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Do CDS Spreads Predict Bank Volatility? Evidence from the Swedish Banking Sector

A study on how Credit Default Swaps affect conditional volatility in the Swedish banking sector from 2008-2025.

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Abstract

This thesis investigates whether Credit Default Swap (CDS) spreads predict bank stock volatility in the Swedish banking sector, focusing on Nordea, Swedbank, Handelsbanken, and SEB from July 2, 2008, to April 4, 2025. Employing ARCH-M, GARCH, GJR-GARCH, and EGARCH volatility models within a Vector Autoregressive (VAR) framework, the thesis examines Granger causality across the Global Financial Crisis, the COVID-19 crisis, and the entire sample period 2008-2025. Results show that five-year CDS spreads significantly predict bank-stock volatility, particularly during the GFC, where asymmetric models capture the leverage effect, indicating market inefficiency under the semi-strong Efficient Market Hypothesis. Causality weakens during COVID-19 due to the exogenous nature of the shock and policy interventions. At the same time, the whole sample period shows mixed results, reflecting the averaging of crisis and non-crisis dynamics. Bank-specific patterns highlight Nordea's systemic role during the GFC and Handelsbanken's influence in COVID-19. The findings of the thesis advocate for CDS spreads as a tool in regulatory stress-testing and investor risk management, particularly in Sweden's concentrated banking sector.

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1. Introduction

1.1 Background

The Global Financial Crisis showcased how shocks to the banking sector can swiftly transmit to broader financial systems. Sweden was no exception in this case; share prices of its four major banks dropped, with SEB and Swedbank, the banks with Baltic exposures, experiencing the steepest declines out of the four (Sveriges Riksbank, 2008). This decline in share prices reflected investor uncertainty and triggered rising credit risk, as measured by widening credit default swaps (CDS) spreads (IMF, 2008). Since CDS spreads influence banks' perceived risk and affect lending conditions, an increase in CDS spreads contributed to broader financial instability in Sweden's financial system.

The concurrent movements in equity volatility and CDS spreads show evidence of the role of bank stock prices as systemic risk indicators in market relationships, which this thesis investigates within a Swedish context. Recognising stock market volatility as a key measure of financial conditions, the Riksbank frequently references the VIX volatility index as a benchmark for risk appetite in the Swedish market (Asterlind et al., 2020). Since volatility affects investor confidence and banks' ability to raise capital, understanding the drivers of volatility is of substantial policy relevance. This thesis applies a Granger causality framework, a statistical approach going beyond correlation, to investigate the CDS-volatility dynamic. Instead of measuring simple correlation, Granger causality assesses whether lagged values of one time series help improve the forecast of another. If lagged values of CDS spreads enhance the prediction of bank stock volatility, this would suggest that credit market conditions contain information about future equity risk. The approach is particularly suitable for systemic risk research, as it captures potentially causal linkages between the two indicators. In a banking system as concentrated as Sweden's, where the four major banks account for a dominant share of domestic lending (Sveriges Riksbank, 2024), identifying predictive power is crucial for anticipating how financial stress could affect the banks.

Focusing on the banking sector is especially important in Sweden, where the four major banks, Handelsbanken, Nordea, SEB, and Swedbank, collectively account for approximately 70 percent of domestic lending (Sveriges Riksbank, 2024). Given their systemic importance, distress in any one institution could rapidly trickle down, affect the whole banking system, and

pose risks to the broader financial sector in Sweden. Recent research also highlights significant tail dependence among the returns of Scandinavian banks during stress episodes, suggesting an elevated potential for contagion between the banks (Hedström et al., 2022). While previous literature has demonstrated predictive relationships between CDS spreads and volatility (Ballester et al., 2021; Zhang et al., 2025), as understood from the reading, there remains a lack of focused empirical evidence on whether Swedish bank CDS spreads similarly forecast domestic bank-stock volatility. This thesis aims to fill the gap and analyze how well CDS spreads predict volatility in the stock prices of Swedish banks.

1.2 Research Question and Scope

This thesis analyzes Granger causality between CDS spreads and different measures of conditional volatility in the Swedish banking sector, and examines whether the relationship is time-varying. There are a few reasons for focusing on Sweden. First, while extensive research exists on credit volatility linkages in the U.S. and broader euro area, there is, as understood, a lack of research on the subject in Sweden. Furthermore, Sweden has readily available data on CDS spreads and stock prices. Second, the four largest Swedish banks, Swedbank, Nordea, SEB, and Handelsbanken, account for about 70% of domestic lending as previously mentioned, and these banks differ in business models and funding structures, making Sweden a compelling sample for studying how CDS spreads affect equity volatility.

Furthermore, the data is limited from 2008 to 2025. 2008 marked the year when there was readily available data on CDS spreads on Swedish banks. The two questions that will be answered in this thesis are as follows:

- Do changes in Swedish bank CDS spreads Granger-cause the conditional volatility of the other big Swedish banks' stock prices?

- Is the relationship varying over time or static?

To address these questions, we employ CDS spread data from S&P Global and different conditional volatility measures of stock volatility with stock prices from Yahoo Finance. By extending existing empirical methodologies to the Swedish banking sector, this thesis aims to generate insights with practical implications for academic researchers, financial regulators, and risk managers.

The structure of the thesis is as follows. Section two reviews the relevant literature and provides a technical explanation of the conditional volatility models and Granger causality concepts employed in the analysis. This is followed by an explanation of the data in section three, which describes the data sources, outlines the variables used, and details the procedures for transforming and preparing the data. The methodology in section four then explains how the models are implemented, including model specification, estimation strategies, and criteria for lag selection. The results in section five report the empirical findings of the VAR models and Granger causality tests. Additionally, the analysis in section six interprets these results in light of the research questions and broader economic context. Finally, the thesis concludes by summarizing the key findings, acknowledging limitations, and offering suggestions for future research in section seven.

2. Previous research

This section emphasizes previous research on CDS spreads and conditional volatility, as well as the Swedish banking sector, in section 2.1. Furthermore, section 2.2 discusses the models and explains the theory behind them to give the reader a firm grasp of the literature and theories so that they can better understand the conclusions presented.

2.1 Literature review

Credit Default Swap (CDS) spreads have consistently demonstrated their value as forward-looking credit risk indicators in the banking sector. Avino et al. (2019) illustrate this predictive power in the United States and Europe, highlighting the comparative performance of CDS spreads over traditional accounting-based and equity-based indicators. Similarly, Avino and Cotter (2014) find that bank CDS contracts are similar in terms of informative ability to sovereign CDS, especially in stable economies like Sweden. In the U.S. context, Huang (2019) reports cointegration among the log-level CDS spreads of the six largest U.S. banks, suggesting long-term co-movement in perceived default risk and reinforcing the notion of systemic interconnectedness in the financial sector.

This predictive capacity of CDS premia extends into equity markets. Ballester et al. (2021), using a rolling VAR-GARCH model, document that sovereign CDS returns Granger-cause conditional stock index volatility across European and U.S. markets, particularly under crisis conditions. Trutwein and Schiereck (2011) further show that while equity prices of U.S. banks led to the prediction of CDS spreads during calm periods, the relationship shifted during the 2008 financial crisis, becoming contemporaneous and tightly linked with implied volatility. Likewise, Roberts et al. (2016) find strong bidirectional Granger causality between corporate CDS indices and various exchange rates, emphasising the broader informational role of CDS in financial markets.

CDS instruments are a subset of credit derivatives, first introduced in the mid-1990s as over-the-counter contracts that transfer credit risk between parties (Shim and Zhu, 2013). Functionally analogous to insurance, a CDS contract obliges the protection seller to compensate the buyer if a credit event occurs, in exchange for regular premium payments referred to as the CDS spread (Ericsson et al., 2009). CDS contracts serve both hedging and trading purposes. For hedging, they isolate credit risk from other exposures such as interest rate and currency risk, allowing institutions to manage credit exposure without liquidating the

underlying assets (Naifar & Abid, 2005). For trading, they enable the redistribution of credit risk across market participants, from those seeking to reduce exposure to those willing to take it on.

Despite the benefits, the global financial crisis showed structural weaknesses in the CDS market, including poor transparency and inadequate management of counterparty risk (Gupta, 2012). These vulnerabilities prompted regulatory responses, such as revised capital requirements for structured credit positions under Basel regulations (ECB, 2009). Nevertheless, the European Central Bank (2009) acknowledges that CDS have contributed to improved market completeness and more efficient risk pricing, particularly for illiquid assets.

Given this context, employing bank CDS spreads as a proxy for bank risk is a widely accepted approach in the literature. In line with prior studies (Eichengreen et al., 2012; Yang and Zhou, 2013), this thesis utilizes a five-year CDS contract, the most actively traded maturity, to capture market perceptions of bank creditworthiness and explore their relationship with stock market volatility.

Avşarıgil and Turğut (2021) show short-run causality from equity to CDS in India and Turkey, but cointegration only in the latter, highlighting the role of institutional quality and market depth. A small, highly regulated, bank-centric economy like Sweden's may behave differently due to its structural characteristics.

Accurately modeling volatility is essential to understanding risk dynamics in financial markets correctly. As Andersen et al. (2006) emphasize, "measuring and forecasting volatility is arguably among the most important pursuits in empirical asset pricing, finance, and risk management." Financial time series data, particularly asset returns, frequently exhibit conditional heteroskedasticity, where volatility varies over time rather than remaining constant. Heteroskedasticity often appears as volatility clustering, with turbulent periods followed by more turbulence, and calm periods by continued stability. As Engle (1982) demonstrated, ignoring such time-varying volatility violates the homoskedasticity assumption of the classical Gauss-Markov model. Heteroskedasticity can lead to inefficient parameter estimates, inflated standard errors, and unreliable results.

Various econometric models have been developed over the past four decades to address heteroskedasticity. Engle's (1982) ARCH model was extended by Bollerslev (1986) into the GARCH framework, which improved the ability to capture persistence in volatility. However,

standard GARCH assumes symmetrical responses to shocks, an assumption that often fails in financial markets, where adverse shocks tend to trigger stronger volatility reactions than positive ones. To incorporate these asymmetries, models such as EGARCH (Nelson, 1991), which uses the logarithm of variance, and GJR-GARCH (Glosten et al., 1993), which introduces indicator terms for adverse shocks. Another significant extension is the ARCH-M model (Engle et al., 1987), which integrates volatility directly into the mean equation, allowing risk to influence expected returns.

These advanced volatility models have become essential tools for analyzing systemic risk, investor behavior, and financial market dynamics, especially during heightened uncertainty. In the context of this thesis, which investigates the relationship between bank CDS spreads and stock market volatility, accounting for heteroskedasticity is necessary for drawing valid conclusions.

Furthermore, CDS markets have proven comparable to bond markets in information transmission. Delatte et al. (2012) and Coudert et al. (2013) confirm that CDS spreads offer similar price discovery to corresponding bond yields, particularly in financial institutions.

Previous literature offers an essential rationale for investigating CDS premia as early-warning indicators in Sweden. Swedish policymakers, including the Riksbank, already incorporate VIX-adjusted equity volatility into macro assessments (Asterlind et al., 2020; Frykström, 2022). If Swedish bank CDS spreads are shown to Granger-cause conditional volatility, then CDS spreads could be incorporated into regulatory stress-testing frameworks.

In conclusion, the literature shows that CDS spreads are potent indicators of credit risk and volatility on the financial markets, as in Ballester et al. (2021). However, when exploring the literature, no papers investigated the causal relationship between CDS spreads and volatility in Sweden's concentrated banking system. By examining whether shocks to five-year senior CDS premia Granger-cause conditional volatility are estimated via GARCH, EGARCH, GJR, and ARCH-M, this thesis addresses that gap. It presents findings directly relevant to Swedish financial regulators.

2.2 Theories and models

2.2.1 Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH) is a central theory in modern financial economics. It proposes that financial markets are informationally efficient. According to this theory, asset prices at any given time fully incorporate all available information, making it impossible for investors to consistently achieve returns that exceed average market returns on a risk-adjusted basis without assuming additional risk (Fama, 1970). EMH is commonly articulated in three forms: weak, semi-strong, and strong. Each represents a different level of market efficiency and has distinct implications for investment strategies.

Weak-form efficiency asserts that all historical market data, such as past prices and trading volumes, are already reflected in current asset prices. Consequently, techniques based on technical analysis, which attempt to forecast future price movements using historical trends and patterns, are ineffective in generating persistent excess returns under this form of market efficiency.

Semi-strong-form efficiency extends this view by positing that all publicly available information, such as corporate financial statements, macroeconomic indicators, and media reports, is rapidly and accurately incorporated into market prices. Under this form, neither technical nor fundamental analysis can provide a consistent advantage, as the market adjusts almost instantaneously to new public information.

EMH is incorporated into this thesis because it provides a theoretical benchmark for interpreting the relationship between CDS spreads and stock market volatility. If the market were efficient, new information such as shifts in credit risk reflected by CDS spreads would be instantaneously incorporated into stock prices and volatility measures, leaving no room for predictive power. However, evidence that CDS spreads Granger-cause changes in volatility contradicts the semi-strong form of EMH, suggesting that markets do not constantly adjust instantaneously or completely to new credit risk signals. Implying a degree of informational inefficiency in equity markets. Hence, testing the Granger-causal role of CDS spreads offers empirical insight and a critical challenge to one of the most central theories in financial economics.

2.2.2 Economic Rationale for Volatility and VAR Models.

To investigate whether CDS spreads Granger-cause bank stock volatility, this thesis employs conditional volatility models (ARCH-M, GARCH, GJR-GARCH, EGARCH) to capture time-varying risk in stock prices in Sweden's concentrated banking sector, which closely follows the method proposed by Ballester et al. (2021) using GARCH, GJR, and EGARCH but with the addition of ARCH-M. The specifics and other changes are discussed in section four of the essay. The ARCH-M model is included because it accounts for the risk-return trade-off, where higher volatility increases expected returns, as seen during crises (Engle et al., 1987). However, it doesn't deal with asymmetric effects. GARCH captures volatility clustering, a trademark of financial time series (Bollerslev, 1986). The asymmetric effect of negative shocks captured by GJR-GARCH and EGARCH models, commonly called the leverage effect, is particularly relevant during periods of financial distress, such as the Global Financial Crisis (GFC). GJR, GARCH, and EGARCH were picked as they were core measures in Ballester et al. (2021). Not only do they give a comparative effect of when accounting for asymmetry or not, but they also give a direct comparison to Ballester et al. (2021) results, who found that models that account for asymmetry have more Granger-causal relationships than models that don't. These volatility estimates are then used in a Vector Autoregressive (VAR) framework as the dependent variable to test Granger causality, assessing whether lagged CDS spreads predict future volatility and capturing interdependencies among the four major banks. This approach is suitable for Sweden's banking sector, where systemic risk can propagate due to the dominance of four major banks (Sveriges Riksbank, 2024).

2.2.3 GARCH – Generalized ARCH

This extension of the ARCH model includes p lags of the conditional variance in the equation and q lags of the squared residuals. The GARCH (p, q) model is given as explained by Bollerslev (2009).

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \qquad (1)$$

Where:

- $\sigma_t^2 = Conditional\ variance$

- $\omega = Constant\ term$
- $\sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 = ARCH\ term\ capturing\ effect\ of\ q\ lags\ of\ squared\ residuals$
- $\sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 = GARCH\ term\ capturing\ persistance\ of\ variance\ up\ to\ p\ lags$

The importance of including GARCH in this section lies in the fact that GARCH isolates the pure volatility clustering aspect of heteroskedasticity, even when the sign of the volatility is ignored. By comparing CDS Granger causality on volatility under GARCH with the more complex models, one can benchmark and compare how much of the volatility is driven by simple volatility clustering versus asymmetry or risk-premium feedback when we use GJR, EGARCH, or ARCH-M, which will be explained in the section.

2.2.4 EGARCH – Exponential GARCH

Nelson (1991) developed the EGARCH model, which introduces asymmetries in the relationship between returns and volatility, a feature also explored in models like GJR and TGARCH. Thus, the general model for EGARCH (1,1) can be explained as follows, written in Bollerslev (2009) compendium.

$$\log(\sigma_t^2) = \omega + a\big(\lceil z_{t-1} \rceil - \mathrm{E}(\lceil z_{t-1} \rceil)\big) + \gamma z_{t-1} + \beta \log(\sigma_{t-1}^2) \qquad (2)$$

Where:

- $\log(\sigma_t^2) = Logarithm\ of\ the\ conditional\ variance$
- $\omega = Constant\ term$
- $a\big(\lceil z_{t-1} \rceil - \mathrm{E}(\lceil z_{t-1} \rceil)\big)$= Captures the magnitude effect of shocks where $z_t = \varepsilon_t \sigma_t^{-1}$
- $\beta \log(\sigma_{t-1}^2) = Logarithnm\ of\ the\ volatility\ persistance\ over\ time$
- $\gamma z_{t-1} = Assymetric\ leverage\ effect\ if\ \ \gamma <$ $0\ negative\ shocks\ has\ greater\ effect\ on\ volatility$

When $\gamma<0$, adverse shocks exert a more significant influence on future volatility than positive shocks of the same magnitude. This effect, often observed empirically in returns, is known as the leverage effect.

By modeling the logarithm of the conditional variance, rather than the variance directly, the EGARCH model avoids the need to impose positivity constraints on the process. However, using a logarithmic transformation also complicates the construction of unbiased forecasts for the level of future variances.

Additionally, the importance of having EGARCH lies in accounting for the magnitude of the asymmetry effect, while GJR is sign-dependent. That is, if the shock is positive or negative, EGARCH takes into account the magnitude of the negative shock, providing yet another insight stressing its importance in the thesis.

2.2.5 GJR-GARCH

The GJR-GARCH model, developed by Glosten et al. (1993), extends the standard GARCH framework by allowing the conditional variance to respond asymmetrically to past negative and positive innovations. The GJR(1,1) model can be specified as explained by Bollerslev (2009) compendium.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \beta\sigma_{t-1}^2 \qquad (3)$$

Where:

- $\sigma_t^2 = The\ conditional\ variance$
- $\omega = Constant\ term$
- $\alpha\varepsilon_{t-1}^2$= Captures the symmetric effect of lagged squared residuals
- $\gamma\varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) = Captures\ assymetry\ by\ an\ indicator\ function = 1\ if\ \varepsilon_{t-1} < 0$
- $\beta\sigma_{t-1}^2 = GARCH\ term\ capturing\ volatility\ clusetring$

Where I(·) is the indicator function. This formulation is sometimes referred to as the Sign-GARCH model. The GJR model is closely related to the Threshold GARCH (TGARCH) model proposed independently by Zakoian (1994) and to the Asymmetric GARCH (AGARCH) model of Engle (1990).

When applied to returns, the parameter γ is typically positive, indicating that adverse shocks increase volatility more than positive shocks of the same magnitude. This behavior is often labeled the "leverage effect," although it is now generally recognized that the observed asymmetry is not necessarily due to actual financial leverage.

Credit shocks are typically counted as negative news, so their impact on volatility is expected to be bigger than that of positive news. A GARCH model does not account for this because GARCH treats positive and negative shocks equally. Ignoring this asymmetry can lead to biased volatility estimates and a misrepresentation of risk, particularly during periods of financial stress.

GJR-GARCH, by contrast, assigns additional weight to adverse shocks $\gamma\varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0)$. Including the GJR specification, therefore, allows the thesis to capture the asymmetry of shocks, which is vital to getting an accurate picture of volatility.

Using GJR and EGARCH provides robustness, as both account for asymmetric effects in different ways. Therefore, if accounting for asymmetric effects provides any benefits, this further emphasizes the validity of the results.

2.2.6 ARCH-M

The ARCH-M model, introduced by Engle, Lilien, and Robins (1987), was used to model risk-return trade-offs in U.S. interest rate terms and was later applied to financial derivatives. It extends the ARCH regression framework of Engle (1982) by allowing the conditional mean to depend directly on the conditional variance, as explained by Bollerslev (2009).

$$(y_t|\mathrm{F}_{t-1}) \sim N\left(x_t'\beta + \delta\sigma_t^2, \sigma_t^2\right) \quad (4)$$

Where:

- $y_t = Dependent\ variable$
- $\mathrm{F}_{t-1} = Information\ set\ available\ at\ t-1$
- $\beta = Vector\ of\ coefficent\ associated\ with\ x$
- $x_t' = Vector\ of\ explanatory\ variables$
- $\sigma_t^2 = Conditional\ variance\ at\ time\ t$
- $\delta\sigma_t^2 = Influence\ conditional\ variance\ has\ on\ mean$

The equation states that the mean depends on the time-varying volatility and that error terms are normally distributed with mean $x_t'\beta + \delta\sigma_t^2$ and variance σ_t^2.

In their final preferred specification, Engle, Lilien, and Robins (1987) model the conditional mean as a function of $\log(\sigma_t^2)$

When bank equity returns during crises become increasingly risky, investors also demand a higher expected return for holding those riskier shares. ARCH-M is a way to incorporate this relationship, allowing the conditional variance to be incorporated into its returns. If a widening CDS spread drives a sudden jump in conditional variance, ARCH-M immediately translates that jump into a higher required return. The model, therefore, captures the risk-return adjustment mechanism, not just the volatility side, which is why it is essential to have in the context of the essay, looking at bank stocks. However, accounting for the risk to return ARCH-M does not account for asymmetric effects.

The estimated conditional volatilities models throughout section 2.2 are used in the methodology for the Vector Autoregressive (VAR) framework described in Chapter 4, where the relationship between volatility and CDS spreads between banks is examined using Granger causality.

2.2.7 Granger causality & VAR Model

The four conditional volatility models above give us the risk of the banks' stock prices. We insert each bank's CDS into the VAR model to see how that risk is affected by other banks' CDS.

Employing a Vector Autoregressive (VAR) framework to investigate Granger causality between credit default swap (CDS) spreads and conditional volatility in the Swedish banking sector. Granger causality, first introduced by Granger (1969), is a concept that examines whether past values of one time series contain predictive information about the future values of another. Specifically, variable X is said to Granger-cause variable Y if the inclusion of lagged values of X significantly improves the prediction of Y beyond the explanatory power of Y's lags. Importantly, this form of causality is more informational rather than causality in the philosophical sense (Granger, 1980).

In the context of this thesis, Granger causality is tested within a multivariate VAR model to assess the directional relationships between CDS spreads and stock return volatility across Sweden's four major banks: Swedbank, SEB, Nordea, and Handelsbanken. A VAR model expresses each variable in the system as a function of its own past values and those of all other variables, thereby capturing the dynamic interdependence (Sims, 1980) and enabling a joint estimation of interactions between conditional volatility and credit risk indicators over time.

Rather than estimating isolated bivariate systems, a multivariate VAR specification is employed, whereby the volatility of a given bank (denoted as Bank A) is regressed on its own lags, its own CDS spreads, and the lagged CDS spreads of the three peer banks. Facilitating the analysis of cross-institutional risk transmission and allowing for a comprehensive examination of systemic interdependence. The general specification of the model for Bank A's conditional volatility is given by:

$$\sigma_{A,t}^2 = \alpha_0 + \sum_{k=1}^{p} \alpha_{1k}\sigma_{A,t-k}^2 + \sum_{k=1}^{p} \alpha_{2k} CDS_{A,t-k} + \sum_{k=1}^{p} \alpha_{3k} CDS_{B,t-k} + \sum_{k=1}^{p} \alpha_{4k} CDS_{C,t-k} + \sum_{k=1}^{p} \alpha_{5k} CDS_{D,t-k} + \varepsilon_t \quad (5)$$

Where

- $\sigma_{A,t}^2 = Conditional\ volatility\ for\ bank\ A$
- $\sum_{k=1}^{p} \alpha_{1k}\sigma_{A,t-k}^2 = Conditional\ volatility\ for\ bank\ A\ up\ to\ p\ lags$
- $\sum_{k=1}^{p} \alpha_{2k} CDS_{A,t-k} = Credit\ default\ swap\ spread\ for\ bank\ A\ up\ to\ p\ lags$
- $\sum_{k=1}^{p} \alpha_{3k} CDS_{B,t-k} = Credit\ default\ swap\ spread\ for\ bank\ B\ up\ to\ p\ lags$
- $\sum_{k=1}^{p} \alpha_{4k} CDS_{C,t-k} = Credit\ default\ swap\ spread\ for\ bank\ C\ up\ to\ p\ lags$
- $\sum_{k=1}^{p} \alpha_{5k} CDS_{D,t-k} = Credit\ default\ swap\ spread\ for\ bank\ D\ up\ to\ p\ lags$
- $\varepsilon_t = Error\ term$

This structure tests whether the lagged CDS spreads of banks B, C, and D Granger-cause changes in bank A's conditional volatility. A statistically significant coefficient in the Granger causality test on any of the lagged CDS variables provides evidence of predictive credit risk transmission, indicative of information flow across institutions.

The Bayesian Information Criterion (BIC) determines the optimal lag order to ensure appropriate lag selection and mitigate risks of overfitting, as in AIC. BIC is favored over the Akaike Information Criterion (AIC) in this thesis because it imposes a stricter penalty on model complexity, thereby encouraging parsimony (Schwarz, 1978). While AIC often selects models with better in-sample fit, it may result in overparameterization, particularly in finite samples (Neath & Cavanaugh, 2012). The two information criteria are defined as follows:

:

$$AIC = -2\ln(\mathcal{L}) + 2k \quad (6)$$

$$BIC = -2\ln(\mathcal{L}) + kln(n) \quad (7)$$

$where$:
$\mathcal{L} = maximised\ value\ of\ the\ liklehood\ function\ for\ the\ model$
$k = number\ of\ estimated\ paramaters$
$n = sample\ size$

3 Data

The CDS spread data measured in basis points (bps) was collected from S&P Global, from which daily observations were collected for the four largest Swedish banks: Nordea, Swedbank, Handelsbanken, and SEB. The range is from July 2, 2008, until April 4, 2025, with 3200 observations per series. In addition, stock price data were collected from Yahoo Finance, and are computed as the, logged first differences. The conditional volatility ($\sigma^2_{Bank,t}$) as previously explained) is estimated using the volatility model in section 2. Handelsbanken and Swedbank did not have stationary data (see Appendix A), so the first difference was taken from the two credit default swaps to ensure stationarity, which in the results are written as: $\Delta CDS_{Swedbank,t-k}$,$\Delta CDS_{Handelsbanken,t-k}$ where the triangle represents the first difference.

As the stationary properties of the CDS series varied across banks, cointegration tests were not pursued since some CDS were stationary and some were first differentiated to become stationary. Instead, the thesis uses a standard Granger causality framework using VAR and conditional volatility models. A summary of the variables and their descriptive statistics is presented below.

Variable	Type	Observations	Mean	Std. Dev.	Min	Max
Swedbank CDS	5-year CDS spread (bps)	3,200	80.50	57.63	22.47	361.50
Handelsbanken CDS	5-year CDS spread (bps)	3,200	56.30	27.48	19.18	174.21
SEB CDS	5-year CDS spread (bps)	3,200	73.13	46.91	21.10	281.50
Nordea CDS	5-year CDS spread (bps)	3,200	61.10	33.51	19.84	218.35
Handelsbanken	Stock price (SEK)	3,200	90.40	22.02	29.22	136.75
Nordea	Stock price (SEK)	3,200	86.78	22.05	31.48	144.35
SEB	Stock price (SEK)	3,200	87.47	32.87	15.99	177.75
Swedbank	Stock price (SEK)	3,200	154.30	52.05	15.22	266.70

Table 1: Summary statistics

Table 1 reports the summary statistics for the four banks' five-year CDS spreads and stock prices. Swedbank shows the highest average CDS spread among the banks at 80.50 basis points, indicating that market participants have historically priced greater credit risk into its default protection. Conversely, Handelsbanken records the lowest mean spread at 56.30 basis points, which aligns with its conservative reputation. Considerable variation in stock price levels is also observed across the sample. Swedbank's shares not only have the highest average price, but also the most significant standard deviation.

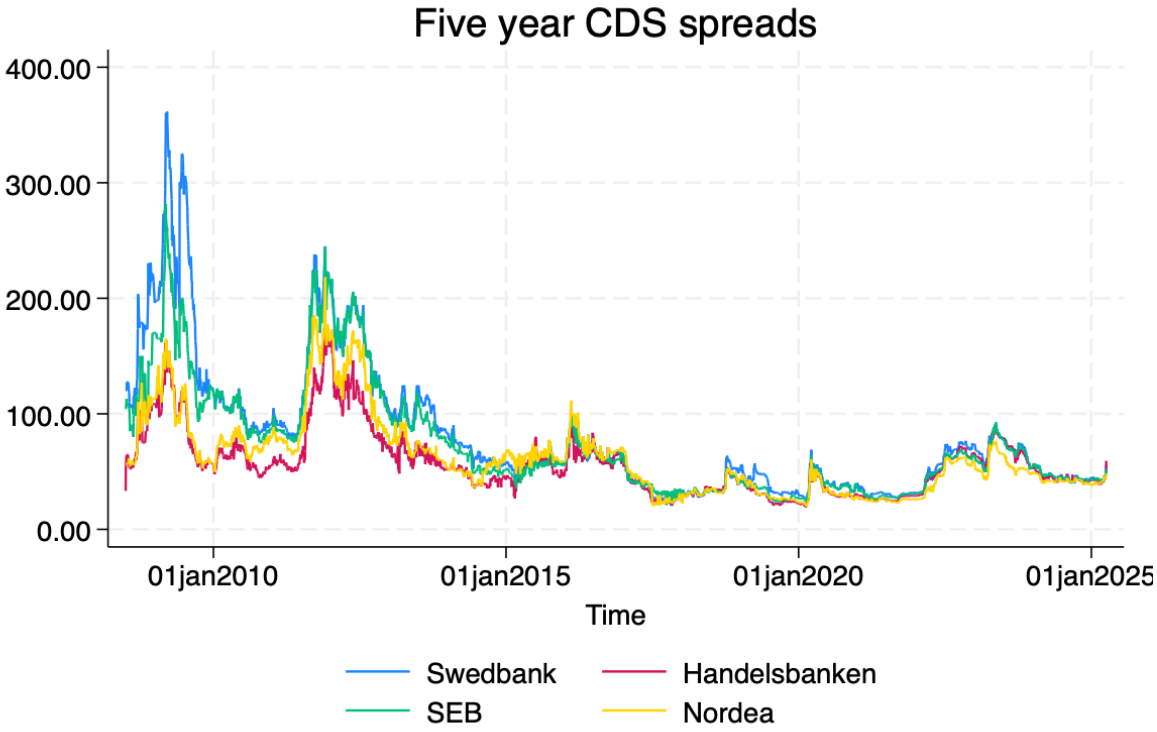

Figure 1: Five-year CDS spreads from 2008 to 2025

Figure 1 shows the five-year CDS spreads for Swedbank, Handelsbanken, SEB, and Nordea over the sample period from July 2008 to April 2025. The figure highlights significant movements during the Global Financial Crisis (2008–2009) and the European sovereign debt crisis (2011–2012). While all banks experienced a sharp increase in spreads during these episodes, Swedbank's and SEB's CDS spreads appear more volatile, while Handelsbanken is the least volatile. After 2014, the graph seems to revert around a mean and does not experience any big jumps similar to 2008-2014.

3.2 Stock Prices

Stock prices were collected as daily prices from Yahoo Finance, covering the period from July 2, 2008, until April 4, 2025. Since none of the stock prices exhibited stationarity (see Appendix A), the logged first difference of the stocks was taken to ensure stationarity.

3.3 Nordea Bank

Nordea is one of the largest financial services groups in the Nordics, with a significant presence in Sweden, Finland, Denmark, and Norway. In 2018, Nordea relocated its headquarters from Stockholm to Helsinki to benefit from being under the European Central Bank's supervisory

framework instead of Swedish banking laws (Ekstrand et al., 2017). However, Nordea remains a key bank in Sweden's banking system (Nordea, 2024). In addition, Nordea's business model allows multiple services to stand out among other Swedish banks, providing private banking, corporate banking, wealth management, pension, and life insurance services, to name a few (Nordea 2025).

3.4 Swedbank

Swedbank holds a dominant position in the Swedish mortgage and retail banking sectors. The bank also has operations in Estonia, Latvia, and Lithuania (Swedbank, 2025). Historically, it has maintained significant operations in these Baltic countries (Swedbank, 2025) and has been associated with conservative lending practices. However, the bank faced reputational damage during the Baltic money laundering investigations (Makortoff, 2022), which raised concerns about the effectiveness of its internal controls and regulatory compliance in the region.

3.5 Handelsbanken

Handelsbanken is recognized for its decentralized management style and strong emphasis on local customer relationships. It has consistently sustained high capitalization levels and low loan loss ratios compared to its peers (Handelsbanken, 2025). Handelsbanken offers banking services outside of Sweden, operating offices in the Netherlands, the UK, and Norway (Handelsbanken, 2024).

3.6 SEB

SEB is a Swedish financial group with a significant presence in corporate and investment banking, asset management, and private banking. SEB focuses on large corporate clients, which in turn could lead to sensitivity to shifts in business cycles and financial market conditions (Skandinaviska Enskilda Banken AB (SEB), 2025).

4 Methodology

The methodology largely follows Ballester et al.'s (2021) approach to evaluating conditional heteroskedasticity, similarly using GARCH, GJR, and EGARCH to identify any similarities. Furthermore, this thesis focuses on the banking sector and aims to identify CDS spreads as a signal for bank risks. Turning towards the specifics of the thesis, the methodology explains the specifics of the essay. More specifically, the methodology is unfolded within three main blocks.

First is diagnostics testing and how we ensured stationarity and dealt with heteroskedasticity; second is the volatility estimations and the specifics of how it is used in the thesis and why. The third part shows the VAR model and discusses how the VAR model is estimated, as well as discussing distinctions from Ballester et al. (2021) method.

4.1 Period Specification

This thesis adopts a period-based approach to study time-varying causality because of the computational limitations associated with using bootstrapped rolling Granger causality algorithms. The selected time intervals aim to compare whether CDS spreads Granger-cause bank stock volatility during different periods of financial distress and also examine potential time variation in the Granger-causal relationship. The adopted time-based structure aligns with earlier research, especially the approach taken by Ballester et al. (2021), which supports the comparability of findings.

Global Financial Crisis (GFC)	July 2, 2008 – September 9, 2009
Covid-19 Crisis	March 10, 2020 – May 16, 2023
Whole sample	July 2, 2008 –April 4, 2025

Table 2: Showing the period specifications

The periods of this thesis are grounded in methodological necessity and theoretical relevance. Given the computational limitations associated with bootstrapped rolling Granger causality algorithms, a period-based approach offers a practical alternative for exploring potential time variation in the causal relationship between CDS spreads and bank stock volatility.

Each period represents a distinct financial environment, enabling an investigation into whether the Granger-causal dynamics shift in response to different shocks to the economic system. The

Global Financial Crisis reflected an endogenous shock with the financial market crashing, and the COVID-19 crisis showed an exogenous shock with the health crisis. Both reflect episodes of heightened economic uncertainty and market volatility. In contrast, the entire sample period serves as a broader benchmark to assess whether any observed causality is persistent over time or confined to specific turbulent intervals.

Furthermore, from the reading, I have not found any inclusion of COVID-19 from start to finish. Although Ballester et al. (2021) include COVID-19, they do not include the whole period from lockdown until the lockdowns were lifted. Exact crisis cut-off dates differ across sources. Therefore, an estimation was made from various news outlets, as there seems to be no official consensus on an actual end or start date for COVID and no exact end date for the GFC.

4.2 Stationarity & Homoskedasticity

Before estimating the models, a diagnostic test for stationarity and volatility clustering was made to ensure valid inference and appropriate model specification. Augmented Dickey-Fuller (ADF) tests were conducted on all variables. The CDS spreads of Swedbank and Handelsbanken were found to be non-stationary and were, therefore, transformed by taking the first difference. Stock prices for all banks also exhibited non-stationarity. Taking the logarithm and then the first difference of the prices ensured stationarity.

The ARCH-LM tests the presence of volatility clustering in the data. The test results confirmed heteroskedasticity in the first logged difference in all stock prices. The test results necessitate using models capable of capturing conditional variance dynamics. Full test results are provided in Appendix B.

4.3 Conditional Volatility Models

The choice of modeling volatility broadly aligns with Ballester et al's (2021) approach, incorporating GJR, GARCH, and EGARCH. The distinction here is that this thesis utilizes ARCH-M, whereas Ballester et al's (2021) used Exponentially Weighted Moving Average (EWMA). Employing ARCH-M offers insights into the trade-off dynamics between risk and returns, which is useful when analyzing individual stocks. Furthermore, the GARCH (1,1) model was employed, as in Ballester et al.'s (2021), along with EGARCH (1,1) and GJR. Not only do the specifications compare favorably with Ballester et al's (2021), but they also do not demand a high amount of computing power, as higher levels of GARCH-type models can require substantial computational resources.

4.4 Optimal Lag Length and VAR Model

The methodology of the VAR model follows a two-step process. First, the conditional volatility for each bank's stock price is estimated using the four volatility models (see Section 2.2), similar to the method of Ballester et al. (2021). The importance of these models lies in capturing different volatility dynamics: ARCH-M gives the relationship between risk and return, GARCH volatility clustering, GJR, and EGARCH account for asymmetric shocks. Second, the estimated conditional volatilities are used as the dependent variable in a multivariate VAR where each bank's conditional volatility is regressed on its own lags and the lags of other banks´ CDS spreads to test the Granger-causal relationship between the two. An example where we test for Granger causality in Nordea's conditional volatility looks like the following, where ΔCDS shows in what variables the first difference has been taken :

$$\sigma^2_{Nordea,t} = \alpha_0 + \sum_{k=1}^{p} \alpha_{1k}\sigma^2_{Nordea,t-k} + \sum_{k=1}^{p} \alpha_{2k} CDS_{Nordea,t-k} + \sum_{k=1}^{p} \alpha_{3k}\Delta CDS_{Handelsbanken,t-k} + \sum_{k=1}^{p} \alpha_{4k}\Delta CDS_{Swedbank,t-k} + \sum_{k=1}^{p} \alpha_{5k} CDS_{SEB,t-k} + \varepsilon_t \quad (8)$$

Where:

- $\sigma^2_{Nordea,t} = Conditional\ volatility\ for\ Notdea$
- $\sum_{k=1}^{p} \alpha_{1k}\sigma^2_{Nordea,t-k} = Conditional\ volatility\ for\ Nordea\ up\ to\ p\ lags$
- $\sum_{k=1}^{p} \alpha_{2k} CDS_{Nordea,t-k} = credit\ default\ swap\ spread\ for\ Nordea\ up\ to\ p\ lags$
- $\sum_{k=1}^{p} \alpha_{3k}\Delta CDS_{Handelsbanken,t-k} =$ $First\ diffrence\ credit\ default\ swap\ spread\ for\ Handelsbanken\ up\ to\ p\ lags$
- $\sum_{k=1}^{p} \alpha_{4k}\Delta CDS_{Swedbank,t-k} =$ $First\ diffrence\ credit\ default\ swap\ spread\ for\ Swedbank\ up\ to\ p\ lags$
- $\sum_{k=1}^{p} \alpha_{5k} CDS_{SEB,t-k} = Credit\ Default\ Swap\ spread\ for\ SEB\ up\ to\ p\ lags$
- $\varepsilon_t = Error\ term$

Although Ballester et al. (2021) selected a combination of AIC and BIC to determine lag length to deal with autocorrelation, this thesis uses BIC to determine the optimal lag length to maintain consistency. Optimal lag lengths vary from 1 to 4 lags, and the process of finding the optimal lag length is repeated for each bank and volatility model.

5. Results

Dependent Variable	*Regressor*	*Coefficient*	*Std. Error*	*z-value*	*P-value*	*R-squared*
$\sigma^2_{SEB,t}$ *(EGARCH)*	EGARCH SEB Lag 2	0.0597	0.0177	3.37	0.001***	0.976
$\sigma^2_{SEB,t}$ *(EGARCH)*	$\Delta CDS_{Swedbank,t-2}$ Lag 2	0.008	0.0047	1.72	0.085	0.114
$\sigma^2_{SEB,t}$ *(EGARCH)*	$CDS_{Nordea,t-2}$ Lag 2	-0.0425	0.0065	-6.52	0.000***	0.9918
$\sigma^2_{SEB,t}$ *(EGARCH)*	$\Delta CDS_{Handelsbanken,t-2}$ *Lag* 2	-0.0228	0.0073	-3.13	0.002**	0.009
$\sigma^2_{SEB,t}$ *(EGARCH)*	$CDS_{SEB,t-2}$ Lag 2	0.0074	0.006	1.24	0.216	0.994

Table 3: VAR output for SEB conditional volatility estimated using EGARCH (1,1); full sample period 2008-2025[1]

Table 3 shows the VAR model result for SEB's conditional volatility estimated using an EGARCH (1,1) during the whole sample period being 2008 until 2025, which is regressed on its volatility, the lagged CDS spreads of Nordea, SEB, Swedbank, and Handelbanken, with optimal lag length being 2, determined by using BIC. Table 3 shows that only significant p-values for predicting SEB volatility are the CDS for Nordea and Handelsbanken, both being significant at the 5% level, with a negative effect on volatility; that is, an increase in Nordea and Handelsbanken CDS decreases SEB volatility, which is counterintuitive and might be reflelcted as investors shifting capital to SEB when Nordea or Handelsbanken appears to be risky. Furthermore, the R-squared values are exceptionally high for Nordea CDS, 0.994, reflecting a strong explanatory power for SEB volatility.

Dependent Variable	*Regressor*	*Coefficient*	*Std. Error*	*z*	*P-value*	*R-squared*
$\sigma^2_{Nordea,t}$ *(GARCH)*	GARCH Nordea Lag 2	0.0805	0.0394	2.04	0.041**	0.924
$\sigma^2_{Nordea,t}$ *(GARCH)*	$\Delta CDS_{Swedbank,t-2}$ Lag 2	0.0294	0.073	0.4	0.687	0.014
$\sigma^2_{Nordea,t}$ *(GARCH)*	$CDS_{Nordea,t-2}$ Lag 2	0.0035	0.0447	0.08	0.938	0.981
$\sigma^2_{Nordea,t}$ *(GARCH)*	$\Delta CDS_{Handelsbanken,t-2}$ *Lag* 2	0.3699	0.0855	4.33	0.000***	0.030
$\sigma^2_{Nordea,t}$ *(GARCH)*	$CDS_{SEB,t-2}$ Lag 2	0.0039	0.0434	0.09	0.928	0.984

[1] L2 denotes 2 lags, $\Delta CDS_{Swedbank,t-k}$ $\Delta CDS_{Handelsbanken,t-k}$ represents the first diffrence of Swedbank and Handelsbankens CDS spreads $\sigma^2_{SEB,t}$ represents volatility derived from EGARCH model (section 2.2.4).

Table 4: VAR output Nordea conditional volatility estimated using GARCH (1,1); During COVID-19 2020-2023[2]

Table 4 shows results for the VAR model for Nordea's conditional volatility estimated using GARCH (1,1) during COVID-19. The dependent variable, Nordea's volatility, is regressed on the lagged CDS spreads of Swedbank, Nordea, SEB, and Handelsbanken as well as its own lagged volatility. The optimal lag length selected using BIC is 2. The only CDS that is statistically significant is Handelsbanken CDS, which is significant at the 1% level, with a positive effect on volatility; that is, an increase in Handelsbanken CDS increases Nordea volatility. This might be explained by Handelsbanken's conservative lending standards, which will be discussed later.

Dependent Variable	*Regressor*	*Coefficient*	*Std. Error*	*Z-value*	*P-value*	*R-squared*
$\sigma^2_{Swedbank,t}$ *(ARCH-M)*	ARCH-M Nordea Lag 2	0.8244	0.0347	23.78	0.000***	0.832
$\sigma^2_{Swedbank,t}$ *(ARCH-M)*	$\Delta CDS_{Swedbank,t-2}$ Lag 2	0.026	0.0265	0.98	0.327	0.072
$\sigma^2_{Swedbank,t}$ *(ARCH-M)*	$CDS_{Nordea,t-2}$ Lag 2	0.0692	0.0213	3.25	0.001***	0.923
$\sigma^2_{Swedbank,t}$ *(ARCH-M)*	$\Delta CDS_{Handelsbanken,t.2}\ Lag\ 2$	0.0627	0.0598	1.05	0.295	0.008
$\sigma^2_{Swedbank,t}$ *(ARCH-M)*	$CDS_{SEB,t-2}$ Lag 2	-0.0197	0.0129	-1.52	0.128	0.939

Table 5: VAR output for conditional volatility estimated using ARCH-M; the GFC 2008-2009[3]

Table 5 displays the VAR model results for Swedbank's additional volatility estimated with an ARCH-M model during the GFC. The dependent variable is Swedbank's volatility ($\sigma^2_{Swedbank,t}$) regressed on its own lagged volatility and the lagged CDS spreads from Nordea, Swedbank, SEB, and Handelsbanken. The optimal lag length is two, as selected using BIC. The only CDS that reveals statistical significance is Nordea CDS, which is significant at the 1% level, with a positive effect on volatility; that is, an increase in Nordea CDS increases Swedbank volatility. This might be explained by Nordea's substantial market cap, which will later be discussed.

[2] L2 denotes 2 lags, $\Delta CDS_{Swedbank,t-k}$ $\Delta CDS_{Handelsbanken,t-k}$ represents the first diffrence of Swedbank and Handelsbankens CDS spreads $\sigma^2_{Nordea,t}$ represents volatility derived from GARCH model (section 2.2.3).

[3] L2 denotes 2 lags, $\Delta CDS_{Swedbank,t-k}$ $\Delta CDS_{Handelsbanken,t-k}$ represents the first diffrence of Swedbank and Handelsbankens CDS spreads $\sigma^2_{Swedbank,t}$ represents volatility derived from ARCH-M model (section 2.2.6).

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
ARCH-M	Swedbank	GFC	Nordea CDS	0.001	Yes
ARCH-M	Swedbank	GFC	Handelsbanken CDS	0.295	No
ARCH-M	Swedbank	GFC	SEB CDS	0.128	No
ARCH-M	Swedbank	GFC	ALL CDS (joint)	0.002	Yes
ARCH-M	Nordea	GFC	Swedbank CDS	0.087	No
ARCH-M	Nordea	GFC	Handelsbanken CDS	0.138	No
ARCH-M	Nordea	GFC	SEB CDS	0.100	No
ARCH-M	Nordea	GFC	ALL CDS (joint)	0.00	Yes
ARCH-M	SEB	GFC	Swedbank CDS	0.08	No
ARCH-M	SEB	GFC	Nordea CDS	0.001	Yes
ARCH-M	SEB	GFC	Handelsbanken CDS	0.116	No
ARCH-M	SEB	GFC	ALL CDS (joint)	0.000	Yes
ARCH-M	Handelsbanken	GFC	Swedbank CDS	0.025	Yes
ARCH-M	Handelsbanken	GFC	Nordea CDS	0.000	Yes
ARCH-M	Handelsbanken	GFC	SEB CDS	0.000	Yes
ARCH-M	Handelsbanken	GFC	ALL CDS (joint)	0.000	Yes

Table 6: Granger Causality during the Great Financial Crisis using ARCH-M as a conditional volatility measure

In Table 6, ARCH-M detects several instances of Granger causality during the GFC. Nordea CDS significantly affects SEB, Swedbank, and Handelsbanken at the 1% level. Swedbank CDS influences Handelsbanken's volatility, and SEB CDS affects Handelsbanken, too. The joint CDS measure is significant for all banks, emphasizing the sector-wide credit risk.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
GARCH	Swedbank	GFC	Nordea CDS	0.246	No
GARCH	Swedbank	GFC	Handelsbanken CDS	0.654	No
GARCH	Swedbank	GFC	SEB CDS	0.726	No
GARCH	Swedbank	GFC	ALL CDS (joint)	0.444	No
GARCH	Nordea	GFC	Swedbank CDS	0.078	No
GARCH	Nordea	GFC	Handelsbanken CDS	0.915	No
GARCH	Nordea	GFC	SEB CDS	0.186	No
GARCH	Nordea	GFC	ALL CDS (joint)	0.000	Yes
GARCH	SEB	GFC	Swedbank CDS	0.030	
GARCH	SEB	GFC	Nordea CDS	0.188	No
GARCH	SEB	GFC	Handelsbanken CDS	0.716	No
GARCH	SEB	GFC	ALL CDS (joint)	0.000	Yes
GARCH	Handelsbanken	GFC	Swedbank CDS	0.895	No
GARCH	Handelsbanken	GFC	Nordea CDS	0.016	Yes
GARCH	Handelsbanken	GFC	SEB CDS	0.213	No
GARCH	Handelsbanken	GFC	ALL CDS (joint)	0.072	No

Table 7: Granger Causality during the Great Financial Crisis using GARCH as a conditional volatility measure

Table 7 Compared to Table 6, the GARCH model captures fewer links during the GFC. Only Nordea CDS significantly influences Handelsbanken volatility ($p = 0.016$). The joint CDS measure is significant for Nordea and SEB but not for Handelsbanken or Swedbank. Showing that symmetric volatility models like GARCH are less responsive to the asymmetric risk nature of a financial crisis.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
GJR	Swedbank	GFC	Nordea CDS	0.001	Yes
GJR	Swedbank	GFC	Handelsbanken CDS	0.007	Yes
GJR	Swedbank	GFC	SEB CDS	0.031	Yes
GJR	Swedbank	GFC	ALL CDS (joint)	0.001	Yes
GJR	Nordea	GFC	Swedbank CDS	0.263	No
GJR	Nordea	GFC	Handelsbanken CDS	0.845	No
GJR	Nordea	GFC	SEB CDS	0.002	Yes
GJR	Nordea	GFC	ALL CDS (joint)	0.000	Yes
GJR	SEB	GFC	Swedbank CDS	0.034	Yes
GJR	SEB	GFC	Nordea CDS	0.000	Yes
GJR	SEB	GFC	Handelsbanken CDS	0.365	No
GJR	SEB	GFC	ALL CDS (joint)	0.001	Yes
GJR	Handelsbanken	GFC	Swedbank CDS	0.083	No
GJR	Handelsbanken	GFC	Nordea CDS	0.514	No
GJR	Handelsbanken	GFC	SEB CDS	0.557	No
GJR	Handelsbanken	GFC	ALL CDS (joint)	0.088	No

Table 8: Granger Causality during the Great Financial Crisis using GJR as a conditional volatility measure

Table 8 reveals more frequent causality patterns than Table 7. For example, Swedbank volatility is Granger-caused by all CDS spreads, and Swedbank and Nordea CDS influence SEB. Swedbank at the 5% level, while Nordea is at the 1% level.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
EGARCH	Swedbank	GFC	Nordea CDS	0.002	Yes
EGARCH	Swedbank	GFC	Handelsbanken CDS	0.002	Yes
EGARCH	Swedbank	GFC	SEB CDS	0.025	Yes
EGARCH	Swedbank	GFC	ALL CDS (joint)	0.000	Yes
EGARCH	Nordea	GFC	Swedbank CDS	0.546	No
EGARCH	Nordea	GFC	Handelsbanken CDS	0.628	No
EGARCH	Nordea	GFC	SEB CDS	0.003	Yes
EGARCH	Nordea	GFC	ALL CDS (joint)	0.001	Yes
EGARCH	SEB	GFC	Swedbank CDS	0.258	No
EGARCH	SEB	GFC	Nordea CDS	0.000	Yes
EGARCH	SEB	GFC	Handelsbanken CDS	0.596	No
EGARCH	SEB	GFC	ALL CDS (joint)	0.004	Yes
EGARCH	Handelsbanken	GFC	Swedbank CDS	0.578	No
EGARCH	Handelsbanken	GFC	Nordea CDS	0.990	No
EGARCH	Handelsbanken	GFC	SEB CDS	0.300	No
EGARCH	Handelsbanken	GFC	ALL CDS (joint)	0.260	No

Table 9: Granger Causality during the Great Financial Crisis using EGARCH as a conditional volatility measure

Table 9 detects strong causality in the GFC. Nordea and Handelsbanken CDS drive Swedbank's volatility, and Nordea influences SEB's volatility. The joint CDS factor is again significant across most banks. Table 9 also shows a similar performance to Table 8 since both capture asymmetry effects. Once again, outperformed GARCH in Table 7 by a substantial amount.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
ARCH-M	Swedbank	Covid	Nordea CDS	0.327	No
ARCH-M	Swedbank	Covid	Handelsbanken CDS	0.028	Yes
ARCH-M	Swedbank	Covid	SEB CDS	0.409	No
ARCH-M	Swedbank	Covid	ALL CDS (joint)	0.096	No
ARCH-M	Nordea	Covid	Swedbank CDS	0.487	No
ARCH-M	Nordea	Covid	Handelsbanken CDS	0.036	Yes
ARCH-M	Nordea	Covid	SEB CDS	0.888	No
ARCH-M	Nordea	Covid	ALL CDS (joint)	0.244	No
ARCH-M	SEB	Covid	Swedbank CDS	0.003	Yes
ARCH-M	SEB	Covid	Nordea CDS	0.708	No
ARCH-M	SEB	Covid	Handelsbanken CDS	0.003	Yes
ARCH-M	SEB	Covid	ALL CDS (joint)	0.000	Yes
ARCH-M	Handelsbanken	Covid	Swedbank CDS	0.165	No
ARCH-M	Handelsbanken	Covid	Nordea CDS	0.606	No
ARCH-M	Handelsbanken	Covid	SEB CDS	0.396	No
ARCH-M	Handelsbanken	Covid	ALL CDS (joint)	0.116	No

Table 10: Granger Causality during COVID using ARCH-M as a conditional volatility measure

During COVID, ARCH-M detects fewer significant casualties compared to Table 6. Swedbank and SEB volatility is Granger caused by Handelsbanken CDS, and SEB also responds to

Swedbank CDS. However, joint CDS measures are mostly insignificant except for SEB, where significance is at the 1% level.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
GARCH	Swedbank	Covid	Nordea CDS	0.350	No
GARCH	Swedbank	Covid	Handelsbanken CDS	0.011	Yes
GARCH	Swedbank	Covid	SEB CDS	0.40	No
GARCH	Swedbank	Covid	ALL CDS (joint)	0.081	No
GARCH	Nordea	Covid	Swedbank CDS	0.687	No
GARCH	Nordea	Covid	Handelsbanken CDS	0.000	Yes
GARCH	Nordea	Covid	SEB CDS	0.928	No
GARCH	Nordea	Covid	ALL CDS (joint)	0.000	Yes
GARCH	SEB	Covid	Swedbank CDS	0.027	Yes
GARCH	SEB	Covid	Nordea CDS	0.497	No
GARCH	SEB	Covid	Handelsbanken CDS	0.000	Yes
GARCH	SEB	Covid	ALL CDS (joint)	0.000	Yes
GARCH	Handelsbanken	Covid	Swedbank CDS	0.321	No
GARCH	Handelsbanken	Covid	Nordea CDS	0.677	No
GARCH	Handelsbanken	Covid	SEB CDS	0.831	No
GARCH	Handelsbanken	Covid	ALL CDS (joint)	0.613	No

Table 11: Granger Causality during COVID using GARCH as a conditional volatility measure

Table 11 finds only a handful of significant Granger causality. It is similar to Table 10, with Handelsbanken CDS affecting Swedbank and SEB, and Swedbank CDS influencing SEB mainly at the 1% significance level.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
GJR	Swedbank	Covid	Nordea CDS	0.463	No
GJR	Swedbank	Covid	Handelsbanken CDS	0.019	Yes
GJR	Swedbank	Covid	SEB CDS	0.531	No
GJR	Swedbank	Covid	ALL CDS (joint)	0.102	No
GJR	Nordea	Covid	Swedbank CDS	0.123	No
GJR	Nordea	Covid	Handelsbanken CDS	0.010	Yes
GJR	Nordea	Covid	SEB CDS	0.952	No
GJR	Nordea	Covid	ALL CDS (joint)	0.038	Yes
GJR	SEB	Covid	Swedbank CDS	0.000	Yes
GJR	SEB	Covid	Nordea CDS	0.678	No
GJR	SEB	Covid	Handelsbanken CDS	0.003	Yes
GJR	SEB	Covid	ALL CDS (joint)	0.000	Yes
GJR	Handelsbanken	Covid	Swedbank CDS	0.912	No
GJR	Handelsbanken	Covid	Nordea CDS	0.941	No
GJR	Handelsbanken	Covid	SEB CDS	0.928	No
GJR	Handelsbanken	Covid	ALL CDS (joint)	0.986	No

Table 12: Granger Causality during COVID using GJR as a conditional volatility measure

Table 12 shows similar causality as Table 11 during COVID-19. Notably, SEB volatility is affected by both Swedbank and Handelsbanken CDS. GJR also captures the Granger causality in Nordea's volatility and Handelsbanken CDS. Furthermore, Table 12 also seems to perform relatively similarly to GARCH during COVID-19, showing evidence of a lack of asymmetric effects during COVID.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
EGARCH	Swedbank	Covid	Nordea CDS	0.880	No
EGARCH	Swedbank	Covid	Handelsbanken CDS	0.174	No
EGARCH	Swedbank	Covid	SEB CDS	0.960	No
EGARCH	Swedbank	Covid	ALL CDS (joint)	0.332	No
EGARCH	Nordea	Covid	Swedbank CDS	0.067	No
EGARCH	Nordea	Covid	Handelsbanken CDS	0.108	No
EGARCH	Nordea	Covid	SEB CDS	0.682	No
EGARCH	Nordea	Covid	ALL CDS (joint)	0.122	No
EGARCH	SEB	Covid	Swedbank CDS	0.001	Yes
EGARCH	SEB	Covid	Nordea CDS	0.621	No
EGARCH	SEB	Covid	Handelsbanken CDS	0.063	No
EGARCH	SEB	Covid	ALL CDS (joint)	0.001	Yes
EGARCH	Handelsbanken	Covid	Swedbank CDS	0.641	No
EGARCH	Handelsbanken	Covid	Nordea CDS	0.471	No
EGARCH	Handelsbanken	Covid	SEB CDS	0.442	No
EGARCH	Handelsbanken	Covid	ALL CDS (joint)	0.869	No

Table 13: Granger Causality during COVID using EGARCH as a conditional volatility measure

Table 13, using EGARCH during COVID-19, shows only two isolated significant relationships, notably Swedbank CDS affecting SEB volatility ($p = 0.001$). Joint CDS is only significant for SEB. By far being the worst performer during the COVID period emphasises the lack of asymmetric effects during COVID.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
ARCH-M	Swedbank	Whole sample period	Nordea CDS	0.824	No
ARCH-M	Swedbank	Whole sample period	Handelsbanken CDS	0.201	No
ARCH-M	Swedbank	Whole sample period	SEB CDS	0.090	No
ARCH-M	Swedbank	Whole sample period	ALL CDS (joint)	0.000	Yes
ARCH-M	Nordea	Whole sample period	Swedbank CDS	0.000	Yes
ARCH-M	Nordea	Whole sample period	Handelsbanken CDS	0.318	No
ARCH-M	Nordea	Whole sample period	SEB CDS	0.062	No
ARCH-M	Nordea	Whole sample period	ALL CDS (joint)	0.000	Yes
ARCH-M	SEB	Whole sample period	Swedbank CDS	0.000	Yes
ARCH-M	SEB	Whole sample period	Nordea CDS	0.945	No
ARCH-M	SEB	Whole sample period	Handelsbanken CDS	0.002	Yes
ARCH-M	SEB	Whole sample period	ALL CDS (joint)	0.000	Yes
ARCH-M	Handelsbanken	Whole sample period	Swedbank CDS	0.383	No
ARCH-M	Handelsbanken	Whole sample period	Nordea CDS	0.000	Yes
ARCH-M	Handelsbanken	Whole sample period	SEB CDS	0.000	Yes
ARCH-M	Handelsbanken	Whole sample period	ALL CDS (joint)	0.001	Yes

Table 14: Granger Causality for the whole sample period using ARCH-M's conditional volatility measure

Table 14 highlights many relationships. Notably, Nordea CDS Granger causes volatility in Swedbank and Handelsbanken. SEB volatility responds to Swedbank CDS and Handelsbanken CDS. The joint CDS variable is consistently significant throughout the sample.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
GARCH	Swedbank	Whole sample period	Nordea CDS	0.000	Yes
GARCH	Swedbank	Whole sample period	Handelsbanken CDS	0.017	Yes
GARCH	Swedbank	Whole sample period	SEB CDS	0.000	Yes
GARCH	Swedbank	Whole sample period	ALL CDS (joint)	0.000	Yes
GARCH	Nordea	Whole sample period	Swedbank CDS	0.000	Yes
GARCH	Nordea	Whole sample period	Handelsbanken CDS	0.211	No
GARCH	Nordea	Whole sample period	SEB CDS	0.000	Yes
GARCH	Nordea	Whole sample period	ALL CDS (joint)	0.000	Yes
GARCH	SEB	Whole sample period	Swedbank CDS	0.170	No
GARCH	SEB	Whole sample period	Nordea CDS	0.000	Yes
GARCH	SEB	Whole sample period	Handelsbanken CDS	0.001	Yes
GARCH	SEB	Whole sample period	ALL CDS (joint)	0.000	Yes
GARCH	Handelsbanken	Whole sample period	Swedbank CDS	0.783	No
GARCH	Handelsbanken	Whole sample period	Nordea CDS	0.519	No
GARCH	Handelsbanken	Whole sample period	SEB CDS	0.316	No
GARCH	Handelsbanken	Whole sample period	ALL CDS (joint)	0.733	No

Table 15: Granger Causality for the whole sample period using GARCH as a conditional volatility measure

The GARCH model finds more causality than in the COVID or GFC subperiods, suggesting some stability in CDS-volatility relationships; the only part where no CDS explains volatility is for Handelsbanken. Furthermore, GARCH seems to perform similarly to all the other volatility measures, suggesting some form of smoothing in the asymmetric effects.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
GJR	Swedbank	Whole sample period	Nordea CDS	0.404	No
GJR	Swedbank	Whole sample period	Handelsbanken CDS	0.000	Yes
GJR	Swedbank	Whole sample period	SEB CDS	0.018	Yes
GJR	Swedbank	Whole sample period	ALL CDS (joint)	0.000	Yes
GJR	Nordea	Whole sample period	Swedbank CDS	0.001	Yes
GJR	Nordea	Whole sample period	Handelsbanken CDS	0.019	Yes
GJR	Nordea	Whole sample period	SEB CDS	0.041	Yes
GJR	Nordea	Whole sample period	ALL CDS (joint)	0.000	Yes
GJR	SEB	Whole sample period	Swedbank CDS	0.000	Yes
GJR	SEB	Whole sample period	Nordea CDS	0.918	No
GJR	SEB	Whole sample period	Handelsbanken CDS	0.115	No
GJR	SEB	Whole sample period	ALL CDS (joint)	0.000	Yes
GJR	Handelsbanken	Whole sample period	Swedbank CDS	0.157	No
GJR	Handelsbanken	Whole sample period	Nordea CDS	0.786	No
GJR	Handelsbanken	Whole sample period	SEB CDS	0.775	No
GJR	Handelsbanken	Whole sample period	ALL CDS (joint)	0.142	No

Table 16: Granger Causality for the whole sample period using GJR as a conditional volatility measure

Table 16 shows a network of Granger-causal links in the entire sample. Handelsbanken and SEB CDS significantly influence Swedbank's volatility, p-value =0.00. Nordea is influenced by all banks' CDS at least at the 5% level. Once again, Handelsbanken is not influenced by any CDS.

Volatility Model	Bank (Volatility)	Period	CDS Source	p-value	Granger Causality?
EGARCH	Swedbank	Whole sample period	Nordea CDS	0.723	No
EGARCH	Swedbank	Whole sample period	Handelsbanken CDS	0.000	Yes
EGARCH	Swedbank	Whole sample period	SEB CDS	0.090	No
EGARCH	Swedbank	Whole sample period	ALL CDS (joint)	0.000	Yes
EGARCH	Nordea	Whole sample period	Swedbank CDS	0.001	Yes
EGARCH	Nordea	Whole sample period	Handelsbanken CDS	0.010	Yes
EGARCH	Nordea	Whole sample period	SEB CDS	0.023	Yes
EGARCH	Nordea	Whole sample period	ALL CDS (joint)	0.000	Yes
EGARCH	SEB	Whole sample period	Swedbank CDS	0.000	Yes
EGARCH	SEB	Whole sample period	Nordea CDS	0.363	No
EGARCH	SEB	Whole sample period	Handelsbanken CDS	0.332	No
EGARCH	SEB	Whole sample period	ALL CDS (joint)	0.000	Yes
EGARCH	Handelsbanken	Whole sample period	Swedbank CDS	0.021	Yes
EGARCH	Handelsbanken	Whole sample period	Nordea CDS	0.009	Yes
EGARCH	Handelsbanken	Whole sample period	SEB CDS	0.000	Yes
EGARCH	Handelsbanken	Whole sample period	ALL CDS (joint)	0.000	Yes

Table 17: Granger Causality for the whole sample period using EGARCH as a conditional volatility measure

Table 17 provides extensive Granger causal relations for the entire sample. Swedbank, Nordea, and SEB are all influenced by multiple peer CDS series, and the joint CDS factor is significant for every bank. In addition, Handelsbanken is affected by all banks' CDS at a minimum of the 5% level, which contrasts with Tables 16 and 15. Furthermore, EGARCH outperforms GJR, suggesting that there is some benefit to the model, which could lie in EGARCH's ability to model extreme events with fatter tails better, since the model is logged as well as giving a magnitude to the asymmetric shock.

Taken as a whole, the evidence shows that CDS prices remain as forward-looking indicators, but only when volatility is modelled in a way that accounts for asymmetric, crisis-specific periods and the institution-specific nature of financial stress. Ignoring those features, as a symmetric GARCH specification does, risks not capturing volatility correctly during certain periods, such as the GFC.

6. Discussion

Empirical results, as presented in Tables 6 through 17, indicate that CDS spreads Granger-caused bank stock volatility, answering the first question of the thesis. However, the strength and consistency of the Granger causal relationship vary across periods, volatility models, and individual banks answering the second question of the thesis. Three key findings give insights into the relationship between CDS spreads and equity market volatility in the Swedish banking sector.

6.1 Bank Heterogeneity and Systemic Risk

Bank-specific patterns show the structural differences in Sweden's concentrated banking sector. Nordea's CDS spreads dominate as a predictor during the GFC (e.g, Table 9: EGARCH, $p = 0.000$ for SEB), reflecting Nordea's stature as the largest bank in the Nordic by market capitalisation (Statista, 2024), making Nordea a systemic risk barometer for financial status in the Nordic including Sweden. Handelsbanken's influence during COVID-19 (e.g, Table 11: GARCH, $p = 0.000$ for Nordea) most likely stems from its conservative lending profile (S&P Global Market Intelligence, 2021), where CDS movements would signal unusual stress.

The whole sample period shows varied bank-specific causality (e.g, Table 16: GJR, $p = 0.000$ for Nordea's Swedbank CDS, but $p = 0.786$ for Handelsbanken's Nordea CDS), indicating that individual bank characteristics such as funding models and market exposure influence the CDS-volatility link over time. The consistent significance of the joint CDS factor across periods (e.g, Table 14: ARCH-M, $p = 0.000$ for all banks) highlights a sector-wide credit risk component, reinforcing the literature of findings of tail dependence among Scandinavian banks (Hedström et al., 2022).

6.2 Crisis Typology and Market Efficiency

The Granger causal relationship varies significantly across periods, challenging the semi-strong Efficient Market Hypothesis (EMH) form during the GFC, which states that all publicly available information, including CDS spreads, is instantly reflected in asset prices. During the GFC, characterized by an endogenous financial shock, CDS spreads robustly Granger-caused volatility (e.g, Table 8: GJR, $p = 0.001$ for Swedbank's joint CDS), indicating that stock prices did not immediately incorporate credit risk signals. The Granger causality suggests market inefficiency, as CDS spreads provide predictive content that has not yet been priced into

equities. In contrast, the COVID-19 crisis, an exogenous health shock mitigated by swift policy interventions such as quantitative easing, weakened this causality (e.g, Table 10: ARCH-M, p = 0.096 for Swedbank's joint CDS). Here, banks' stock prices are likely to have adjusted to diverse information sources, such as policy announcements, reducing the relative informativeness of CDS spreads.

The whole sample period presents a mixed picture, with significant causality in asymmetric models (e.g, Table 14: ARCH-M, p = 0.000 for Nordea's joint CDS; Table 17: EGARCH, p = 0.000 for Handelsbanken's joint CDS) but less consistency than the GFC. The causality over the whole sample reflects the averaging effect of combining crisis and non-crisis periods. The GFC's intense financial distress amplified CDS signals, while COVID-19's policy-driven stabilization and calmer intervening years in CDS spreads diluted their predictive power. The sample's results suggest that CDS spreads remain relevant over long horizons but are less reliable during exogenous shocks or regulatory interventions, aligning with semi-strong EMH deviations primarily during endogenous financial stress shocks to banks and the market. These results are similar to Ballester et al. (2021), who found that Granger causality in European sovereign CDS and index volatility was higher during the European debt crisis, which is an endogenous shock, vs the rest of the sample period.

6.3 Asymmetric Models

The superior performance of more complex and asymmetric volatility models (ARCH-M, GJR-GARCH, EGARCH) over the symmetric GARCH model highlights the leverage effect, where adverse shocks amplify volatility more than positive ones. For example, during the GFC, ARCH-M reveals strong Granger causality from CDS spreads to volatility for all banks (e.g, Table 6, p = 0.000 for joint CDS). At the same time, GARCH shows fewer significant results (e.g, Table 7, p = 0.444 for Swedbank's joint CDS). ARCH-M's ability to incorporate conditional variance into expected returns captures investors' demand for higher risk premia during crises, as seen in Handelsbanken's GFC results (Table 6, p = 0.000 for Nordea CDS). This finding directly addresses the research question, confirming that CDS spreads anticipate equity market risk when correctly modeled to account for shock responses. The results closely resemble the conclusion from Ballester et al. (2021), who also found that models that account for asymmetry had greater predictive power, although not having ARCH-M as a measure for volatility, they still prove that asymmetric models outperform GARCH, similar to this thesis.

6.4 Further Study & Limitations

Focusing on the four major banks limits the essay to smaller institutions or other Nordic markets. The period-based approach, constrained by computational limitations, may miss dynamic shifts in causality that a rolling Granger test could capture. Excluding macroeconomic controls such as interest rates, GDP growth might overstate the predictive power of CDS spreads. Future research could include smaller banks, cross-country analysis through the Scandinavian countries, and adopting dynamic methodologies such as a rolling VAR-Granger.

Furthermore, the volatility measurement itself could be critical. This thesis relies on four volatility filters, which are well-suited to daily stock price data as they all deal with volatility clustering. Still, they may miss information that other models could measure.

By broadening the geographical scope, volatility metrics, and econometric techniques, future research can test the robustness of the Swedish findings, determine whether credit-market signals provide an equally powerful early-warning tool throughout Scandinavia, and deliver even more granular insights for regulators charged with safeguarding financial stability in the Nordic region.

7 Conclusion

This thesis aimed to see if CDS spreads Granger caused conditional volatility in the stock prices of the four significant Swedish Banks and if that relationship was varying over time. The thesis shows that CDS spreads predict volatility in bank stocks in Sweden during some periods, especially during the Global Financial Crisis (2008–2009), characterized by heightened systemic risk and increased sensitivity to credit market signals. Asymmetric models consistently outperformed GARCH, which accounts for differential volatility responses to negative versus positive shocks. In contrast, the predictive role of CDS spreads was weaker during the COVID-19 crisis, likely due to the exogenous nature of the shock and the influence of government interventions. The results are mixed over the entire sample period, reflecting a blend of volatile and more stable market conditions.

At the institutional level of the banks, heterogeneity in the predictive power of CDS spreads is observed throughout the thesis. During the GFC, Nordea's CDS spreads exhibited the most substantial predictive relationship, potentially due to having the highest market cap in the Nordic region. During COVID-19, Handelsbanken's effect was more persistent, consistent with the bank's conservative lending philosophy. A sector-wide CDS factor also consistently predicted volatility, emphasising the interconnectedness of Sweden's highly concentrated banking system.

The results challenge the semi-strong Efficient Market Hypothesis (EMH) that holds that publicly available information is reflected in asset prices. The ability of CDS spreads to predict equity volatility, particularly during the GFC, suggests that markets do not always incorporate credit risk information efficiently. However, this inefficiency appears context-dependent and is not a clear-cut relationship.

The thesis offers practical implications for both regulators and investors. For regulatory bodies, the findings support the integration of CDS indicators into risk monitoring and early-warning systems. For investors, CDS spreads may be a forward-looking tool for anticipating volatility and managing portfolio risk, especially in financial distress. The thesis contributes to the literature on credit-equity linkages by providing evidence from a Swedish context, an area that remains highly uncharted.

Nonetheless, certain limitations apply. The focus on Sweden's four largest banks may restrict generalizability to smaller institutions or other banking systems. While suitable for structural comparison, the period-based methodology may not capture all evolving dynamics that rolling-window or time-varying models would reveal. Additionally, excluding macroeconomic control variables may exaggerate the predictive power of CDS spreads. Future research could address these limitations by broadening the sample and applying dynamic econometric approaches.

In summary, CDS spreads predict bank stock volatility in Sweden, particularly during financial turbulence. Their usefulness depends on the nature of the shock, model specification, and institutional characteristics. These insights enhance the understanding of market efficiency and risk transmission, with potential applications for financial supervision and investment strategy.

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9. Appendix

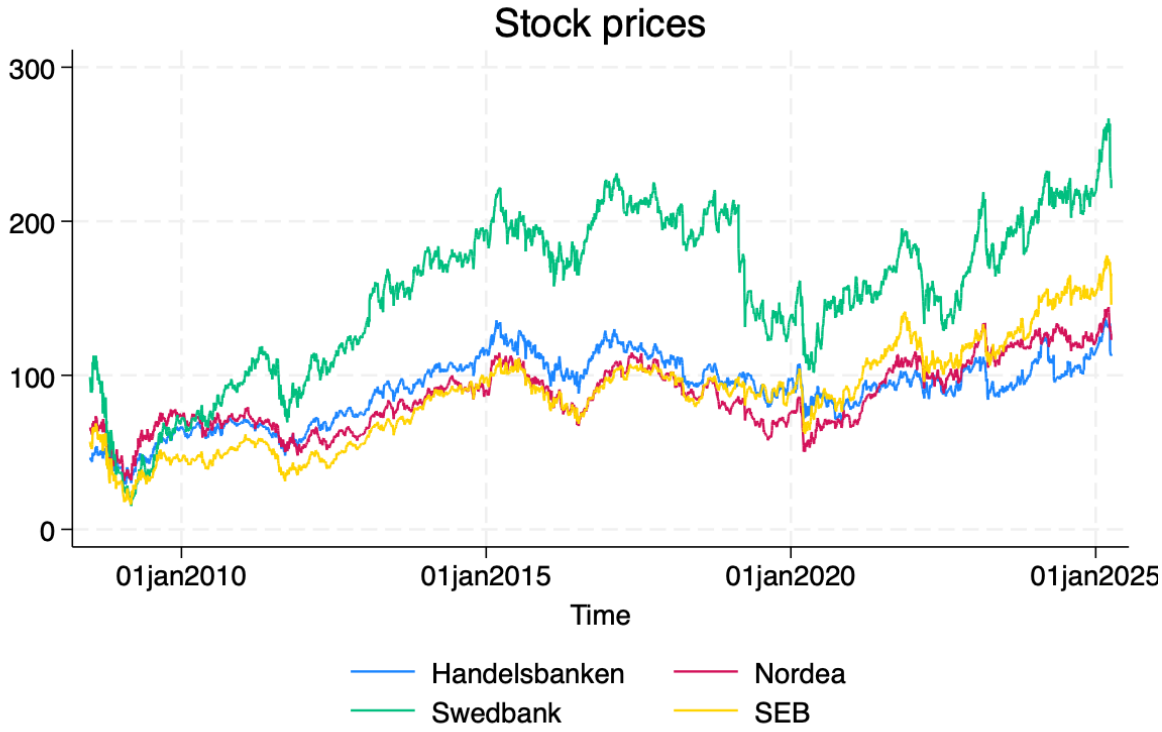
Appendix A Advanced Dicky Fuller test results

P value 1 lag	Bank CDS
0.0007	SEB
0.0012	Nordea
0.8933	Handelsbanken
0,0365	Swedbank
0.0000	First diffrence Handelsbanken
0.0000	First diffrence swedbank

Appendix B: ARCHLM test results

ArchLM p-value	Logged first difference of the bank stock price
0.000	Swedbank
0.000	Nordea
0.000	Swedbank
0.000	SEB

Appendix C: Stock prices



10. AI statement

In this thesis, Chat GPT, Grok, and Grammarly were mainly used to aid in writing and formulating sentences and passages, ensuring the text was as academically serviceable as possible. This was used throughout the thesis to write the text, double-check with an AI if the text was academically correct, ask for suggestions on improvements to make the text more readable, and ensure the text always followed an academic tone.

In addition, AI was a helpful search tool. The deep search tool feature in most AI was used to help find academic papers that could be used in the literature review, to gain a deeper understanding of the current landscape of the research, and to help interpret and understand some academic papers.

Furthermore, ChatGPT and Grok were used to write code, help interpret results in Section 5, and provide a possible explanation for why the results look like they do, as used in Sections 6 and 7. Furthermore, in Section 7, AI was used to share ideas with and get feedback on my ideas about what the results might mean. However, all final interpretations, general ideas, final code, and conclusions are the authors' own work.