on the dependence between individual bank and the aggregate banking sector in the low (0.05) and high (0.95) quantiles but not in the median quantile (0.50). The coefficient is positive in the low quantile indicating that larger bank is systemically more important. This result is consistent with Brunnermeier, Dong, and Palia (2012), Beltratti and Stulz (2012), Karimalis and Nomikos (2018), López-Espinosa, et al., (2015), among others. However, interestingly, the coefficient turns into positive in the high quantile, implying that when both individual bank's and aggregate banking sector's returns are in high quantile, the co-movement between them is weaker for large banks compared to small banks.

The coefficients of ROA and $\frac{Loan}{Dep}$ are negative and statistically significant at the 1% significance level in the low quantile. This result is in line with our priori expectations, that banks with high profitability and liquidity are more resilient toward different economic shocks, therefore, are subject to less degree of systemic risk. Our result supports Varotto and Zhao (2018) who reveal a significant negative relationship between bank profitability and systemic risk. In the case of both of these variables (ROA and $\frac{Loan}{Dep}$), the coefficients turn into positive in the high quantile. This result manifest that highly profitable and liquid banks appears to have higher correlation with the aggregate banking sector when both return series are in high quantile. These results are typically robust to two different model specifications such as including only firm-specific variables and including both firm-specific and market-wide explanatory variables in the regression model.

Although two other liquidity ratios, $Cash/IA$ and IA/Dep, do not contribute to systemic risk as their coefficients are statistically insignificant in low quantile, they appear to contribute to higher correlation between individual bank and the aggregate banking sector in the high quantile. Surprisingly, $RCAR$ does not have a statistically significant impact on the cross-quantile dependence. Although this result supports Weiß et al. (2014) who show that leverage is not a significant determinant of systemic risk, our findings is at odds with Laeven et al. (2016) who report that bank capital has a significant negative relationship with its contribution to systemic risk. The cross-quantile dependence is found to be mostly invariant to MV[14] and $\%\,\Delta\,RWA$. Among the bank-specific variables, ROA has the largest effect size across all quantiles. The magnitude of the coefficient is typically greater in the left tail

[14] MV's coefficient is marginally significant in low and high quantiles. This result is however not robust to different model specifications.

compared to that in the right tail. For example, in the left tail, an 1% increase (decrease) in ROA would decrease (increase) CQC by about 3%, whereas in the right tail, an 1% increase (decrease) in ROA would increase (decrease) CQC by about 2%. However, in the case of *Loan/Dep* ratio, an 1% change in the ratio would bring only 0.03% and 0.02% change in CQC respectively in the left and right tails.

With respect to the market-wide factors, we find that housing index has a statistically significant negative impact on systemic risk indicating that a rise in the housing market leads to lower systemic risk. This result is intuitive. As the Scandinavian banks' loan portfolio is dominated by real estate mortgage loan, a bullish condition in the housing market reduces the housing loan's probability of default which ultimately reduces systemic risk. This relationship however dissipates in the median and higher quantiles as the coefficients turn out to be statistically insignificant. Similar result is found for $\frac{\Delta\%GDP}{\ln GDI}$, though the coefficient is only marginally significant. Systemic risk is found to be invariant to term spread and policy rates as their coefficients are statistically insignificant in low quantile. Nonetheless, higher policy rate contributes to higher correlation between individual bank and aggregate banking sector returns in high quantile.

All in all, we find that $Size$ has a positive relationship with systemic risk while ROA and $Loan/Dep$ ratio exhibit a negative influence. Furthermore, systemic risk responds negatively to housing index. While bank-specific variables' impact on systemic risk has been reported in the previous literature, the uniqueness of our paper is, we use a novel measure of systemic risk and report that bank-specific variables' contribution to cross-quantile dependence between individual bank and the aggregate banking sector is asymmetric across quantiles.

7. Conclusions

After the global financial crisis and European sovereign debt crisis, systemic risk in the banking sector has become a point-of-interest to academia, investors and finance/banking regulators. The main objective of this paper is to examine systemic risk in the Scandinavian banking sector using the cross-quantilogram (CQ) approach. Unlike most other existing systemic risk measures, the CQ approach does not depend on any underlying ex-ante modelling and it is able to capture changes in the dependence between two variables even after introducing large lags. Additionally, while most typical systemic risk measures concentrate on individual financial institution's contribution to systemic risk, the CQ enables us to examine an individual financial institution's exposure to distress condition in the aggregate financial sector as well as their high-quantile dependence.

Our finding can be summarized as follows. First, the estimated cross-quantilograms are positive and statistically significant in the low (0.05:0.05) and high (0.95:0.95). This result is found in both directions, i.e. from individual financial institutions to the aggregate banking index and from aggregate banking index to individual financial institution. The low quantile dependence indicates that the Scandinavian banks are systemically importantly linked, and that they have a significant exposure to the distressed condition of the entire financial system. The high quantile dependence manifests that individual banks and the aggregate banking index co-move both in the bust and the booming conditions as well. This result is robust for the incorporation of two uncertainty measures (equity market volatility and economic policy uncertainty) as control variables.

As we estimate the CQ in the recursive samples, we find that systemic risk (when both individual bank and aggregate banking return are in 5% quantile) exhibits a time-varying characteristic. Although conventionally financial crises are characterized by heightened systemic risk, we observe that systemic was insignificant from the late-1990 to the outbreak of the GFC despite the fact that this period includes 1997-Asian crisis, 1998-Long-term capital management (LTCM) crisis, and 2001-burst of dot-com bubble. Nonetheless, we find that systemic risk has increased substantially and become significant during and after the GFC and Eurozone crisis. This result indicates that all financial crises do not lead to increase in the systemic risk which is consistent with Bartram, Brown, and Hund (2007) and Weiß et al. (2014), among others. Finally, we find that size has a positive relationship with low quantile dependence (a measure of systemic risk) while return on asset and loan to deposit ratio exhibit a negative influence. This relationship, however, is asymmetric across quantiles.Our results have some crucial policy implications. As we find that the Scandinavian banks, irrespective of their size, leverage and liquidity characteristics, pose systemic risk to the aggregate banking system, they should be within the umbrella of a greater regulatory standard. Moreover, the individual bank's significant exposure to system-wide distress indicates that a system-wide macroprudential approach of monitoring and maintaining financial stability needs to be implemented along with typical microprudential or firm-level approach.

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Table 1: Descriptive statistics

Variables	DS code	Mean (%)	SD	Skewness	Kurtosis	J-B	ADF	PP
				Scandinavian Major Banks: Sweden, Denmark and Norway				
Sweden								
NORDEA	M:NBH(P)	0.017	0.021	0.27	8.03	6269.42***	-58.00(1)***	-79.69***
SEB	W:SEA(P)	0.016	0.023	0.06	13.38	26356.47***	-38.48(4)***	-74.48***
SHB	W:SVK(P)	0.022	0.018	0.12	8.27	6803.75***	-57.76(1)***	-79.07***
SWEDBANK	W:SWED(P)	0.014	0.022	-0.11	12.02	19913.82***	-76.92(0)***	-77.19***
Denmark								
DANSKE	DK:DAB(P)	0.023	0.019	-0.13	9.25	9591.43***	-72.92(0)***	-72.85***
JYSKE	DK:JYS(P)	0.035	0.017	0.06	8.79	8203.46***	-71.62(0)***	-71.55***
SYDBANK	DK:SYD(P)	0.043	0.016	-0.40	14.75	33925.13***	-70.45(0)***	-70.37***
Norway								
DNB	N:DNB(P)	0.036	0.022	-0.1	13.11	25021.33***	-55.92(1)***	-75.03***
				Scandinavian Major Banking Indices				
SE_BI	BANKSSD	0.010	0.018	0.31	9.36	9982.93***	-37.84(4)***	-77.24***

NO BI	BANKSNW	0.020	0.020	0.18	19.83	69374.94***	-56.62(1)***	-74.70***
DK_BI	BANKSDK	0.028	0.016	0	10.9	15288.98***	-69.25(0)***	-68.98***
				Uncertainty measures				
US EPU		0.000	0.633	0.07	4.12	313.01***	-45.67(6)***	-45.66(6)***
CBOE VIX		0.000	0.065	0.89	10.07	13015.56***	-34.76(6)***	-34.76(6)***

Notes: J-B is the Jarque-Bera statistic for testing the null hypothesis of normality. ADF and PP are the unit root test statistic for the null hypothesis a unit root. *** indicates statistical significance at the 1% level. BI – Banking index. Source: Datastream International

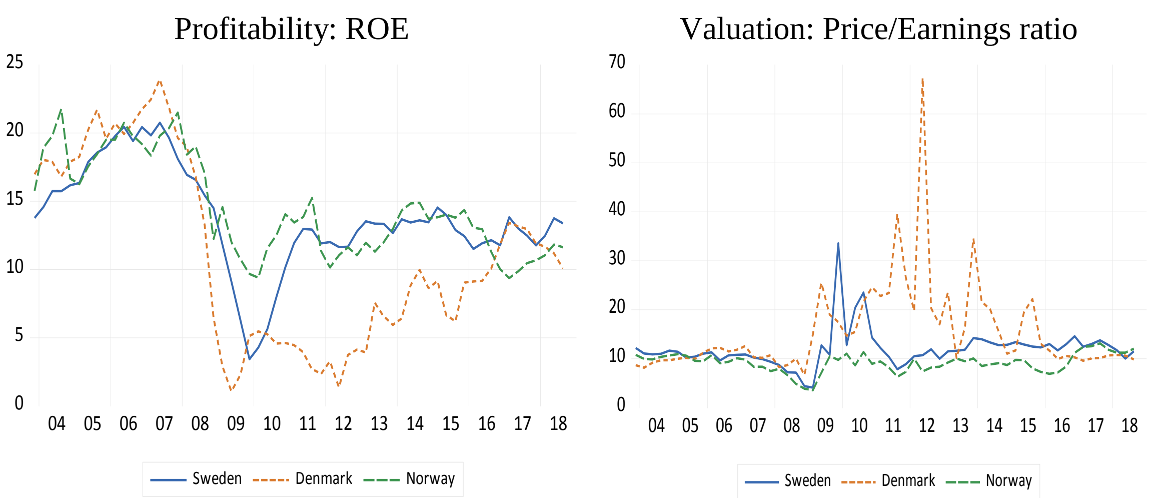
Table 2: Determinants of systemic risk

	$\tau_{0.05}$	$\tau_{0.05}$	$\tau_{0.5}$	$\tau_{0.5}$	$\tau_{0.95}$	$\tau_{0.95}$
Bank specific variables						
$Size$	0.035*** (2.71)	0.049*** (3.189)	0.004 (1.042)	0.003 (0.651)	-0.03*** (-2.703)	-0.037*** (-2.779)
MV	0.739 (1.96*)	0.636 (1.512)	-0.137 (-0.611)	-0.118 (-0.489)	0.461 (1.176)	0.703* (1.900)
$\%\Delta RWA$	-0.013 (-1.029)	-0.017 (-1.336)	0.003 (1.281)	0.003 (1.336)	-0.017 (-1.034)	-0.015 (-1.021)
ROA	-3.288*** (-5.353)	-2.724*** (-5.73)	1.042** (2.458)	0.939** (2.114)	2.758*** (3.306)	2.19*** (3.166)
$Cash/IA$	0.23 (0.267)	-0.141 (-0.186)	0.443 (0.89)	0.429 (0.906)	1.054*** (2.699)	1.381*** (2.781)
$Loan/Dep$	-0.034*** (-3.304)	-0.037*** (-3.986)	-0.001 (-0.136)	-0.001 (-0.139)	0.025*** (3.386)	0.027*** (3.152)

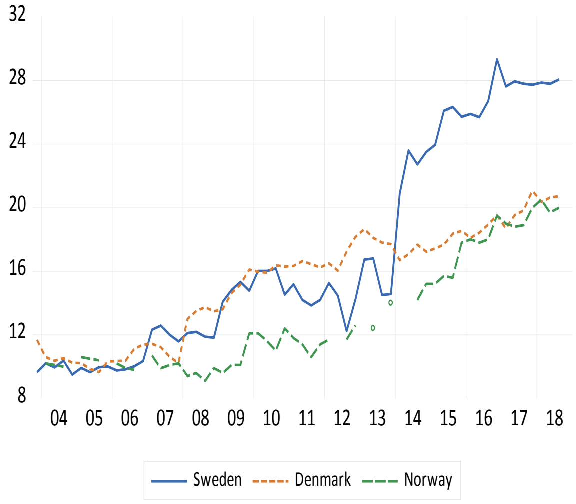
IA/Dep	0.005	-0.007	0.014*	0.015**	0.026	0.039**
	(0.452)	(-0.556)	(1.852)	(2.09)	(1.555)	(2.336)
RCAR	-0.164	-0.151	0.011	0.014	0.025	0.041
	(-1.631)	(-1.472)	(0.300)	(0.447)	(0.312)	(0.427)
Market-wide variables						
HOX		-0.033**		0.002		0.024
		(-1.991)		(0.286)		(1.168)
TS		-0.118		-0.082		0.298
		(-0.393)		(-1.471)		(0.885)
PR		-0.298		0.02		0.442***
		(-1.222)		(0.276)		(3.055)
$\frac{\Delta\%GDP}{\ln GDI}$		-0.143*		-0.013		0.123
		(-1.806)		(-0.517)		(0.997)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No
Adjusted-R^2	0.388	0.419	0.162	0.160	0.403	0.432

Note: The entries are the regression coefficients (t-statistics in parenthesis) derived from estimating equation 6 in a panel setting. Dependent variable is the quarterly average of the cross-quantile correlations generated from recursive sample estimations of the cross-quantilogram model (see section 6.3). $Size$: the natural log of the book value of assets, MV: the book-to-market value of the assets, $\%\Delta RWA$: the percentage change in risk weighted assets, ROA: the return on assets, $\frac{Cash}{IA}$: the cash and liquid securities to invested assets ratio, $\frac{Loan}{Dep}$: the loan to deposit ratio, $\frac{IA}{Dep}$: the invested assets to deposit ratio, $RCAR$: the risk-based capital ratio, HOX: the housing index, TS: the term spread, PR: the policy rate or repo rates for the central banks, $\frac{\Delta\%GDP}{\ln GDI}$: the percentage change in GDP to gross domestic income ratio. All the variables (except for $Size$ and HOX) are transformed using $\ln\left(\frac{x}{100}+1\right)$ for the ease of interpretation and comparison. The regression model is estimated for the low (0.05), median (0.50), and high (0.95) quantiles. For each of the quantiles, two separate regression models are estimated. The first one incorporates bank-specific factors as explanatory variables while the second one incorporates both the bank-specific and market-wide factors. Bank fixed effect is included in the estimation process. *, **, and *** indicates 10%, 5% and 1% significance, respectively. The t-statistic in the parenthesis.

Figure 1: Time-trends of key financial variables of the Scandinavian banks



Capital adequacy: Capital adequacy ratio



Liquidity: (Invested assets + Loans)/Deposits

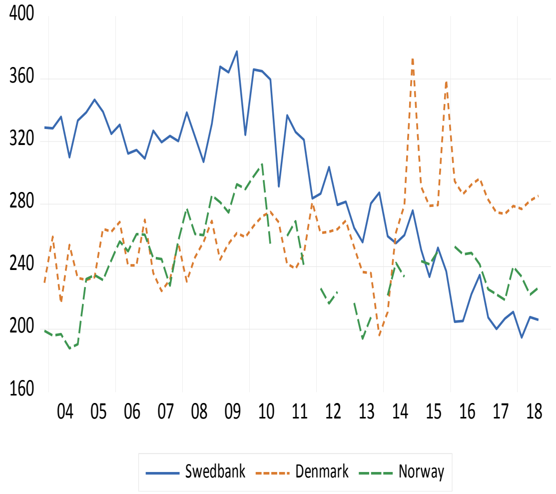
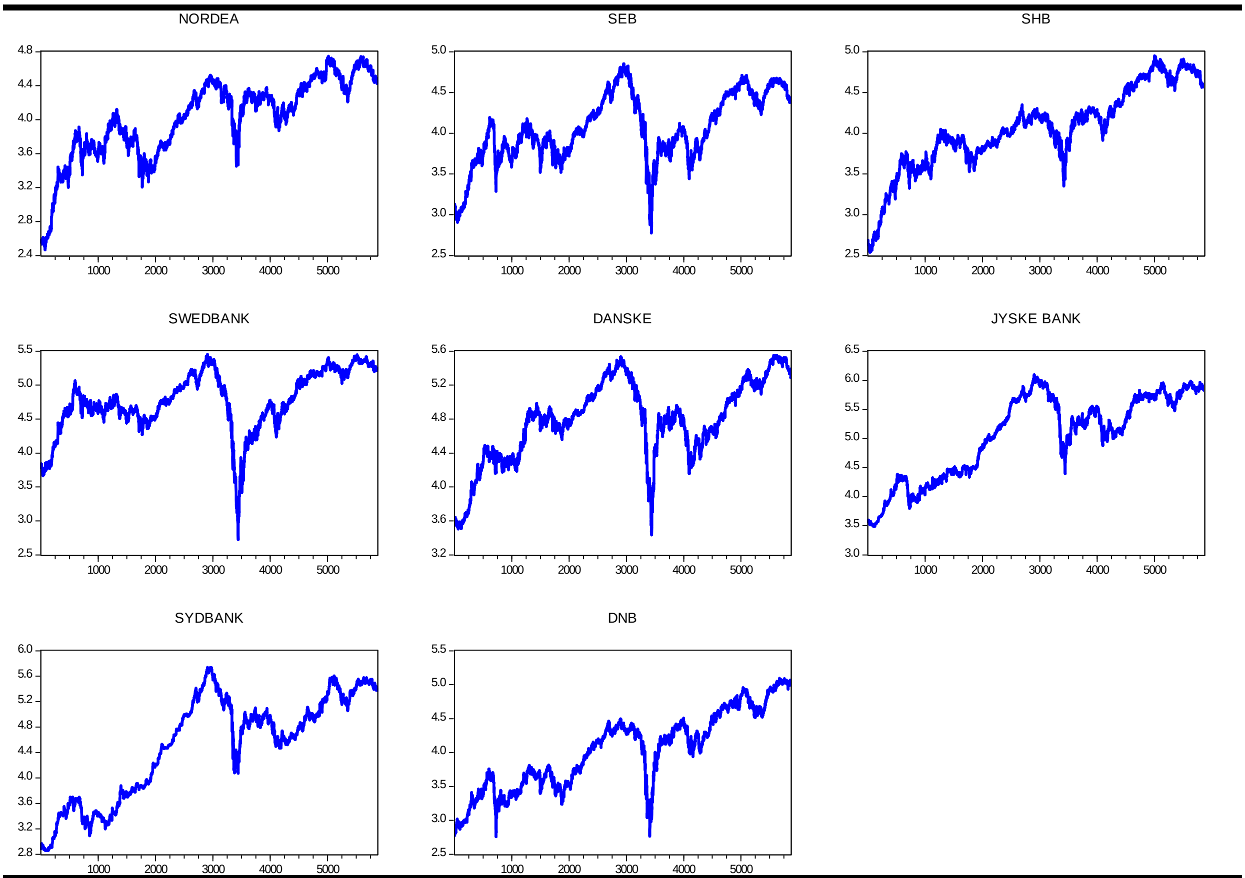
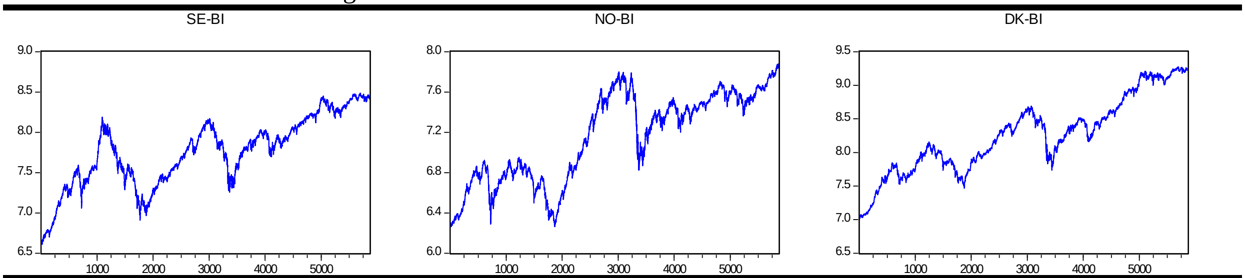


Figure 2: Plots of logarithm of financial institution prices and banking indices

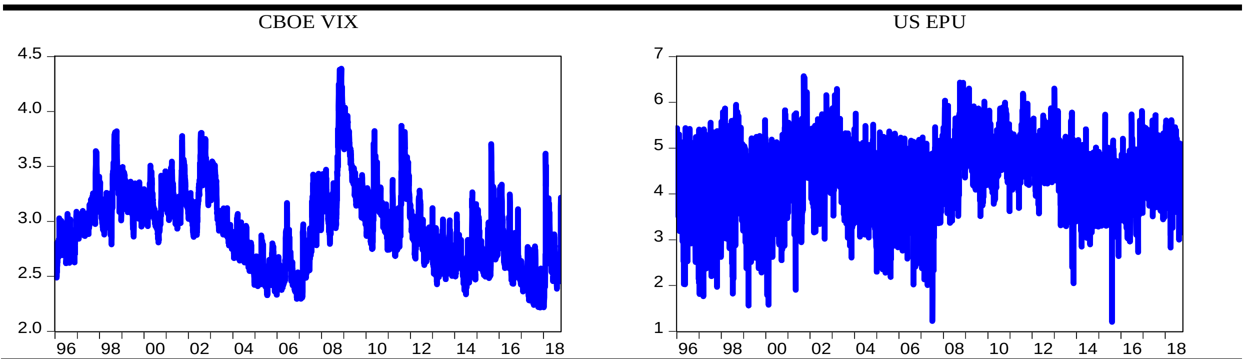
Panel A: Major Banks in Scandinavian Regions



Panel B: Scandinavian Banking indices



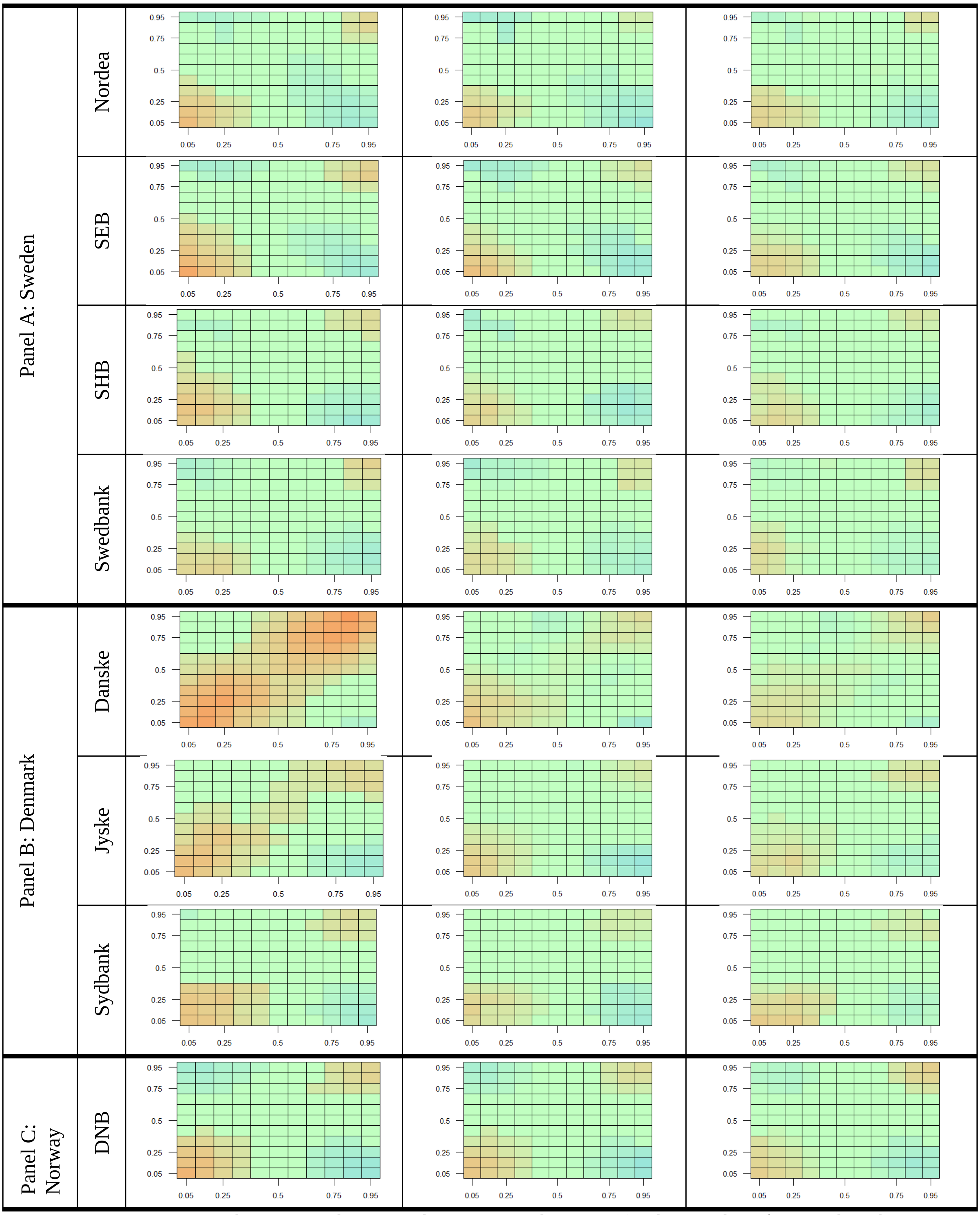
Panel C: Measures of Uncertainties'



Notes: Data extracted from the Datastream International.

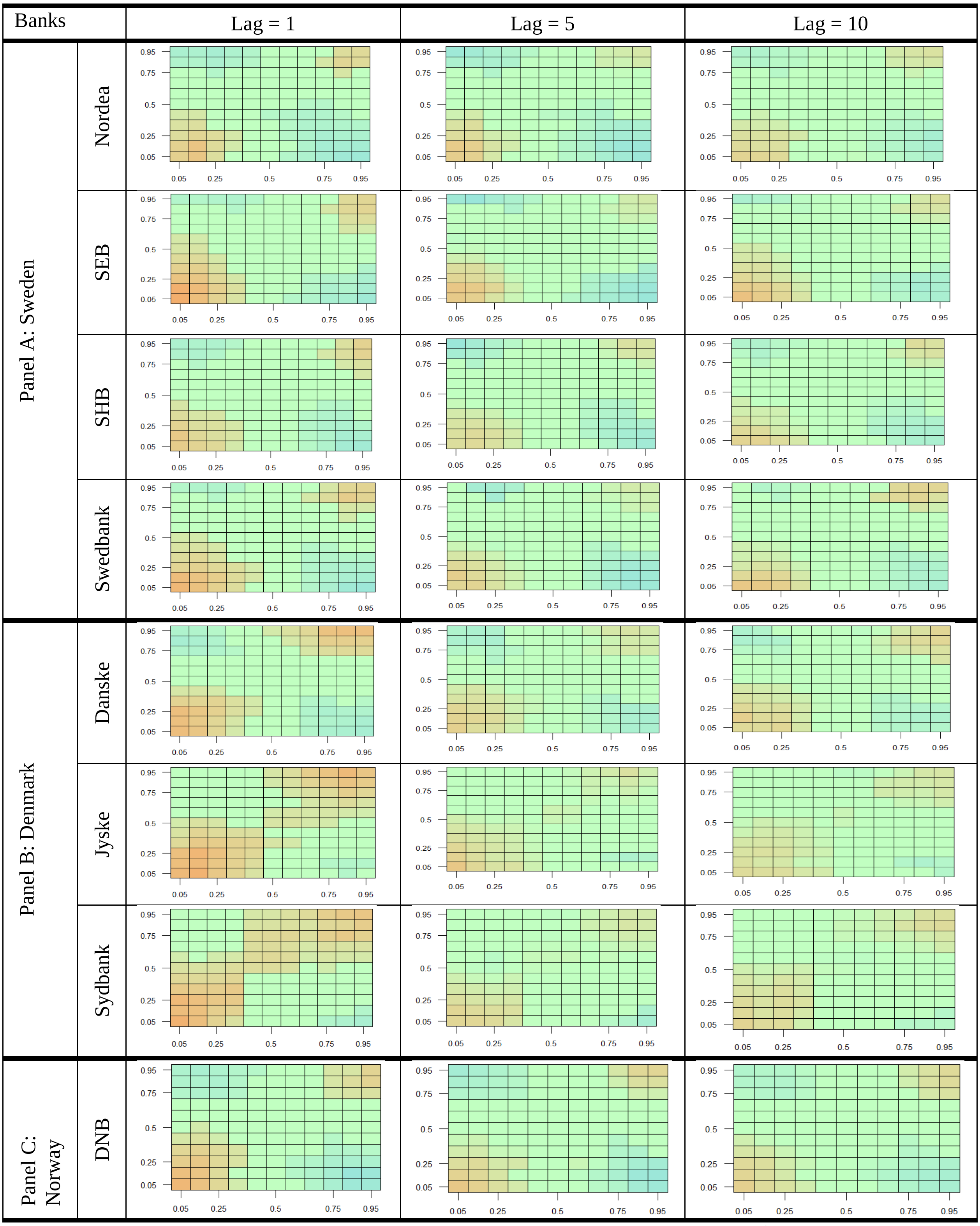
Figure 3: Cross-quantilogram correlation from individual banks to aggregate banking index

Banks	Lag = 1	Lag = 5	Lag = 10



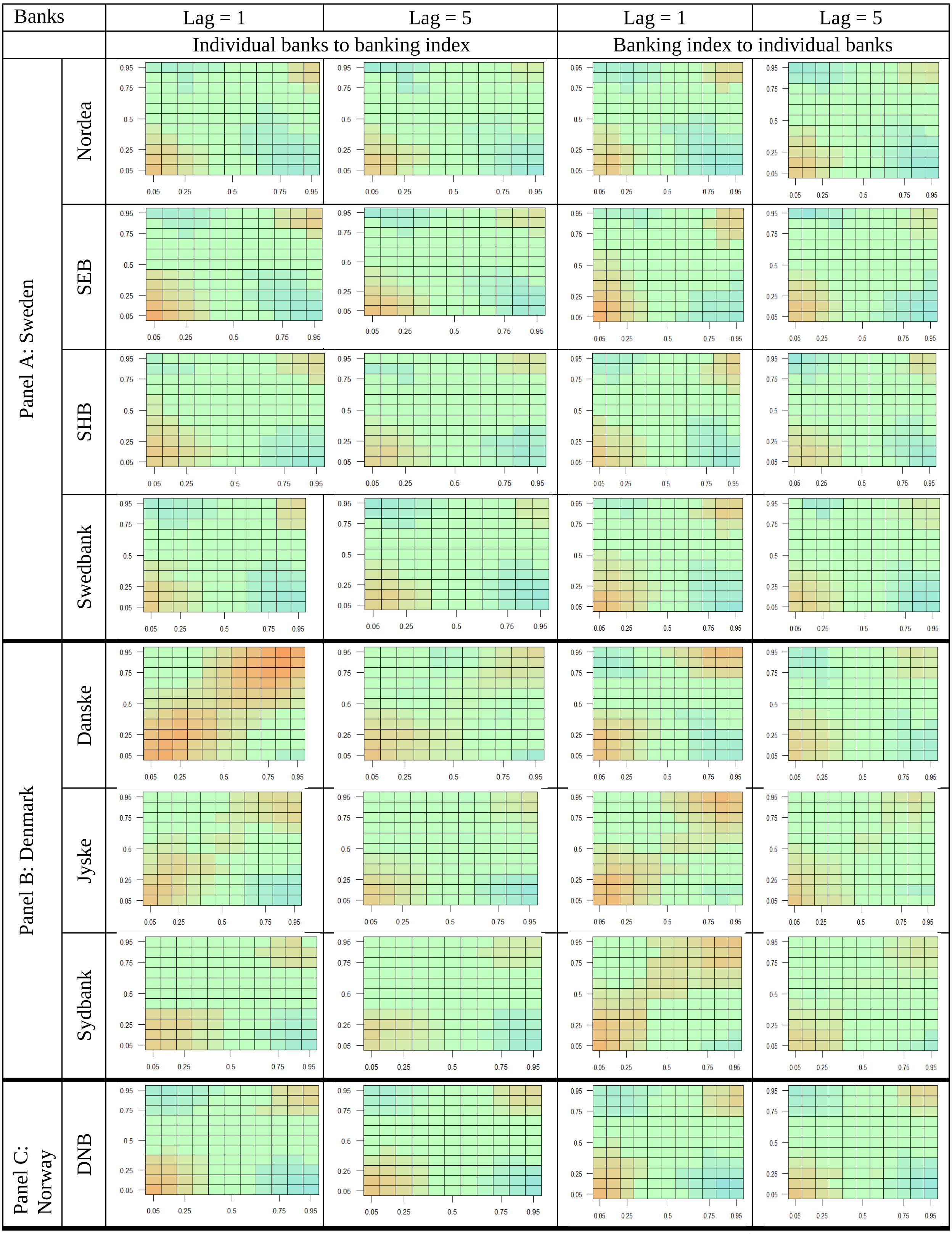
Notes: The cross-quantilogram correlation is estimated using eq. (1) and statistical significance is derived using Box-Ljung test. Colour scale presented in the left indicates the direction of relationships.

Figure 4: Cross-quantilogram correlation from aggregate banking index to individual banks



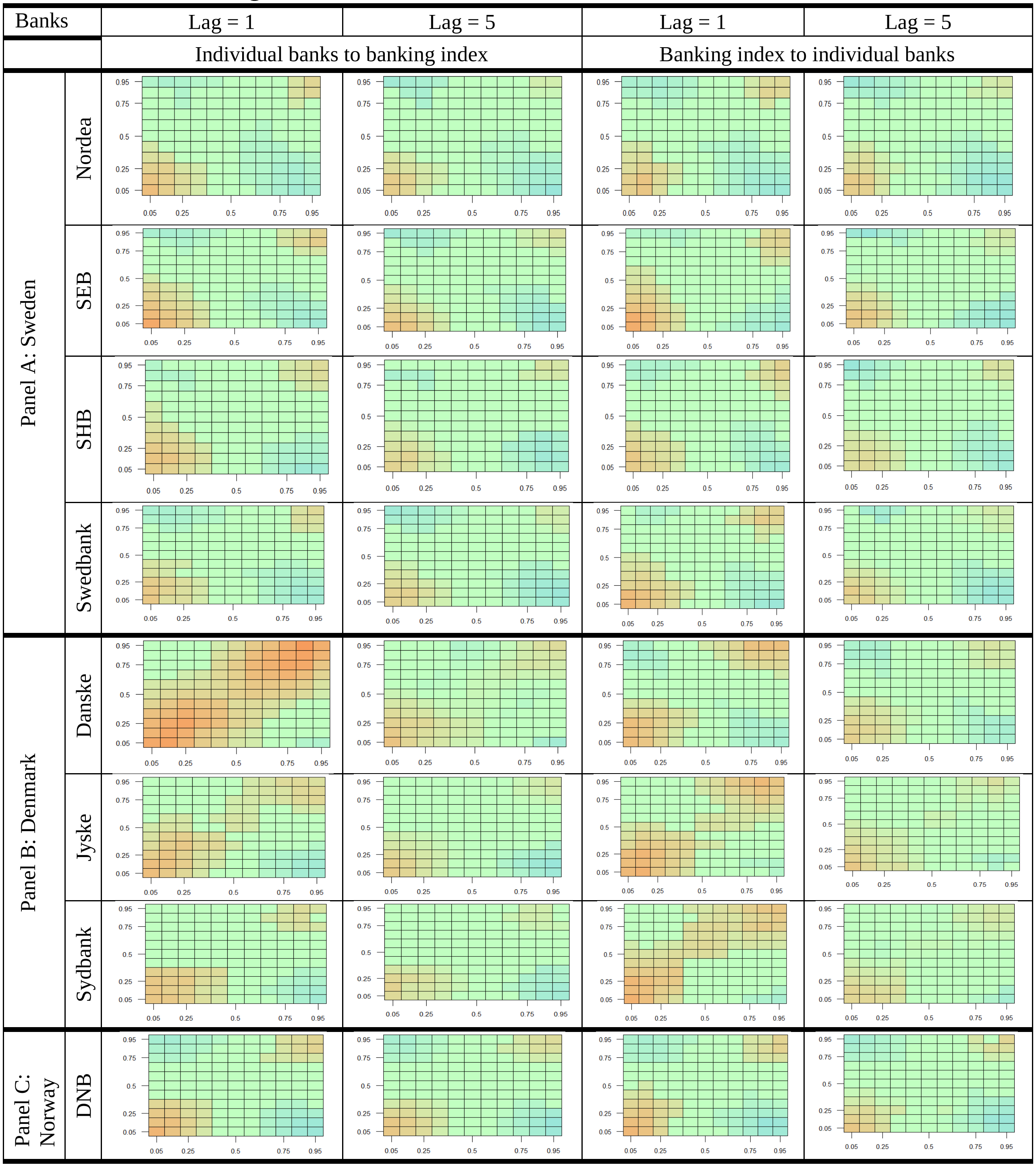
Notes: The cross-quantilogram correlation is estimated using eq. (1) and statistical significance is derived using Box-Ljung test. Colour scale presented in the left indicates the direction of relationships.

Figure 5: Cross-quantilogram correlation between individual banks and aggregate banking Index after controlling VIX



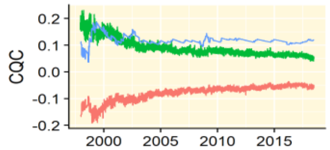
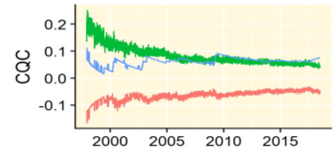
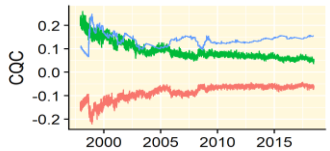
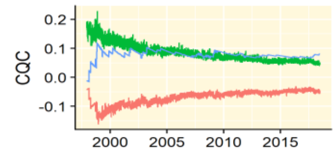
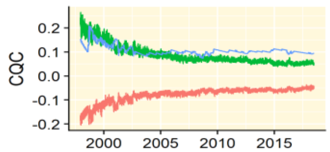
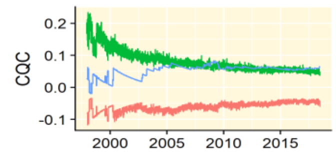
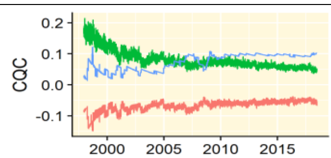
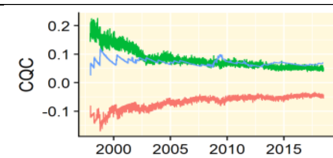
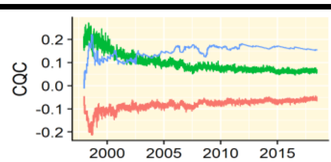
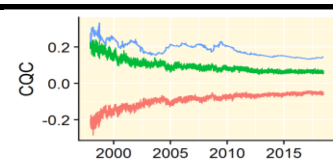
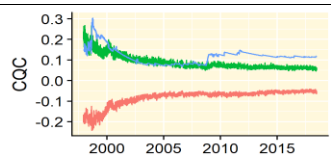
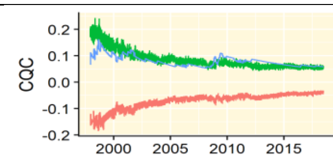
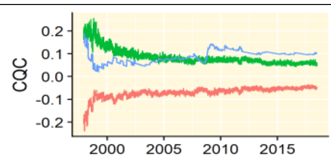
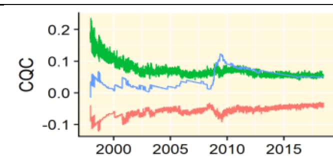
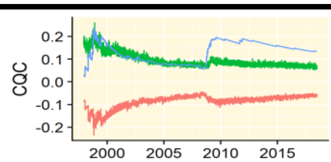
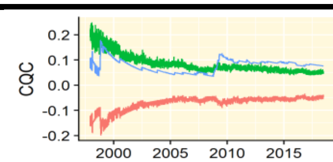
Notes: The cross-quantilogram correlation is estimated using eq. (1) and statistical significance is derived using Box-Ljung test. Colour scale presented in the left indicates the direction of relationships.

Figure 6: Cross-quantilogram correlation between individual banks to aggregate baking index after controlling EPU



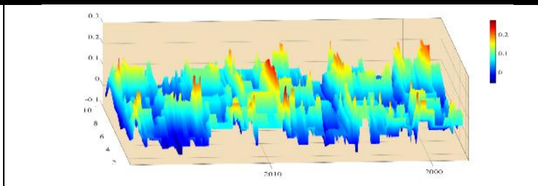
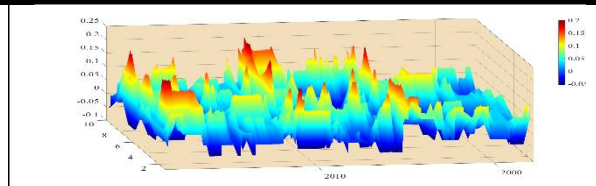
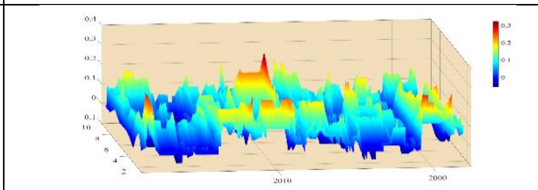
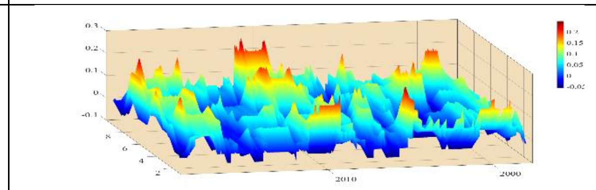
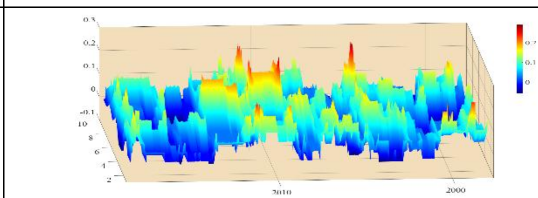
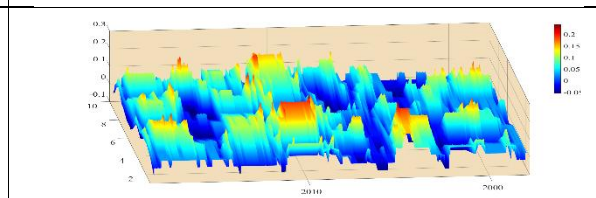
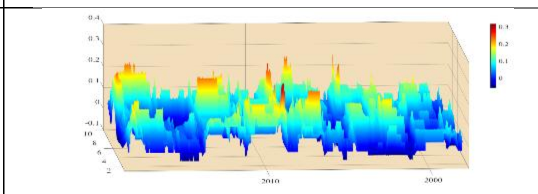
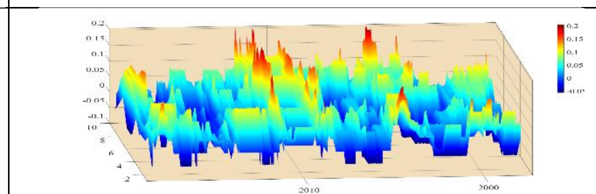
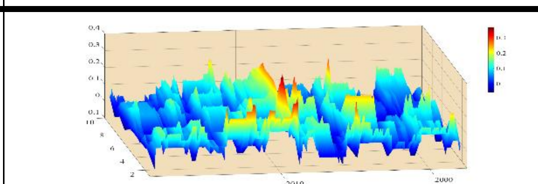
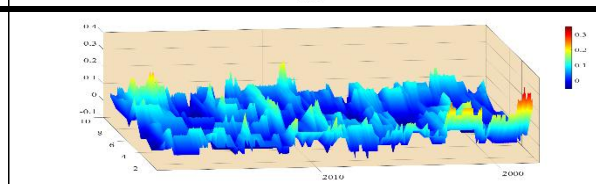
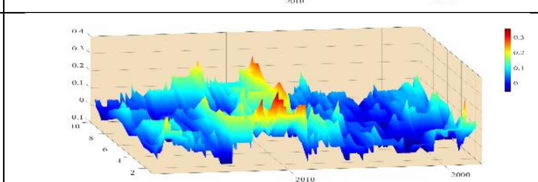
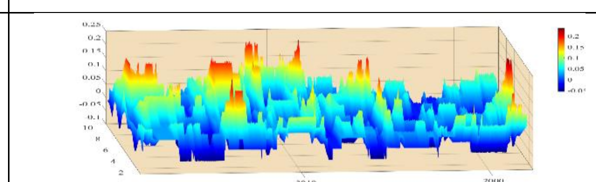
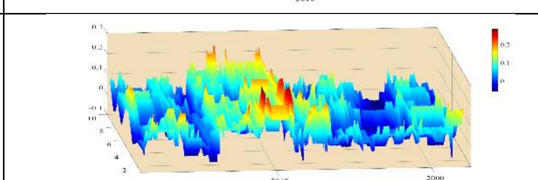
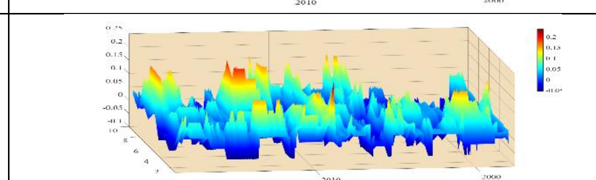
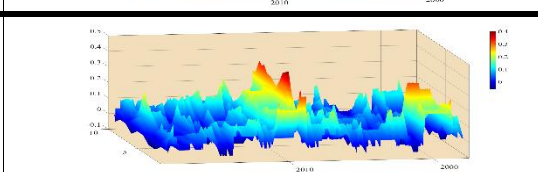
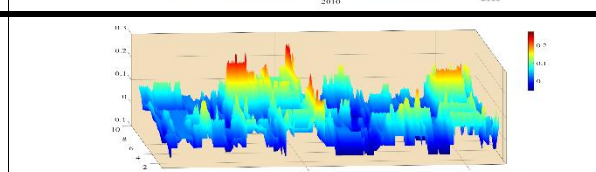
Notes: The cross-quantilogram correlation is estimated using eq. (1) and statistical significance is derived using Box-Ljung test. Colour scale presented in the left indicates the direction of relationships.

Figure 7a: Cross-quantilogram correlation from individual banks to aggregate banking index in recursive subsamples (lag 1)

Banks		[0.05-0.05]	[0.95-0.95]
Panel A: Sweden	Nordea		
	SEB		
	SHB		
	Swedbank		
Panel B: Denmark	Danske		
	Jyske		
	Sydbank		
Panel C: Norway	DNB		

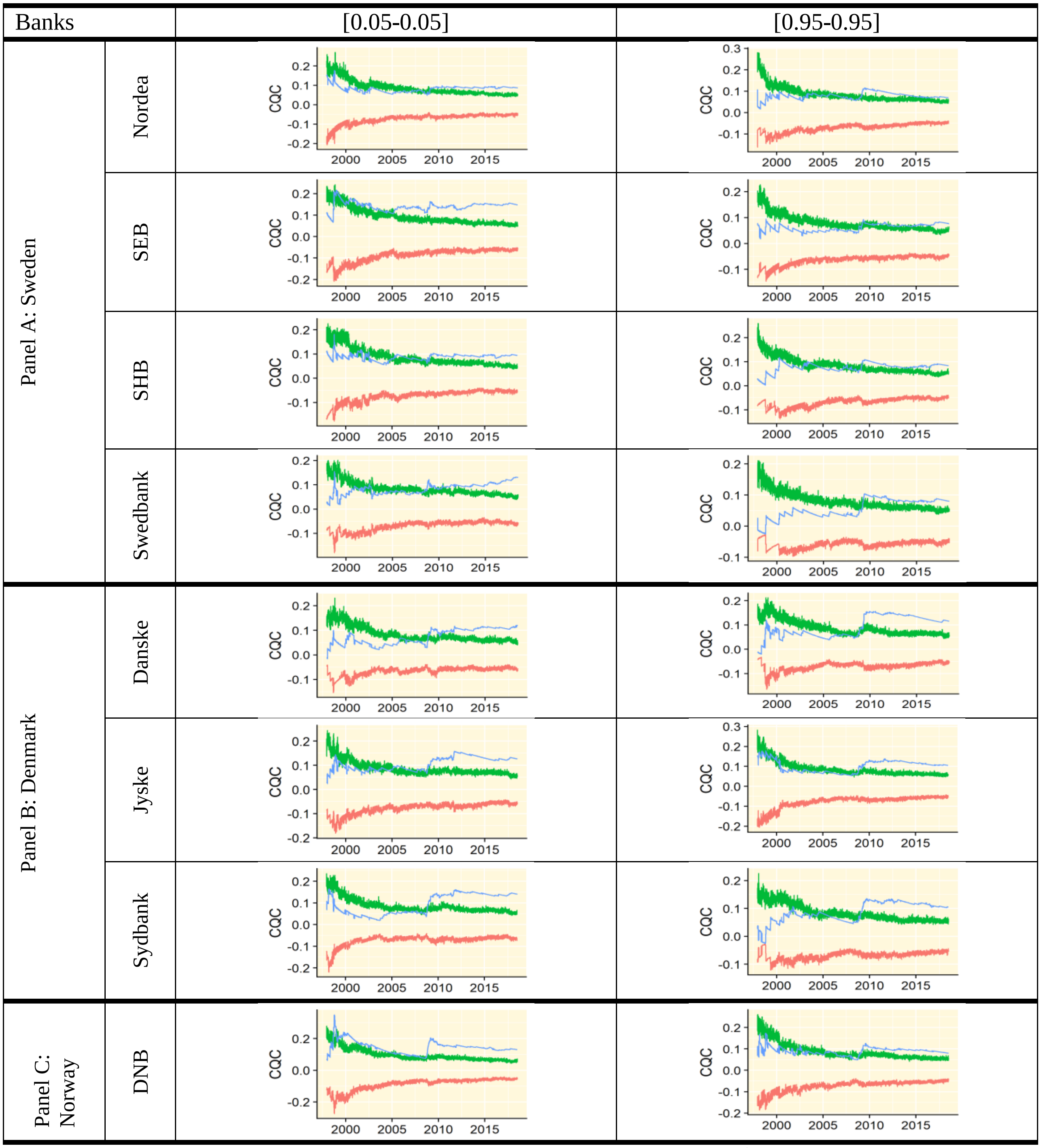
Notes: The recursive sample cross-quantilogram correlation is estimated using eq. (1), with two years of observations (n=504) and one lag. The cross-quantilogram correlation-based directionality goes from aggregate banking index to individual banks. The green and red lines indicate the 95% and 5% significance, respectively. The blue line is the cross-quantilogram correlation and when it cross either the green line from below or the red line from above indicate a statistical significance at the 95% and 5% level respectively.

Figure 7b: Cross-quantilogram correlation from individual banks to aggregate banking index in recursive subsamples (up to lag 10)

Banks		[0.05-0.05]	[0.95-0.95]
Panel A: Sweden	Nordea		
	SEB		
	SHB		
	Swedbank		
Panel B: Denmark	Danske		
	Jyske		
	Sydbank		
Panel C: Norway	DNB		

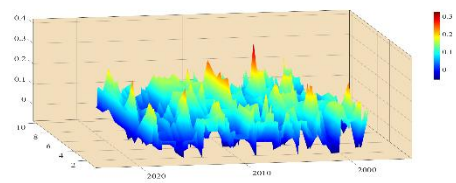
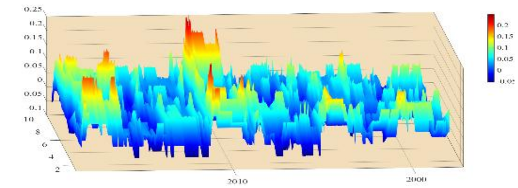
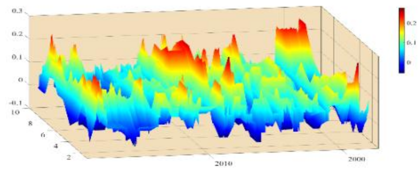
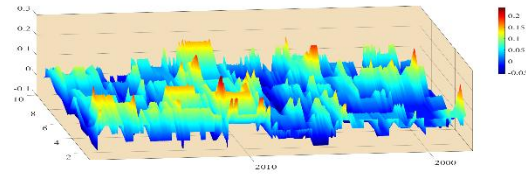
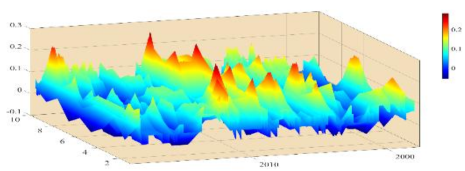
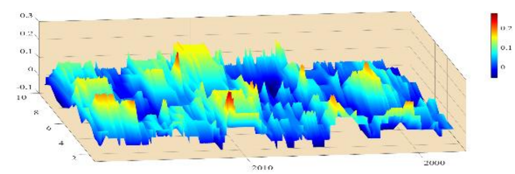
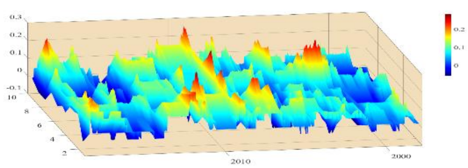
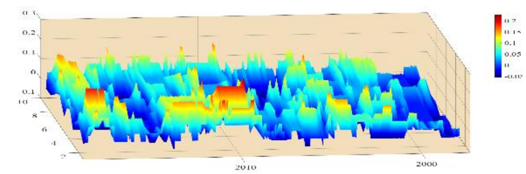
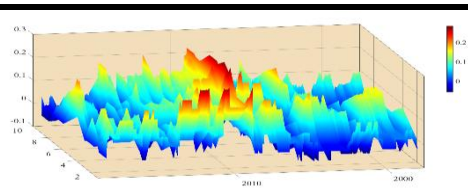
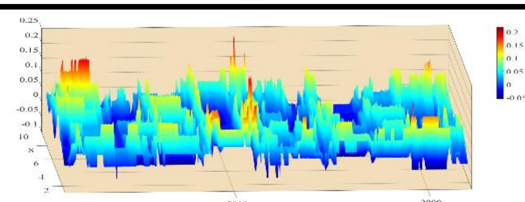
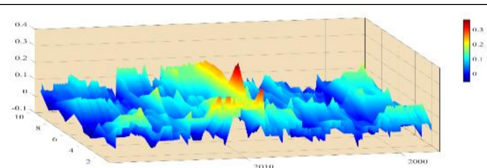
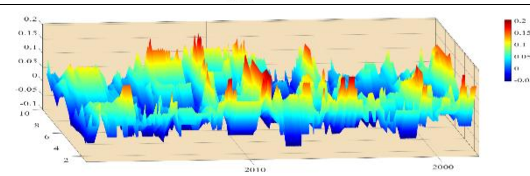
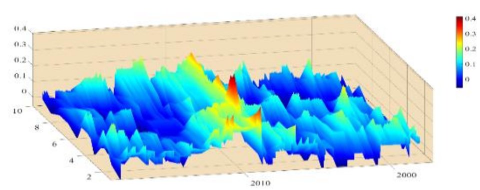
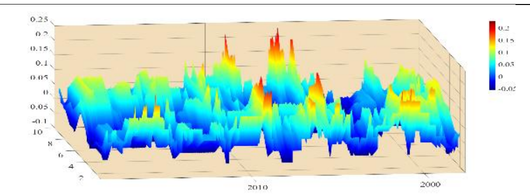
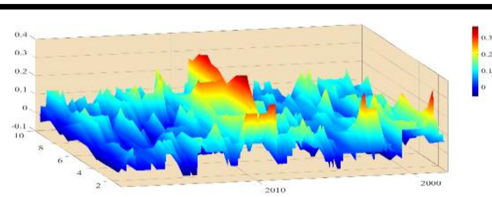
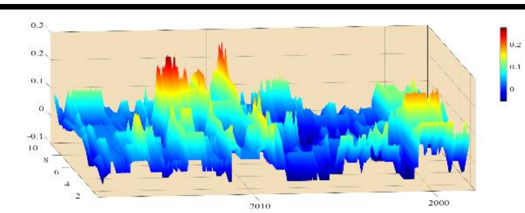
Notes: The recursive sample cross-quantilogram correlation is estimated using eq. (1), with two years of observations (n=504) and ten lag. The cross-quantilogram correlation-based directionality goes from aggregate banking index to individual banks.

Figure 8a: Cross-quantilogram correlation from aggregate banking index to individual banks in recursive subsamples (lag 1)



Notes: The recursive sample cross-quantilogram correlation is estimated using eq. (1), with two years of observations (n=504) and one lag. The cross-quantilogram correlation-based directionality goes from aggregate banking index to individual banks. The green and red lines indicate the 95% and 5% significance, respectively. The blue line is the cross-quantilogram correlation and when it cross either the green line from below or the red line from above indicate a statistical significance at the 95% and 5% level respectively.

Figure 8b: Cross-quantilogram correlation from aggregate banking index to individual banks in recursive subsamples (up to lag 10)

Banks		[0.05-0.05]	[0.95-0.95]
Panel A: Sweden	Nordea		
	SEB		
	SHB		
	Swedbank		
Panel B: Denmark	Danske		
	Jyske		
	Sydbank		
Panel C: Norway	DNB		

Notes: The recursive sample cross-quantilogram correlation is estimated using eq. (1), with two years of observations (n=504) and ten lag. The cross-quantilogram correlation-based directionality goes from aggregate banking index to individual banks.