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CDS Pricing Contagion

An event study into SVB's collapse and its effects on European banks

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ABSTRACT:

International Swaps and Derivatives Association (2019) show that the market activity in bilateral CDS contracts was approximately $5.8 trillion in executed notional value during the second quarter of 2019. The CDS-market has also informational value. Norden and Weber (2004) analyze the effect of credit rating changes to credit default swap and stock markets and find that both markets anticipate the upcoming rating change in advance. With growing interest on the market and the qualities of the Silicon Valley Bank's collapse, it is of significant interest to evaluate the effects from the event through the lens of credit risk.

This thesis investigates the existence and scale of financial contagion effects in European credit default swap spreads following and preceding the collapse of Silicon Valley Bank in March 2023. Utilizing a panel of CDS spreads from 24 major European banks, the thesis utilizes an event study framework with OLS modeling to capture potential relationship in CDS spreads and the collapse of SVB.

Within the context and scope of this thesis the results indicate that there did exist a consistent and statistically significant relationship between SVB default event and European CDS spreads. While some individual banks exhibited no effects following the event, broader data suggests that SVB's collapse did lead to widespread and systemic contagion across the European CDS market .

The findings of this thesis are partly contrarian to the current literature on the topic of financial contagion and volatility spillovers and that might be due to the event windows used and the more granular type of more frequent data.

The study emphasizes the sensitivity of modern financial markets to systemic events. The results reinforce the importance of monitoring derivative markets and adopting tools to mitigate possible contagion and spillover effects. By highlighting the channels through which contagion transitions, this research contributes to academic literature and is useful for practitioners of financial markets and regulators alike.

KEYWORDS: CDS, Credit Default Swap, Silicon Valley Bank, SVB, Financial Contagion, Volatility Spillover, Regional banking, European banks

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Abbreviations

ARCH : Autoregressive Conditional Heteroskedasticity

CDS : Credit Default Swap

SVB : Silicon Valley Bank

OLS: Ordinary Least Squares

MGE: Mean Group Estimation

BPS: Basis Points

1 Introduction

Credit default swaps are financial contracts in which two parties agree to make payments to one another when certain conditions are met. CDS's as they are referred to from now on are derivative contracts, meaning their value is derived from some other asset or benchmark. Regarding CDS, the benchmark is the default of the agreed upon reference entity.

In this context, the agree to a notional amount of money which the seller of the contract is to fulfill to the buyer if the reference entity defaults during the term of the contract. For this protection, the buyer of the contract makes recurring payments to the seller the amount of agreed upon percentage of the notional value of the contract.

In effect, a CDS can be thought of as insurance against the default of the reference entity. The purpose of the contract is to shift the risks derived from the credit risk of the reference entity from the buyer to the seller. It is no wonder, therefore, that the market size of the Credit default swap contracts is among the largest ones in the world. International Swaps and Derivatives Association (2019) show that the market activity in bilateral contracts was approximately $5.8 trillion in executed notional value during the second quarter of 2019.

In addition, the transactions in the CDS-market have informational value. Norden and Weber (2004) analyze the effect of credit rating changes to credit default swap and stock markets and find that both markets anticipate the upcoming rating change in advance. Hull et al. (2004) find supporting evidence as in their analyzation of CDS spreads and credit quality changes show that CDS spreads incorporate information more rapidly than the bond market, Blanco et al. (2004) and Zhu (2004) have also come to the same conclusion. Flannery et al. (2010) even propose replacing credit ratings with CDS spreads and show that new information gets incorporated to the spreads about the same rate as to equity.

1.1 Purpose, motivation and hypothesis of the study

The purpose of this study is to evaluate whether the issues in the American regional banking sector have had spillover effects to the European banking sector, and whether this possible spillover can be explained by the current economic theories and models.

As indicated by Merton (1974) and concluded by Ericsson et al. (2005) and Collin-Dufresne et al. (2002), the premia of credit default swaps are linked to the financial standing of the reference entity itself. Namely leverage, equity volatility and the risk-free rate are theoretical key variables in explaining the price levels of the CDS contracts. Ericsson et al. (2005)

In contrast to this theoretical and empirical proof of the pricing being mainly a result of financial characteristics of the reference entity, Ballester et al. (2016) show that global factors can also be factors of the spreads of the CDS. Moreover, they found that even idiosyncratic components had effects not just for the reference entity in question, but also for other reference entities.

Against this interconnectedness of the CDS-market, it is intriguing to analyze the possible systemic effects of the reported bank run of regional U.S banks during March of 2023. (Federal Deposit Insurance Corporation 2023). This bank run, which has also been coined as the start of a banking crisis, began by a sentiment change towards the bank and eventually led to investors selling the stock in huge quantities and to customers withdrawing their balances. Before the crisis, Silicon Valley Bank, or SVB from now on, had large positions in fixed-income securities. (Board of Governors Of The Federal Reserve System 2023). These positions produced unrealized losses to the bank due to the rising interest rates, eventually leading to realized losses as SVB had to cover the deposits of their customers. (Board of Governors Of The Federal Reserve System 2023). In the end SVB filed for bankruptcy and regulators agreed to make all depositors whole to prevent larger systemic collapse in the banking sector.

As a result of this event and despite the bailout by U.S regulators, the sentiment towards the banking sector was more negative, this time also reflecting to nonregional banks. (Board of Governors Of The Federal Reserve System 2023).

Equity prices of affected banks started to decline, possibly because of fears of systemic risk to the banking sector. Credit Suisse, a Swiss investment bank, had its stock price decline nearly 25% in a single day. Another example, HSBC, a multinational British bank, had its share price tumble 6.2%. The list goes on for affected banks and the beforementioned banks were only mere examples to shed light that the effects of the crisis had also reached outside the U.S.

CDS spreads are used as indicators for business cycle changes by institutions like Bank of England (2023) and European Central Bank (2024). Also relevant to the general finance theory, Hull et al. (2004) demonstrate how CDS spreads are closely related to credit spreads of bonds under restrictive assumptions. Estimating credit risk through CDS contracts instead of credit spreads of bonds is, however, preferrable because of

This study aims to elaborate the determinants of the CDS spread changes in Europe during the U.S banking crisis and whether the crisis induced financial contagion.

The hypothesis is that the collapse of SVB induced financial contagion in the CDS quotes of European banks.

1.2 Structure of the study

The study begins with explanations for terms like credit defaults swap spreads, financial contagion, and the U.S banking crisis.

Having cleared up the terminology, the study then explains the framework for the observable phenomenon through a literature review including economic theory and empirical results.

Thereafter the forementioned phenomenon is examined through statistical analysis. Data and methodology are also presented in this chapter.

Finally, conclusion sums up the results and implications of the study.

2 Credit default swaps

This chapter explains the relevant concepts to understand the terminology of this study.

2.1 Derivatives and derivative markets.

A derivative is a contract the value of which derives from other underlying variables, these usually being prices of other assets such as stock or oil prices. These contracts can be entered into through exchange traded markets or over-the-counter markets. (Hull 2021. p.2-4).

Contracts on the exchange traded markets are defined and standardized by the exchange. The clearinghouse of the exchange acts as an intermediary between the buyers and sellers of the contract by being the opposing party to both other parties itself. This eliminates the counterparty risk that would stem if the buyer and the seller were the sole parties in the contract. (Hull 2021. p. 2-4)

In over-the-counter markets, OTC for short, market makers such as banks quote buying and selling prices for contracts, and the trade can also be executed bilaterally between the two parties. (Hull 2021. p.2-4)

The frequency of trades in the OTC market is fewer than in exchange traded markets, but the average notional amount of the transaction is larger. During December 2019, the size of the derivatives OTC market were approximately 559 trillion dollars and the size of the exchange traded markets were approximately 97 trillion dollars. (Hull 2021. p.2-4).

2.2 Credit default swaps

Derivatives can be characterized by four popular types of contracts: futures, forwards, options and swaps.

Credit default swaps are a particular type of swap contracts in which the buyer of the CDS gets a payoff if a reference entity defaults. For this protection similar to insurance, the buyer pays a premium which is also referred to as CDS spread. The seller of the CDS gets to collect said premium until the reference entity defaults or until the contract term expires. (Hull 2021 p.568–590) The contract is written on the reference party's debt such as a bond, the price of which on the event of default determines the amount of payment the seller must make to the buyer. (Hull 2021 p. 568–590) See figure 1 below for a description of a CDS.

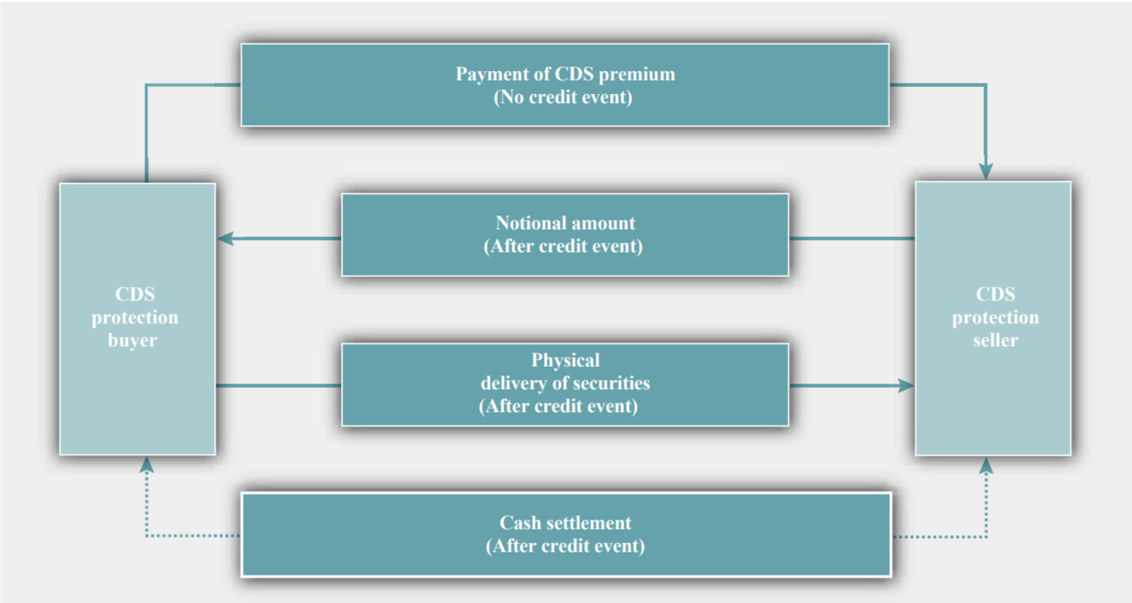

Figure 1. Description of a CDS (European Central Bank, 2009 *Credit default swaps and counterparty risk*.)

As mentioned earlier, the payoff of the buyer in the event of default depends on the price of the reference party's debt on the event of default. It is a possibility that the whole notional price cannot be recovered but only some fraction of it. This fraction of the notional value to be recovered in the event of default is called the recovery rate. A bond's recovery rate depends on the possible collateral and the seniority of the bond. The rate is calculated as follows: (Hull 2021 p.569)

$$L(1 - R) \tag{1}$$

Where L = notional principal of the bond and R = recovery rate

In practice, it is common for a CDS to specify that different bonds of same seniority can be delivered to satisfy the payoff. The different bonds can have different recovery rates due to different accrued interests or sentimental characteristics. With the help of ISDA, a price for cheapest-to-deliver bond is determined and as a product, the payoff of the buyer is derived. A common recovery rate for bonds is 40% meaning, that the payoff for a CDS holder would be 60% of the notional principle of the bonds. (Hull 2021 p.569)

Hull et al (2008) present an alternative formula that accounts for accrued interests as follows:

$$L(1 - R - A(t) \tag{2}$$

Where A(t) = accrued interest of the reference entity's bond at time t as a percentage of the bond's face value.

It is also worthwhile to mention that, in addition to default, there are also other factors that can trigger the payoff. The events triggering a payoff are called credit events and are negotiable, though usually consisting of cases of failure to make a payment, restructuring of a debt and bankruptcy. (Hull 2021 p.567)

3 Credit default swap valuation

As Campbell and Taksler (2003) note, the relevant literature divides the theory of CDS valuation into two different categories of structural models and reduced form models. The distinguishing difference is the way the two models consider the definition and probability of default. The following chapters present both ways of CDS valuation starting with the reduced form models and continuing onto structural form models.

3.1 Hazard rates

Hazard rates are a theoretical framework for credit default swap valuation. Hazard rate is defined as the probability of default conditional on no earlier default. This framework assumes that the reference entity defaults can happen on any maturity date of the bonds. Moreover, it includes assumptions of deterministic interest rates and known recovery rates and claim amounts. In addition, it is assumed that there is no systematic risk in recovery rates which makes historical data suitable for estimating real world rates. Hull et al. (2008)

The mathematical logic of hazard rates is quite simple as it relies primarily on basic algebra and probabilities. Concisely, default probabilities for individual years can be calculated from historical cumulative default probabilities that are based on some characteristics of investments such as credit ratings. These default probabilities for years in isolation are then conditioned on no earlier default, the probability of which can be derived from the cumulative default probabilities. This process is shown in the formula below:

$$[V(t) - V(t + \Delta \mathrm{t})]/\mathrm{V(t)} \tag{3}$$

Where V(t) = the cumulative probability of the company not defaulting by time t.

Per Hull and Hull et al example, this formula is usually reduced to the following form :

$$V(t + \Delta\mathrm{t}) - V(t) = -\lambda(t)V(t)\Delta\mathrm{t} \tag{4}$$

Where $\lambda(t)$ = hazard rate.

After formula (x) is derivated with respect to time, the following is left:

$$\frac{dV(t)}{dt} = -\lambda(t)V(t) \tag{5}$$

From which V(t) is expanded as follows :

$$V(t) = e^{-\int_0^t \lambda(t)dt} \tag{6}$$

By Hull et al example if Q(t) is defined as the probability of default by time t, then it also happens that :

$$Q(t) = 1 - e^{-\int_0^t \lambda(t)dt} \tag{7}$$

Which can be further reduced to

$$Q(t) = 1 - e^{-\bar{\lambda}(t)t} \tag{8}$$

Where $\bar{\lambda}$ = average hazard rate from time 0 to time t.

3.2 Reduced form models

3.2.1 A static reduced form model

With a supposed hazard rate and assumed contract term, the CDS spread for a reference entity can be calculated using cumulative default probabilities. Using formula 8 with assumed average hazard rate of 2%, the probability of a reference entity surviving until time t is $e^{-0,02t}$. This probability is also used for the probabilities of payments and payoffs of the contract. Payments of unknown amount of x are assumed to be made semi-annually and the risk-free interest rate is assumed to be continuously compounding at 5%. The payoff is assumed to be made at the end of the year, principle is assumed to be 1$ and the recovery rate is assumed to be 40%. Moreover, defaults are assumed to happen at the middle of the year and the contract term to be 5 years.

With this knowledge, valuation of the contracts begins by estimating the expected payments and payoffs and discounting them to the present time. The price discovery begins by deriving the present values of the expected payments for the contract as follows:

$$\sum_{t=1}^{t=5}(e^{-0,02*t}) * \left(\frac{1}{e^{0,05*t}}\right) = 4,0729x \tag{9}$$

Where $\frac{1}{e^{0,05*t}}$ = discount factor.

Next, present value of expected payoffs are calculated as follows:

$$\sum_{t=0,5}^{t=4,5}(1 - e^{-0,02t}) * \left(\frac{1}{e^{0,05*t}}\right) = 0,0507x \tag{10}$$

3.3 Structural form models

Structural models build on the studies of Black & Scholes (1973) and Merton (1974) in which the respective authors developed valuation models for corporate debt. In the context of CDS, the main principle is that if the value of the firm is less than the value of the debt, the firm should declare bankruptcy. By the way of Merton (1974), this relationship can be represented through options contracts as the equity of a firm can be thought of as a call option on the value of the assets with a strike price of the value of the debt of the firm. This is illustrated in the following formula:

$$E_T = \max\,(V_T - D, 0) \tag{11}$$

Where E_T is the value of equity at time T, V_T is the value of the assets at time T and D is the debt repayment at time T.

The Black & Scholes (1973) formula coupled with the model by Merton (1974) gives the equity value of a firm at current time with a following formula:

$$E_0 = V_0 N(d_1) - De^{-rT} N(d_2) \qquad (12)$$

Where E_0 is the value of equity at current time, V_0 is the value of the firm's assets at current time, r is the risk-free rate.

The parameters d_1 and d_2 are further defined in the following way:

$$d_1 = \frac{\ln\left(\frac{V_0}{D}\right) + \left(r + \frac{\sigma_V^2}{2}\right)T}{\sigma_V \sqrt{T}} \quad and \quad d_2 = d_1 - \sigma_V \sqrt{T} \qquad (13)$$

Where σ_V is the constant volatility of assets.

Some of these variables cannot be directly observed and need to be derived. For example, the risk neutral probability of the firm defaulting on its debt is N(-d_2), the required parameters of which can be inferred from the value of equity with the help of Itô's lemma. As the value of equity can be directly observed if the firm is traded publicly, the values of shared parameters from formula 12 and Itô's lemma can be backtracked. This will give a value for V_0 and σ_V, after which the probability of default can be calculated and the expected loss on the debt. (Hull & White 2008)

3.4 CDS spread determinants in empirical research

Collin-Dufresne et al. (2002) estimate the credit spreads of corporate bonds through different proxies of credit risk. They analyze the relevant determinants such as changes in spot rate, changes in the slope of yield curve, changes in leverage, changes in volatility, changes in business climate and changes in likelihood or magnitude of a decline in a company's value. The proposed factors include credit spreads, firm leverage ratio, 10-year treasury yield, 10-year treasury yield over 2-year treasury yield, option-implied volatility of S&P 500, return on S&P 500 and the slope of Volatility Smirk. Having done regressions based on forementioned factors, the authors explain that the theoretical variables are economically and statistically significant, but they only manage to explain about 25% of the spread variation. Moreover, principal component analysis implied that the regression residuals are affected by a shared common factor. In other words, there seemed to be a large systemic component which influenced the residuals in unison. To ensure the robustness of the study, the authors conduct additional regression in which several additional factors are utilized. These alternate regressions do not, however, manage to explain the majority of the residuals, meaning, that the newly added factors have limited explanatory power and that the regression residuals are still highly cross-correlated.

Eom et al. (2004) set out to explain the differences among corporate and government bond pricing. They explicitly wanted to find out whether a risk premium was existent between the two bond classes. The authors reduce the price differences between these classes to three different factors; expected default loss, tax premium and risk premium. These factors are estimated separately for various rating classes and maturities, the data consists of 95 278 bond months for the years between 1987 and 1996. The authors exclude bonds with special features, problematic return data and maturities of less than a year. They define the spreads as the yield difference between zero coupon bonds of the same maturity with differing classes. To estimate the differences, the authors first calculated the yields, or spot rates as they called them, for the considered time period and were thereafter able to analyze the spreads. Preliminary analysis of the spreads showed that average estimation error was negligible and the spread results were in line with previous literature.

Next, default premium and tax premium were calculated. These were derived by assuming risk neutrality and for the default probability calculations to be Markovian and stationary. It was reported that these factors together did not adequately explain the variation in the spread. What followed was the consideration of the risk premium. The authors emphasized how previous literature had shown that government bond returns were not affected by trends in the equity market while on the other hand corporate bonds may have been. The yet unexplained spreads were then regressed on Fama & French (1993) three factor model. The addition of these factors explained between 66% and 85% of the unexplained spread that was left after accounting for default premium and tax premium.

Elton et al. (2001) examined the spread between corporate and government bonds. The assumption is that among other factors, investors are expected to require compensation for the default risk that is uniquely associated with corporate bonds, meaning that government bonds are seen as default-free. Factors in addition to expected default loss were tax premium and risk premium. Somewhat diverting from previous studies, the authors use spot rates instead of yields as they state that arbitrage arguments are concerned with spot rates, not yields. The drawback of utilizing spot rates is that they have to be estimated. First spread changes are conditioned for expected default premium and the tax premium. Then Fama and French (1993) three factor model is deployed for deriving the risk premium. Lastly, risk premium is derived and individual factors' effect can be calculated.

When the authors inspected the spread, they found that only a small part of it could be explained by the default risk attributable to the corporate bonds. They report that for 10-year A-rated industrial bonds, the premium of expected default loss explained only about 18% of the spread. After also accounting for taxes in the case of 10-year corporate bonds, 46% of the spread is still unexplained by these two factors. Out of this unexplained spread, Fama and French (1993) factors explained 85%. Contributing also to the study by Collin-Dufresne et al. (2002), the authors propose that the expected default loss premium can only influence a small part of the spread among investment-grade bonds because of the infrequency of defaults in that class.

Eom et al. (2004) empirically tested structural models of Merton (1974), Geske (1979) Longstaff and Schwartz (1995), Leland and Toft (1996) and Collin-Dufresne et al. (2002). They estimate the different variables needed and examine the models under equivalent assumptions to evaluate their abilities to predict corporate bond spreads. The authors' findings were that all of the examined models had considerable prediction errors and that the errors differed in magnitude and in sign.

What is more, every model seemed to generate lower than normal spreads for low leverage and low volatility firms, and higher than normal spreads for high leverage and high volatility firms. The authors conclude that while the models accounted for credit risks in a logical way that the predicted spreads were higher for higher risk companies, the models systemically underpredicted the lower spreads. Geske and Merton models tend to underestimate corporate bond spreads while Toft and Leland models overpredict the spreads on average. The underestimation of Merton and Geske models could be in part attributed to deadweight loss during financial distress while the overprediction of Leland and Toft models was broad and not related to a particular regressor. The authors explain that this might be due to the handling of the bond coupon in the study, the assumption of continuous coupons might misrepresent the weights of the coupons and which leads to the overestimation of credit risk.

Longstaff and Schwartz alter the model by Merton by also considering stochastic interest rates and the correlation between interest rates and firm value. Out of the two additions, only stochastic interest rates appear to be of significance as the credit spread estimates from them are sensitive to interest rate volatility estimated with Vasicek model. Collin-Dufresne and Goldstein model complimented the previous models by estimating more parameters, and they achieved a better result in a sense that bonds belonging to corporations with lower than target leverage got lowest predicted spreads and bonds belonging to firms with higher leverage got overpredicted spreads. With this information the authors conclude that credit spreads on corporate bonds cannot be accurately predicted by structural models. They add that in addition to the prevalent factors usually considered in similar studies, the inclusion of the volatility of interest rates might help the estimation of the spreads although estimation models aside to Vasicek might be needed.

Campbell & Taksler (2003) analyzed the effect of equity volatility on corporate bond yields and found that credit ratings and idiosyncratic firm-level volatility perform equivalently in explaining cross-sectional variations in corporate bond yields. The sample consists of investment grade corporate bonds for years 1995-1999. The authors run panel regressions in which equity volatility, credit ratings, accounting and macro data are considered. Having done the regressions the authors noted the following results. Equity volatility alone had more explanatory power than credit ratings alone. What is more, equity volatility and credit ratings can be used together for better explanatory power. Accounting data explained less of the yield spread than credit ratings did. Also, coupling accounting variables with credit ratings did not explain the spread more. The equity volatility therefore

While empirical studies speaking in favor of structural models are few and far between, Zhang et al. (2005), Zhou (2001) demonstrate how volatility and jump risk estimates calculated from high frequency equity data can explain the asset valuing progress of CDS contracts, and that the estimates can help to identify theoretical variables explaining CDS spreads.

They build on the findings by Campbell & Taksler (2003), where increases in corporate yields could be attributed to the upward trend of idiosyncratic volatility in equities. The authors' study is also influenced by previous studies of Barndorff-Nielsen & Shephard (2004), Huang & Tauchen (2005) and Andersen et al. (2007) where jump components of realized variance have been utilized. They decompose realized volatility into continuous and jump components measured by realized variance and jump detection variables. This helps in the identification process of different aspects of jump risk on credit spreads. Additionally, they consider different time frames of realized volatility and jump measures, which can help the predictions of the model be more accurate. Focusing solely on volatility and jump measures, the model is able to explain 53% of credit spread changes which is a greater part than previous studies have been able to produce. Extending the model to include researched macro variables such as credit ratings, S&P 500 return, short rate and VIX index, as well as firm specific variables such as recovery rate, leverage ratio, return on equity and dividend payout ratio, the model achieves adjusted R^2 of 0,73.

In other words, the equity volatility and jump risks together with firm specific variables and macro variables are able to explain 73% of the credit spread variation. The included equity volatility and jump risk variables contributed 14% to the explanatory power when compared to a model in which only firm specific and macro variables were considered. Their findings indicate that realized volatility in the short run, historical volatility and various jump measures are economically and statistically significant in explaining CDS spreads. In excess of the findings, the authors demonstrate how a structural model can reach the same empiric results if default probabilities are controlled for appropriately. The authors calibrate structural models with equity volatility and jump risk variables and conclude that the inclusion of these variables may help structural credit risk models in explaining credit spread changes.

A study by Annaert et al. (2013) is of particular importance to the topic of this study. The authors conducted a study on the CDS spread changes of 32 listed euro area banks. The data consists of investment grade bonds of banks from a period of 2003-2010. The panel data is unbalanced as for 23 banks more than 200 observations could be gathered and for 2 banks only 100 observations were available. The time period is divided into subintervals which helps in analyzing the effects of the great financial crisis, in addition to the full period, subperiods of pre-crisis and crisis are considered. The relevant bonds are divided into different categories based on their credit rating. They analyze this phenomenon empirically by utilizing the Merton (1974) model while also adding some macroeconomic variables themselves. These factors are linked to liquidity, market, and business cycle and it is stated that the inclusion of these variables increases the explanatory power of the model by 30% at best.

The authors first conduct univariate logit regressions in which they estimate whether the unbalanced dataset makes the gathered sample endogenous which might lead to causal regression's estimates being biased and inconsistent. They analyze this possibility by testing whether the probability of an observed quote is systematically related to the explanatory variables and find insignificant links for most variables at the 10% level for a two-sided test. Additionally, univariate regressions of explorative nature are conducted over the crisis and pre-crisis periods. The results indicate that the dynamics between credit spread changes, and the determinants vary over time and in general the volatility of the variable estimates increased during and after the great financial crisis.

Having done univariate regressions the authors then initially conducted multivariate panel regressions in which the forementioned three different risk drivers were analyzed. All of the risk drivers were able to some part of the CDS spread changes when the period was considered at whole, credit risk variables explaining 9.92%, liquidity variables 6,42% and business- and market cycle related variables explaining 14,86%. Market returns, swap spread and term structure slope are statistically significant in the analysis while, surprisingly, estimates of market volatility turned out to be insignificant. Moreover, market variables and business cycle factors explain the variation in CDS spread changes more for better rated banks than for lower rated banks while the liquidity factor was able to explain more of the variation for A-rated bonds than for AA-rated bonds.

It is then concluded that the determinants of bank CDS spreads are not constant over time but somewhat constant over rating categories. Another finding follows in that variables proposed by structural models were significant predominantly for the time period beginning from the crisis. As a worthwhile mention, the liquidity factor is significant for the whole period and should, as advised by the authors, be explicitly considered when analyzing CDS spreads.

4 Volatility spillovers and financial contagion

This chapter presents the relevant definitions for volatility spillovers and financial contagion. What is more, the following topics also touch upon the literature and empirical research on the topics.

4.1 Contagion channels

Kaminsky et al (2003) set out to explain why in some financial crises the consequent effects are contained in the origin country and why in some cases the effects spill over to global markets. The authors separate the ways of contagion into three different categories: Herding, Trade Linkages and Financial Linkages.

Banerjee (1992) Herding is described to be a behavioral channel in which individuals disregard their private information in favor of mimicking the actions of others. This phenomenon relies on the premise that the actions of others might tell of possession of non-public information that is more valuable than the actor's own information. Moreover, herding behavior exhibits characteristics of a positive feedback loop in which the inclusion of an individual encourages other individuals to follow suit. The initial few decisionmakers forming the herd in its early stage determine the direction and sentiment of the eventual crowd. Calvo & Mendoza (2000) present alternative motivation to the herding behavior, they approach the problem from an information friction point of view. The authors explain how the herding behavior is efficient in environment where there are costs in gathering information. Because of these costs, there is an equilibrium above which the additional benefit of gathering more information is offset by the costs of obtaining the information. In these circumstances, it is rational for investors to mimic the actions of others.

Kaminsky & Reinhart (2000), Glick and Rose (1999) present trade linkages as one of the main propagants of financial crises. Domestic demand is usually subdued during financial crises, also resulting in reduced imports. This affects the international trading partners which are heavily dependent on exports. What is more, countries might engage in price competition to maintain trade competitiveness which can in turn lead to regional instability.

With Financial Linkages the contagion is transferred through global financial integration. When a crisis occurs in some domestic market, global investors extrapolate the issues to a broader market although that might not always be warranted. This kind of widespread reassessment of risk due to idiosyncratic crisis is coined as the "Wake-Up Call Effect" by Calvo (1999) in his research concerning contagion in emerging markets. This behavior is demonstrated by capital flight and rising risk premiums and documented by studies from the beforementioned authors.

4.2 Interconnectedness and contagion analysis

Financial contagion is generally considered a financial phenomenon in which one instance affects another, yet there isn't a definitive definition for it. Davidson (2020) and Gravelle et al. (2006), among others, define financial contagion as a statistically significant increment in cross-market correlation occurring after a major shock in between crises and stable periods. Eichengreen (1996) relates the definition to crises by stating that it is a significant increase in the probability of a crisis in one country, given there is a crisis in another country. Forbes and Rigobon (2002) define financial contagion as a significant increase in linkages across markets after a shock to one country or to a group of countries. What is shared by these different definitions is that contagion is distinguished from ordinary interdependencies and spillovers across markets as contagion can be regarded as unanticipated transmission of shocks.

4.2.1 Empirical models for contagion analysis

The frameworks for the analyzation of financial contagion are as many as its definitions. One common method is the cross-market correlation coefficient method in which return relationships between two markets are analyzed during a stable period and a shock period Forbes and Rigobon (2002). If the increase in the correlation coefficient is statistically significant between the time periods, the method suggests that contagion occurred. One of the first major papers using this technique was the study by King and Wadhwani (1990) in which they investigated the transmission of volatility between London and New York stock markets and found financial contagion to be statistically significant. Later the same model had been also implemented in other study conducted by Calvo and Reinhart (1996) which have managed to find evidence of financial contagion as well.

Other favored methods for financial contagion estimation are the Autoregressive Conditional Heteroscedasticity framework by Engle (1982) and General Autoregressive Conditional Heteroscedasticity framework by Bollerslev (1986). In these models, variance is not assumed constant but to be a function conditional on past sample variances and white noise. As Engle (1982) demonstrates, a simple case of an ARCH model can be formulated as follows:

$$y_t = h_t^{0,5} \epsilon_t \tag{14}$$

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2 \tag{15}$$

Where ϵ is white noise with a variance of 1.

GARCH model is an extension of ARCH model in which not only the past sample variances are included, but also the lagged squared errors. (Bollerslev 1986). A simple case of a GARCH model can be formulated as follows:

$$h_t = \alpha_0 + \sum_{i=0}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=0}^{p} \beta_i h_{t-i} \tag{16}$$

Some studies utilizing the implementation of ARCH and GARCH are studies by Engle et al. (1993), Nelson (1991).

In their study, Engle et al. (1993) construct a news impact curve to measure the incorporation of new information into volatility estimates. They analyze this by first regressing daily Japanese stock market index returns on day-of-the-week dummy variables in order to get an error term. They then adjust for the autocorrelation by regressing the error term on its past values up to six lags, also achieving the residual needed for the ARCH estimations. The authors use extensions of ARCH such as GARCH, EGARCH, VGARCH, AGARCH and GJR model, the variations of which also control for asymmetricity in the volatility. The authors conclude that all of the models found negative shocks to affect volatility more than positive shocks. Out of all the models, the GJR model was the best in capturing the asymmetric effect.

Nelson (1991) criticized the GARCH models of having three crucial pitfalls. The first one was that there had been well established research suggesting that there is a negative correlation between the volatilities of current returns and future returns – a phenomenon which is ruled out as an assumption in GARCH models. The second point of criticism was that the GARCH models are too restrictive on their parameter impositions, and that these restrictions are frequently violated by the estimated coefficients. According to Nelson, this might have also led to excessive restrictions on the process of conditional variance. The final point of criticism was that the interpretation of shocks on conditional variance and their persistence is difficult in GARCH models.

Having provided this criticism, Nelson proposed a new approach in which the different issues were taken into account. Nelson called this new approach exponential ARCH model. Exponential ARCH model does not impose restrictions on the parameters, which is the opposite for ARCH models. Also, the conditional variance is modeled in logarithmic form in the exponential ARCH model whereas the process is linear in ARCH models. The logarithmic transformation allows for the observation of asymmetry in the conditional volatility.

Using the exponential ARCH model, the authors find that the asymmetry between changes in volatility and returns is statistically significant. In other words, volatility does not change in a linear way between positive and negative returns.

Edwards (1998) used GARCH model to estimate the volatility contagion from Mexico to Chile and Argentina, finding partial volatility contagion.

4.3 Volatility spillovers

Like financial contagion, volatility spillover too has slightly different definitions depending on the specific topic at hand. It can be, however, generally regarded as a change in the transmission of volatility between markets during differing market conditions. (Beirne et al. 2009). The difference to financial contagion is very nuanced – Kanas (1998), among others, calls it by interdependency in variance between returns. Somewhat of a discerning factor, however, is that contagion usually has some sort of event or psychological component which partly drives the interconnectedness while spillovers could be regarded as more general concept where the interconnectedness emphasizes the process of transmission and is not necessarily dependent on any specific event or psychological component.

4.3.1 The Spillover index

Diebold and Yilmaz (2009) measured asset return and volatility spillovers in a global equity market context. They constructed a statistical measure which takes into account the different sources of return or volatility dependencies among variables and their past values. In essence, the authors utilize vector autoregressive models to decompose autoregressive returns or variances between variables into parts where the variance can be stemming from the respective variable or from some another variable that has an effect on another variable. They call this measure the spillover index and it is calculated by summing up the parts of prediction errors of variables attributable to covariances between the variables and dividing it by the sum of total prediction error of the autoregressive model. With this framework the Yilmaz and Diebold demonstrate how 22% of the 10-week Mexican return variation is explained by spillovers from the U.S. On the full sample analysis, the authors find that for their data the cross-country spillovers account for nearly 40% of the forecast error variance. This effect was found for both volatility and return spillovers.

The Diebold and Yilmaz (2009) decomposition model, however, has certain issues as voiced by Diebold and Yilmaz (2012). Namely, the model is a simple VAR framework where the model results might be influenced by variable ordering. This is due to the fac that the model identifies factors with Cholesky decomposition. The authors remediate this by measuring the spillovers directionally instead of aggregately, and by utilizing a generalized vector autoregression model by Koop et al. (1996), Pesaran & Shin (1998).

In addition to producing results not biased by the variable ordering, the improved model allows the measurement of spillovers across asset classes. For example, one finding by the authors was that in their sample, out of equities, commodities, bonds and FX, the bond market was the most influenced by spillovers from other markets. Moreover, the cyclicality of the spillovers is demonstrated by analyzing total spillovers between the markets with respect to time. Anecdotally, the tech bubble in the 2000's increased the spillover index between the capital markets from 13% to 20%. In other words, during the bubble, a fifth of the returns among the markets were from spillovers in total. The spillover index can also demonstrate the effect of policy changes as an increase in federal funds rate doubled the index in 8 months, transmitted to other markets by bond and forex markets.

Relating to the topic of this thesis, Diebold & Yilmaz (2012) demonstrate how an unanticipated significant event can generate spillovers. This was the case for the credit crunch of 2007 and the default of Lehman Brothers in 2008 when the spillover index rose close to and even above 30 index points. During these times, the stock market was a major contributor in the transmission of volatility to other markets.

5 Data and methodology

This chapter presents the data and methodology used in the study.

5.1 Scope and data

Originally the sample consisted of the 50 biggest banks by balance sheet in Europe. As the intent was to contrast the contagion between SVB and other credit institutions, a geographical and supervisory distinction was formed to emphasize the contagion. After data quality check in which the banks with illiquid contracts were ruled out, 24 of these banks remained in the sample. The CDS are quoted daily in Euros and represent the mid premium in that day and are fetched from Refinitiv's Datastream -database. Five-year senior contracts were chosen as they are considered to be the most liquid (Raunig & Scheicher 2008). To make most of the observations comparable, contracts with modified-modified restructuring terms were chosen whereas few included contracts had the more flexible full restructuring clauses. Said restructuring clauses affect the pricing of the CDS and although it is statistically significant, it isn't economically so. (Packer & Zhu 2005). The sample consists of 349 observations for each bank, making the total of all observations 8376. SVB bond yields are gathered from Bloomberg terminal.

5.2 Descriptive statistics

The data consists of 8376 observations from 3/1/2022 until 25/5/2023. The sample of daily CDS spreads measured in basis points portray a skewed distribution with a long right tail reflecting periods of elevated credit risk. The average CDS spread across all banks is approximately 79 basis points while the median is slightly lower at 67 basis points.

The upper tail of the distribution shows considerable variation. The 75th percentile CDS spread reaches approximately 113 basis points while the 90th and 95th percentiles jump to 177 basis points and 302 basis points, respectively. The standard deviation of spreads is sizable, confirming that a subset of banks experienced significant CDS spread repricing during the sample period. The minimum spread is at around 25 basis points whereas maximum spread was 982 basis points and 99th percentile 553 basis points. These elevated values are consistent with market reactions to financial distress. Figure 2 displays a sub-sample of the daily changes of CDS spreads around the event window highlighting the heterogeneity and heteroscedasticity in the data.

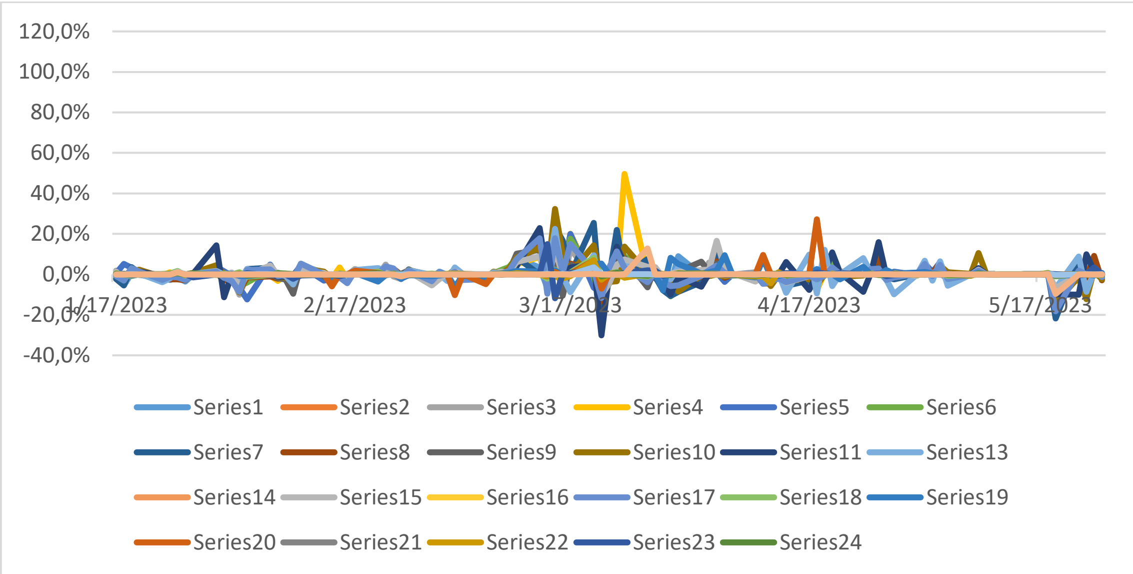

Figure 2. Sub-sample around the event.

5.3 Methodology

To evaluate the effect of SVB's collapse on the CDS spreads of European banks, the following equation is estimated for 24 European banks:

$$\Delta y_{i,t} = \alpha_i + \mathrm{F}_{1i} x_{i,t-1} + \beta D_t + \varepsilon_{i,t} \qquad (17)$$

Equation 17 expresses the daily changes in the dependent variable $\Delta y_{i,t}$ (the changes in the log-CDS spreads for bank i at time t). The changes are estimated by lagged factors $x_{i,t-1}$ (daily log-CDS spread change and daily log-return on bond of Silicon Valley Bank and daily premium of euro short-term rate over 3-month Euribor rate) as well as D_t (dummy variable taking value of one during the SVB event window). β is a coefficient of the event effect and F denotes a matrix of coefficients for endogenic variables. α_i is a bank-specific vector for constant and $\varepsilon_{i,t}$ is a vector of residuals.

The equation 17 is motivated by similar studies from Altavilla et al. (2014) and Cesa-Bianchi et al. (2018). Altavilla et al. studied financial and macroeconomic effects of outright monetary transaction announcements. They conducted the study by regressing sovereign bond yields on event dummies while simultaneously having controlling factors to isolate the effect of interest. Cesa-Bianchi et al. estimate the effect of leverage to credit flows with a Panel VAR model. This study is more closely linked to Altavilla et al. in econometric terms but retains some aspects from Cesa-Bianchi et al. such as considerations on event window length, use of mean group estimates and lagged endogenic variables.

The model allows for heterogeneous responses of CDS spread changes on bank level, naturally the statistical inference and hypothesis testing will be explicitly done on bank level for robustness reasons. Altavilla et al. (2014). The hypotheses are:

H0: SVB did not induce or transmit financial contagion or volatility spillovers to European banks' CDS spreads.

H1: SVB did induce or transmit financial contagion or volatility spillovers to European banks' CDS spreads.

As the study employes standard regression techniques, whether null hypothesis is rejected can be inferred from the magnitude and statistical significance of coefficient β. Later the result coefficients are averaged over groups utilizing mean group estimator by Pesaran & Smith (1995). These results are checked for robustness by running a fixed effects panel regression and interpreting the results as motivated by Blanco (2004).

The fixed effects panel regression utilizes a formula as such:

$$\Delta y_{i,t} = \alpha_i + \mathrm{F}_{1i} x_{i,t-1} + \beta D_t + \varepsilon_{i,t} \qquad (18)$$

Equation 18 expresses the daily changes in the dependent variable $\Delta y_{i,t}$ (the changes in the log-CDS spreads for bank i at time t). The changes are estimated by lagged factors $x_{i,t-1}$ (daily log-CDS spread change) as well as D_t (dummy variable taking value of one during the event window). β is a coefficient of the event effect and F denotes a matrix of coefficients. α_i is a bank-specific vector for constant and $\varepsilon_{i,t}$ is a vector of residuals.

6 Results

This chapter presents the results of this study in two sections, first the individual bank-specific regressions are analyzed and thereafter a fixed effects panel regression is conducted for consistency.

6.1 Individual bank-specific regressions

First following the methods by Altavilla et al. regression shown in equation 17 is run for the CDS spreads. The results are divided into two groups in which for the classical group no control variables are used and only dummy variable is used to estimate CDS spread changes. For controlled group variables on CDS spread, SVB bond yield and 3-month Euribor premium are added. Results are shown in table 1.

6.1.1 Results for individual bank-specific regressions without control variables

Table 1. Results for individual bank-specific regressions without control variables. This table presents the results for an OLS regression for the whole sample. The banks are on a descending order on balance sheet basis with rolling event-window from the day of event until the 5th day since the event. The T-statistics are denoted in brackets and statistical significances of 1%, 5% and 10% are reported with ***,**,*, respectively.

Variable	Size of the event window				
	1-day	2-day	3-day	4-day	5-day
SVB_event					
HSBC BANK PLC	0,01	-0,21	0,01	0,04	-0,02
BNP PARIBAS SA	0,05	-0,03	-0,15	-0,04	-0,08
CREDIT AGRICOLE SA	0,1	-0,12	0,01	-0,03	0,07
BARCLAYS BANK PLC	-0,1***	-0,11	-0,11	-0,04	0
BANCO SANTANDER	-0,09***	-0,1	-0,08	-0,06	0,13
SOCIETE GENERALE	0,01	-0,02	-0,13	0,21	0,05
DEUTSCHE BANK AG	-0,03	-0,14	-0,12	-0,02	0,01
INTESA SANPAOLO	-0,03	-0,1	0	-0,07	-0,07
LLOYDS BANK	0,19	-0,02	0,01	0,07	-0,06
UBS AG	-0,04	0,78**	-0,08	0,13	0,22
NATWEST GROUP PLC	0,19	-0,08	-0,09	0,11	-0,06
CREDIT SUISSE GROUP	0,09	0,03	-0,06	-0,03	-0,07
STD CHARTERED BK	0	0,78	-0,09	0,21	-0,01
DZ BK AG ZENTRAL GBK	-0,1	-0,07	0,01	-0,01	-0,07
DANSKE BANK A/S	0,04	-0,05	-0,14	-0,09	-0,07
COMMERZBANK AG	0,09	0,01	-0,14	-0,04	-0,01
KBC BANK	0,19	-0,13	0,01	0,14	-0,06
SVENSKA HB	0	0,79***	-0,08	0,21	0,07
SKANDINAVISKA ENSK BNKN	0,19	0,03	-0,13	0,21	0,15
BAYERISCHE LANDESBK	0,05	-0,12**	-0,11	-0,04	0,04
BANCO DE SABADELL	-0,09*	-0,11**	0,78**	-0,15	0,13
RAIFF BNK INT	0,19	0,05	-0,11	0,21	-0,06
BANK OF IRELAND	-0,09**	-0,11*	-0,06	-0,04	0,13
BANCA MONTE PASCHI	-0,09***	0,01	0,97***	-0,03	0,13

In table 1 the SVB factor measures average CDS spread %-changes during event days compared to all other days – without controlling for any other variables. Out of the 24 banks, 3 had statistically significant effects from the SVB collapse up to five days. This means that, in lack of other control variables, only three of the banks exhibited differing CDS spread changes during the SVB collapse. This is not a surprising result as it is largely referred in the literature, that there are many other variables that act and contribute to CDS spreads. (Jarocinski 2008) (Canova, Ciccarelli 2013). Moreover, it seems that at this stage of the analysis the miniscule effect is also concentrated at the lower end of the list indicating the size of the bank might correlate with the relationship. The sudden significance of Credit Suisse Group most likely comes from the announcement of an acquisition of the group which was made public the 19th of March. It is probable that this information was ingested into the CDS spread changes before the publication of the announcement. This is further demonstrated by the differing sign of coefficient compared to Bayerische Landesbank and Banca Monte Paschi.

At this stage the results do not imply a relationship between the event of default of SVB and changes in CDS spreads. This, however, is more likely to due to the lack of control variables than the existence of the relationship itself. On the other hand, Altavilla et al. (2014) demonstrate that as rudimentary regressions as this is actually able to already find significant results in a similar context. However, the nature of their data has multiple different dummy variables which improves the robustness of the model.

Next the same analysis is done with the help of control variables.

6.1.2 Results for individual bank-specific regressions with control variables

Table 2. Results for individual bank-specific regressions with control variables. This table presents the results for an OLS regression for the whole sample. The banks are on a descending order on balance sheet basis with rolling event-window from the day of event until the 5th day since the event. The T-statistics are denoted in brackets and statistical significances of 1%, 5% and 10% are reported with ***,**,*, respectively.

Variable	Size of the event window				
	1-day	2-day	3-day	4-day	5-day
SVB_event					
HSBC BANK PLC	0,07**	0,04	-0,01	0,04**	0,01
BNP PARIBAS SA	0,06*	0,08***	0,03	0,07***	0,03*
CREDIT AGRICOLE SA	0,07*	0,08***	0,02	0,07***	0,04**
BARCLAYS BANK PLC	0,04	0,04	0	0	-0,02
BANCO SANTANDER	0,05	0,07***	0,01	0,05***	0,04**
SOCIETE GENERALE	0,07*	0,08***	0,01	0,05*	0,03
DEUTSCHE BANK AG	0,07*	-0,01	-0,02	0,05*	0,09***
INTESA SANPAOLO	0,06*	0,09***	0,02	0,05**	0,04**
LLOYDS BANK	0,09***	0,09***	0,03	0,05***	0,01
UBS AG	0,07*	0,06**	0,01	0,1***	0,1***
NATWEST GROUP PLC	0,04	0,11***	0,06**	0,08***	0,06***
CREDIT SUISSE GROUP	0,14	0,14*	0,14**	0,14**	0,37***
STD CHARTERED BK	0	0	0	0	0
DZ BK AG ZENTRAL GBK	0	0	0***	0	0***
DANSKE BANK A/S	0,06**	0,06***	0,01	0,04**	0,02
COMMERZBANK AG	0,07*	0,09***	0,01	0,05**	0,04**
KBC BANK	0,01	0	-0,01	0	-0,01
SVENSKA HB	0,01	0	-0,02	-0,02	-0,02
SKANDINAVISKA ENSK BNKN	-0,01	-0,02	-0,02	-0,02	-0,02
BAYERISCHE LANDESBK	0,01	0	0	0	-0,01
BANCO DE SABADELL	0	-0,01	0,04***	-0,01	-0,01
RAIFF BNK INT	0,01	0	-0,01	-0,01	-0,01
BANK OF IRELAND	-0,01	-0,01	-0,01	-0,01	0
BANCA MONTE PASCHI	0	-0,01	-0,02	-0,02*	-0,02**

In table 2 the SVB factor measures average CDS spread %-changes during event days compared to all other days when controlled with variables of lagged CDS spreads, lagged SVB bond yields and Euribor 3m premium over ESTR. These control variables are backed by literature by Tölö et al. (2014) Palazzo & Yamarthy (2022)

Table 2 presents more robust results than what was presented in table 1. This time 16 of the 24 banks have significantly different CDS spread %-changes during the Silicon Valley Bank event window compared to other days. For 13 of the banks, the effect is highly statistically significant. The coefficients are all positive which is intuitively correct when taken account the nature of the SVB collapse and the likely worries it caused to other markets.

The effect doesn't seem to be concentrated in any specific subsection of the panel, which speaks for the comprehensive effect that the default of Silicon Valley Bank had.

Already it can be statistically inferred that the default of SVB did have an effect on the pricing on CDS spreads of European banks. The effect was notable, having at maximum an 11% increase on an individual bank's CDS spread. The effect looks to be the most significant in statistical and economical terms on a 2-day event window since the event and then decreasing in significance and economics during 4-day and 5-day event windows.

The break on the 3-day trading window is likely due to the coincidentally financial problems of Credit Suisse that were made public the 15th of march 2023, which corresponds to the third trading day counting from the collapse of SVB. This is further demonstrated by the subsequent erratic increase in magnitude which cannot be observed for other banks. Including this unique phenomenon is a display of the robustness of the model. The break in the 3-day window suggests that during that third trading day it was largely Credit Suisse propagating contagion to others instead of SVB, consequently demonstrating how these one of a kind events can bring sudden distress to financial markets.

This is also the case despite controlling for the lags of SVB bond yields, CDS spreads and Euribor premiums as in table 3:

Table 3. Results individual bank-specific regressions – control variables. This table presents the results for an OLS regression for the whole sample. The banks are on a descending order on balance sheet basis with rolling event-window from the day of event until the 5th day since the event. The T-statistics are denoted in brackets and statistical significances of 1%, 5% and 10% are reported with ***,**,*, respectively.

SVB(-1)	**1-day**	**2-day**	**3-day**	**4-day**	**5-day**
HSBC BANK PLC	0,03***	0,02**	0,03***	0,02*	0,02**
BNP PARIBAS SA	0,04***	0,03***	0,04***	0,02**	0,03***
CREDIT AGRICOLE SA	0,03***	0,03**	0,03**	0,02	0,02*
BARCLAYS BANK PLC	0,03***	0,03***	0,03***	0,03***	0,04***
BANCO SANTANDER	0,03***	0,03***	0,03***	0,02**	0,02**
SOCIETE GENERALE	0,05***	0,04***	0,05***	0,04***	0,04***
DEUTSCHE BANK AG	0,06***	0,06***	0,06***	0,04**	0,02
INTESA SANPAOLO	0,03***	0,02**	0,03**	0,02	0,02
LLOYDS BANK	0,03***	0,02**	0,02**	0,02*	0,02***
UBS AG	0,06***	0,05***	0,06***	0,03*	0,02
NATWEST GROUP PLC	0,04***	0,03**	0,03**	0,02	0,02
CREDIT SUISSE GROUP	-0,04*	-0,05**	-0,06**	-0,07***	-0,11***
STD CHARTERED BK	0,03**	0,03**	0,03**	0,03**	0,03**
DZ BK AG ZENTRAL GBK	0***	0***	0***	0***	0***
DANSKE BANK A/S	0,03***	0,02***	0,03***	0,02**	0,02**
COMMERZBANK AG	0,05***	0,03***	0,05***	0,03**	0,03**
KBC BANK	0	0	0,01*	0,01	0,01*
SVENSKA HB	0,02***	0,02***	0,02***	0,02***	0,02***
SKANDINAVISKA ENSK BNKN	0,01	0,01	0,01	0,01	0,01
BAYERISCHE LANDESBK	0	0	0	0	0
BANCO DE SABADELL	0,01***	0,01***	0,01	0,01***	0,01***
RAIFF BNK INT	0,01	0,01	0,01	0,01	0,01
BANK OF IRELAND	0	0	0	0	0
BANCA MONTE PASCHI	0,01***	0,01***	0,02***	0,02***	0,02***

CDS(-1)	**1-day**	**2-day**	**3-day**	**4-day**	**5-day**
HSBC BANK PLC	0,96***	0,96***	0,95***	0,97***	0,96***
BNP PARIBAS SA	0,93***	0,94***	0,94***	0,95***	0,94***
CREDIT AGRICOLE SA	0,94***	0,95***	0,94***	0,96***	0,95***
BARCLAYS BANK PLC	0,94***	0,95***	0,94***	0,94***	0,93***
BANCO SANTANDER	0,93***	0,94***	0,93***	0,94***	0,94***
SOCIETE GENERALE	0,92***	0,93***	0,92***	0,94***	0,93***
DEUTSCHE BANK AG	0,92***	0,92***	0,91***	0,94***	0,96***
INTESA SANPAOLO	0,94***	0,96***	0,95***	0,96***	0,96***
LLOYDS BANK	0,96***	0,97***	0,96***	0,97***	0,96***
UBS AG	0,92***	0,93***	0,92***	0,96***	0,96***
NATWEST GROUP PLC	0,93***	0,94***	0,94***	0,94***	0,94***
CREDIT SUISSE GROUP	0,89***	0,88***	0,88***	0,87***	0,83***
STD CHARTERED BK	0,91***	0,91***	0,91***	0,91***	0,91***
DZ BK AG ZENTRAL GBK	0,8***	0,8***	0,78***	0,78***	0,76***
DANSKE BANK A/S	0,97***	0,97***	0,97***	0,98***	0,97***
COMMERZBANK AG	0,93***	0,94***	0,93***	0,95***	0,94***
KBC BANK	0,97***	0,97***	0,96***	0,96***	0,96***
SVENSKA HB	0,97***	0,97***	0,97***	0,97***	0,97***
SKANDINAVISKA ENSK BNKN	0,98***	0,98***	0,98***	0,98***	0,98***
BAYERISCHE LANDESBK	0,98***	0,98***	0,98***	0,98***	0,98***
BANCO DE SABADELL	0,95***	0,95***	0,96***	0,95***	0,95***
RAIFF BNK INT	0,94***	0,94***	0,94***	0,94***	0,94***
BANK OF IRELAND	0,95***	0,95***	0,95***	0,95***	0,95***
BANCA MONTE PASCHI	0,9***	0,89***	0,89***	0,88***	0,88***

premium_eur3m	1-day	2-day	3-day	4-day	5-day
HSBC BANK PLC	0,01	0,01	0,01	0,01	0,01
BNP PARIBAS SA	0,01	0,01	0,01	0,01	0,01
CREDIT AGRICOLE SA	0,01	0,01	0,01	0	0,01
BARCLAYS BANK PLC	0	0	0	0	0
BANCO SANTANDER	0,03**	0,02*	0,03**	0,02	0,02*
SOCIETE GENERALE	0,01	0,01	0,01	0,01	0,01
DEUTSCHE BANK AG	0	0	0	-0,01	-0,01
INTESA SANPAOLO	0	-0,01	0	-0,01	0
LLOYDS BANK	0,02*	0,02	0,02*	0,02	0,02*
UBS AG	0,02	0,01	0,02	0	0
NATWEST GROUP PLC	0,01	0	0	0	0
CREDIT SUISSE GROUP	-0,07**	-0,08**	-0,08**	-0,08**	-0,09***
STD CHARTERED BK	0,03*	0,03*	0,03*	0,03*	0,03*
DZ BK AG ZENTRAL GBK	0	0	0	0	0
DANSKE BANK A/S	-0,01	-0,01	-0,01	-0,01	-0,01
COMMERZBANK AG	0,01	0	0,01	0	0
KBC BANK	0	0	0,01	0,01	0,01
SVENSKA HB	0	0	0	0	0
SKANDINAVISKA ENSK BNKN	0,05***	0,05***	0,05***	0,05***	0,05***
BAYERISCHE LANDESBK	0,01*	0,01*	0,01*	0,01*	0,01*
BANCO DE SABADELL	0,01*	0,01**	0,01	0,01**	0,01**
RAIFF BNK INT	-0,02	-0,02	-0,02	-0,02	-0,02
BANK OF IRELAND	0,02	0,02	0,02	0,02	0,02
BANCA MONTE PASCHI	0	0,01	0,01	0,01	0,01

6.1.3 Mean Group Estimation

The previous tables provide bank-specific responses to the default of SVB and to the control variables. This chapter provides additional dimension in which the mean group estimator is finalized by summarizing the individual coefficients from table 3 into a panel-wide effect and inference. These results are presented in table 4.

Table 4. Results for Mean Group Estimation with control variables. This table presents the results for an OLS regression for the whole sample. The effect on single banks are summarized with a MGE and a rolling event-window from the day of event until the 5th day since the event. The T-statistics are denoted in brackets and statistical significances of 1%, 5% and 10% are reported with ***,**,*, respectively.

Variable	Size of the event window				
	1-day	2-day	3-day	4-day	5-day
SVB_event	0,04***	0,04***	0,01	0,03***	0,03*

Table 4 summarizes the panel-wide effect which the collapse of SVB had on the 24 banks' CDS spread changes. From this table it can be inferred that for at whole the effect was highly statistically significant with a 4-day event window. The effect on the 3-day event window is likely influenced by the financial distress of the Credit Suisse on the day which corresponds to the third trading day in this framework.

Despite the noise the Mean Group Estimator describes that the effect of SVB's default was most intense in economic terms the day of event and the trading day after. From there on there economic effects decreased slightly with also statistical significance declining afterwards.

During the peak of the event, the default of SVB had an average increase of 4% on credit default swap spreads of European banks.

6.2 Panel fixed-effects regression

For robustness reasons the results from Tables 2 and 4 are replicated with a pooled regression in this chapter. The motivation for this is to validate or challenge the previous results by means of panel data fixed-effects regression.

Table 5. **Fixed effects regression including control variables.** This table presents the results for a fixed effects regression for the whole sample. The effect on single banks are summarized and a rolling event-window from the 2nd day of event until the 5th day since the event. The T-statistics are denoted in brackets and statistical significances of 1%, 5% and 10% are reported with ***,**,*, respectively.

Variable	Size of the event window			
	2-day	**3-day**	**4-day**	**5-day**
SVB_event	0,053***	0,030***	0,045***	0,044***

The fixed effects regression confirms that on average the CDS spreads rose significantly in response to the SVB collapse. The magnitude in panel fixed-effect regression is slightly higher also more statistically significant but supports the findings covered previously.

An interesting observation can be made in the sense that there wasn't a decline in statistical significance around the third trading day in the fixed effects regression. This could imply that the banks experienced correlated shocks or common error components possibly propagated by Credit Suisse.

6.3 Discussion

The findings of this thesis suggest a strong of financial contagion following the default of Silicon Valley Bank. During the default period and shortly thereafter, the statistical analysis exhibited significant relationship between SVB default date and CDS prices of European banks. The change in relationships, however, highlights the CDS market's property of being vulnerable to systemic shocks.

This thesis contributes to the existing body of literature in several meaningful ways. It empirically supports the transmission of financial contagion through CDS markets and the longer effects of contagion, building on earlier studies like Diebold and Yilmaz (2009, 2012) which proposed methods to quantify volatility and spillovers.

Moreover, the study extends the findings of Annaert et al. (2013) who assessed the CDS spread determinants during the Great Financial Crisis. While the authors focused on structural and macroeconomic factors, this thesis introduces an even-driven contagion perspective that had a liquidity concern at its heart. The contemporary focus makes the findings uniquely relevant for understanding how modern financial markets react to sudden stress events.

In terms of methodology, the use of OLS, MGE and fixed effects panel data models add depth to the literature by highlighting volatility and return dependencies that evolve with time and depend on credit events. The study's use of event style design, coupled with high-frequency CDS data provide a fresh point of view into assessing contagion mechanisms. The inclusion of SVB default event as predictor introduces a fresh angle that directly connects intra-sector distress to global derivative market responses. Ultimately this thesis adds to the understanding of how markets gather and utilize information, assess risk and adjust valuation in an interconnected global economy.

6.4 Limitations

Despite its valuable insights, there are limitations to this study which should be noted. Firstly, the sample size of 24 European banks is only representative of one part of the whole derivative market and while being comprehensive in terms of regional representation, will not capture the full diversity of market reactions of smaller institutions and those outside CDS market. The effect and magnitude of possible contagion or spillovers can differ drastically from what was demonstrated in this study in other markets or smaller market participants.

The reliance on OLS models present intuitive statistical reasoning on the return-dependency and volatility but do not necessarily capture more intricate relationships between the banks, especially those in which the different banks' CDS spreads affect one another.

This study could be further studied by employing a VAR model which would capture the dynamic dependencies between the banks. It would also allow for modeling of reciprocal effects and reactions of factors. This kind of model could be employed in figuring out whether the SVB yields were able to predict the CDS changes or European banks.

7 Conclusion

This paper's objective was to investigate the possibility of financial contagion stemming from Silicon Valley Bank and propagating to European banks during the collapse of SVB. The study was driven by the hypothesis that the collapse of SVB would not remain an isolated incident but affect pricing of comparable peers in the European market. In current light this hypothesis was proved correct.

This hypothesis builds on the theoretical frameworks which predominantly relate CDS pricing to company-specific factors like volatility of profits and leverage. (Blanco et al. 2004) However, there is also a growing attention to the macroeconomic factors and global financial linkages. This study bridged the gap between the two approaches to CDS valuation while also uniquely demonstrating the effect of financial contagion and spillovers on international markets.

To test this hypothesis of financial contagion, daily bond prices were obtained for Silicon Valley Bank and CDS prices were obtained for 24 European banks. The data was analyzed using OLS models and robustness was checked by different regression techniques. The models controlled for past values of the variables themselves, bond returns of SVB, short-end credit spread on interbank interest rates and on the event of default. The statistical significance of the SVB event window would then be the main source of statistical interpretation on the financial contagion. By constructing the analysis such a way, the study sought to find out whether the default of SVB had predictive power over the pricing of CDS of European banks and, in turn, the presence and magnitude of financial contagion in the CDS market.

The findings of this thesis suggest a strong financial contagion following the default of Silicon Valley Bank. During the event period, the statistical analysis exhibited significant relationships between SVB default windows and CDS price changes of European banks. On average the CDS spreads increased 3-5% during the SVB collapse, depending on the regression model and event window used.

The empirical results of this study present valuable evidence into how credit markets respond to systemic signals. The statistical significance of SVB default event as predictor of CDS pricing changes indicate that there is a possibility for local crisis to become a market-wide contagion.

This finding supports and builds on the existing theories in financial and behavioral economics relating to financial linkages and behavioral responses. For example, the results can be used as challenge for the “wake-up call” hypothesis or herding behavior, both of which concentrate on the market participants’ ability and readiness to gather information efficiently.

These patterns indicate that contagion is not merely a result of balance sheet dependencies but includes also a behavioral component of collective psychology and market structure. Moreover, the presence of contagion into European banks suggests that if a systemic trigger like SVB’s default occurs, volatility might become a positive feedback loop. This has implications for research concerning volatility modeling and stress testing.

To conclude, this thesis provides evidence that the collapse of Silicon Valley Bank did trigger financial contagion in European bank CDS spreads. The study emphasizes the sensitivity of modern financial markets to systemic events. The results reinforce the importance of monitoring derivative markets and adopting tools to mitigate possible contagion and spillover effects. By highlighting the channels through which contagion transitions, this research contributes both to academic literature and to the practitioners of financial markets and regulators alike.

Given the increasing attention to financial contagion, derivatives market and the determinants of CDS pricing, there are multiple ways to continue researching these topics based on this thesis. Firstly, the event windows could be lengthened to highlight the long-term effects of such event. As the derivative market has experienced more volatility recently, it could be of interest to conduct a comparative study where multiple of these kind of credit events would be evaluated together for joint determinants. Within current scope, a new study could be conducted to determine whether there are multivariate or asymmetric relationships between the sample participants and the reciprocal effects of them as such.

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