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INTEREST RATE REFORM IN THE U.S. – THE DYNAMICS OF SECURED OVERNIGHT FINANCING RATE AND ITS DEVIATION FROM PRECEDING INTEREST RATE FRAMEWORK

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ABSTRACT

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This thesis examines the determinants of the spread between term US dollar LIBOR and secured overnight financing rate (SOFR), which is replacing LIBOR as a risk-free reference rate. The analysis period contains observations between 11/2014 and 4/2021. The study uses proxies for interbank credit risk, interbank unsecured liquidity risk, term risk, and secured liquidity risk to explain the spread between LIBOR and SOFR. Linear regression is applied to examine the spread determinants and the relationships between variables are further examined with Granger-causality, impulse responses, and variance decomposition analyses. Based on analysis, a dynamic spread adjustment is constructed.

The results suggest that during the analysis period, credit risk, interbank liquidity risk, and term risk are significant in explaining the spread between term LIBOR and SOFR. Interbank liquidity has the largest effect on the spread among identified spread determinants. The secured liquidity risk is not found to influence the spread.

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Tämä tutkielma analysoi Yhdysvaltain dollari LIBOR ja Secured Overnight Financing Rate (SOFR) korkojen välisen erotuksen komponentteja, sillä LIBOR-korkouudistuksen myötä SOFR on korvaamassa LIBOR-koron. Tutkimusajanjakso sisältää havaintoja 11/2014 ja 4/2021 väliseltä ajalta. Tutkielma käyttää vakuudetonta pankkienvälistä luotto- ja likviditeettiriskiä, tulevaisuuden odotuksiin liittyvää riskiä, ja vakuudellista rahoituslikviditeettiä selittämään erotusta LIBOR- ja SOFR-korkojen välillä. Lineaarista regressioanalyysia käytetään tutkimaan muuttujien vaikutusta erotukseen, ja muuttujien välistä vuorovaikutusta tutkitaan tarkemmin Granger-kausaalisuus-, impulssivaste- (impulse responses), ja varianssin hajoamisanalyyseillä (variance decomposition). Analyysin pohjalta rakennetaan dynaaminen malli korkoerotuksen korjaamiseksi.

Tutkimustulosten mukaan luottoriskillä, pankkienvälisellä likviditeettiriskillä, ja tulevaisuuden odotuksiin liittyvällä riskillä voidaan selittää erotusta LIBOR- ja SOFR-korkojen välillä. Pankkien välinen likviditeettiriski osoittautui suurimmaksi vaikuttajaksi korkojen välisessä erotuksessa. Vakuudellisen rahoituslikviditeetin vaikutusta ei voida vahvistaa.

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In Copenhagen, 17 June 2021

Iida Herttuainen

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List of Abbreviations

ARRC	Alternative Reference Rate Committee
CDS	Credit default swap
EFFR	Effective federal funds rate
FCA	Financial Conduct Authority
ISDA	International Swaps and Derivatives Association
LIBOR	London Interbank rate
OIS	Overnight index swap
SOFR	Secured overnight financing rate

1. Introduction

London Interbank rate (LIBOR) is an unsecured short-term interest rate which is being charged for wholesale funding of the banks. Moreover, it is also a benchmark for other short-term interest rates all over the world. Daily LIBOR rates for different tenors have been published since the 1st of January 1986. More than $370 trillion of financial contracts are begged to LIBOR, and more than $200 trillion of those are denominated in U.S. Dollars. (Bloomberg 2021) And now the journey of the benchmark is coming to an end (FCA, 2021a).

The rationale behind the replacement of LIBOR is that its relevance and liability has been questioned. It has been discovered in the past that LIBOR rates have been manipulated by the panel banks by inflating or deflating the estimates in order to benefit from trades or to look more creditworthy. On top of the LIBOR manipulation accusations, after financial crisis, the volume of commercial paper and wholesale deposit issuances have significantly reduced. Therefore, there are less transactions for banks to base their LIBOR estimations. Due to aforementioned concerns, it has been announced that no US dollar LIBOR settings will be representative after the June 30, 2023 and no new LIBOR-pegged trades should be executed after the end of 2021. In the U.S., the deadline was extended by 18 months due to the complexity of the transition process. For all other LIBOR settings in other currencies, euro, Swiss franc, Japanese yen, and sterling, the intended deadline for the LIBOR representativeness will come earlier, already at the end of 2021. (FCA, 2021b)

In the US, Secured Overnight Financing Rate (SOFR) is the strongest candidate for the replacement of US dollar LIBOR with the support of Alternative Reference Rate Committee (ARRC), and in 2017, ARRC selected SOFR to be a preferred alternative to US dollar LIBOR (Fed, 2021). SOFR is based on US Treasury repurchasing (repo) market, and the daily volume of its underlying transactions is over $700 billion. Hence, it is not in a risk of manipulation or diminishing market activity in a similar way as LIBOR is. However, the nature of SOFR is drastically different as it is a secured overnight rate whereas LIBOR is an unsecured term reference rate, and therefore, the reform requires a careful preparation from the market counterparties, especially from the banks.

In 2021, FCA confirmed that all remaining US dollar LIBOR settings will either no longer be provided by any administrator or will lose representativeness (FCA, 2021a). In order to make the transition from US dollar LIBOR to SOFR in contracts that are referencing LIBOR, banks need to find a way to measure the difference in risk between US dollar LIBOR and SOFR, and they need to calculate a component that accounts for that basis risk. Calculation of the US dollar LIBOR-SOFR spread has an effect, for example, on banks hedging strategies, risk modelling, asset liability management, and valuation, so overall the impact is significant and therefore, it is vital to ponder the choice of calculation methodology carefully and to ground the decision on comprehensive analysis of the spread determinants.

1.1 Research gap and objectives of the research

While a large amount of research has been conducted in interest rates (e.g. McAndrews et al, 2017; Michaud & Upper, 2008; Poskitt, 2011), despite the rising interest in the swiftly emerged prominence of SOFR (Fed, 2021b), the research around relation between LIBOR and SOFR, the next primary benchmark interest rate, is sparse. This study aims to contribute to filling that gap by enlighten the determinants of the spread and the relationship between US dollar LIBOR and SOFR. Contributions to the literature of fundamental differences between LIBOR and SOFR enable market participants to better prepare for the upcoming interest rate reform and help navigating in changed interest rate risk environment.

The methodology used in this study stems from the underlying methodology of the rates (Fed, 2021c; ICE, 2021) together with previous studies conducted on other interest rates dynamics (e.g. McAndrews et al, 2017; Michaud & Upper, 2008; Yoldas & Senyuz, 2018), which helps identifying the key factors impacting the spread between the two rates. This knowledge is then used to further examine the rate dynamics by applying the research methods that have been proven applicable and competent in literature.

The chosen approach follows several studies. Similar to Taylor & Williams (2019) and McAndrews et al. (2017), the interbank credit risk and liquidity components are identified based on 3-month LIBOR-OIS spread, and CDS premia of LIBOR panel banks. Following Michaud et al, (2008), the forward expectations are modelled by using spread between 3-month OIS and overnight effective fed funds rate (EFFR). The liquidity of SOFR is modelled by using volume of its underlying repo transactions. A linear regression analysis is conducted to gain understanding on how each of the identified determinants contribute to the spread. An additional objective is to find a dynamic spread adjustment that could be used in converting financial contracts from US dollar LIBOR to SOFR. Currently, the most popular adjustment method for the LIBOR-SOFR spread is a static five-year median spread, which is supported by ARRC and ISDA (ISDA 2019). This kind of static adjustment has its strengths in terms of easiness of communication and also implementation, but it is not the most suitable tool for tracking current market conditions, especially during market turbulence. Instead of static spread adjustment, a dynamic one could better track the market conditions prevailing at the time. Finally, the performance of the proposed dynamic model against the static model proposed by ARRC and ISDA (2019) is being evaluated. Like previously done by Frank & Hesse (2009) in relation to study of interbank credit risk, the effects of innovations in identified factors in a vector autoregressive (VAR) system is being examined to analyse the relationship between the spread and some of its determinants further.

The study aims to explain the possible dynamics between SOFR and term LIBOR by answering to following questions:

1) Do interbank liquidity and credit risk factors explain the LIBOR-SOFR spread?

2) Can the LIBOR-SOFR spread be explained by methodological differences between LIBOR and SOFR?

3) Among identified factors affecting LIBOR-SOFR spread, what has been the most significant driver of the difference between the rates?

The first question seeks for answer to whether the findings of previous research about the significance of liquidity and credit risk components in interbank rates are applicable in the context of LIBOR-SOFR spread. The effect of liquidity and credit risk in LIBOR-OIS spread has been widely researched, mainly during financial crisis, but the LIBOR-SOFR perspective is completely missing. SOFR is not seen as an ideal replacement, and the one of the greatest roots for the criticism has been its lack of credit sensitivity, and for this reason market counterparties have developed alternative reference rates with a credit sensitive component. However, currently, those are not endorsed by the regulators. Liquidity risk is the second driver of interbank rates, which can cause significant fluctuations in the spreads. The findings of the first research question add to literature by examining how the findings made in LIBOR-OIS context hold true in SOFR environment, and provide understanding about the relevance of credit risk and liquidity components in LIBOR-SOFR spread.

The second research question aims to observe the effect of methodological differences between LIBOR and SOFR on the spread between the two rates. SOFR is an overnight secured rates, and thus is missing term risk component, and it holds practically no credit risk. Term LIBOR, however, is an unsecured term rate, and therefore is incorporating both credit and term risk. Moreover, rates are based on different underlying markets of which liquidity conditions differ quite drastically (Fed, 2021). The third question intends to provide perspective on the dynamical interaction between main factors of the spread, credit risk, liquidity risk, and forward expectations components. It aims to extend understanding about the interplay of risk components that needs to be taken into consideration when preparing for the reform, and adds to findings of LIBOR-OIS studies with a novel SOFR perspective.

By answering to the determined research questions, the aim is to gain knowledge of the dynamic relationship between SOFR and LIBOR, and to measure the relevance of the methodological differences in the historical performance of the rates. An increased knowledge helps market participants in their preparation for the interest rate transition by enabling identification of the key risks and by helping understanding the behavioural shift encountered when changing the financial contracts to reference SOFR instead of LIBOR.

1.2 Limitations

In this research the focus is on the fluctuations of the spread between US dollar Libor and Secured Overnight Financing Rate (SOFR) caused by the structural differences of the methodologies of these rates. Other macroeconomic factors as such that affect to the movements of these rates are not within the scope of this study as the rates exist in same macroeconomic environment.

In June 2023, LIBOR benchmark will cease to exist once and for all, meaning that the transition to other reference rates is ongoing worldwide, and for other LIBOR fixings, the representativeness of LIBOR will end already at the end of 2021 (FCA, 2021). This study reflects only transition from US Dollar LIBOR to SOFR, and due to different methodologies behind SOFR and new reference rates in other currencies, the implications of this transition outside the US dollar LIBOR settings are left out from this study.

The analysis period is determined by the period of SOFR’s existence, and during this interval the Covid-19 pandemic hit the world economy causing significant market turbulence which is still ongoing. Although the behaviour of the reference rates under such extreme market conditions is being analysed, the results may not be generalised to explain their behaviour under other type of distress the world economy may face. As the crisis is still ongoing, the data from the crisis period is incomplete. Nonetheless, the crisis period gives important insight about the variation in performance of the rates caused by structural dissimilarities, and therefore, the crisis period is incorporated into the study.

In this study, a daily data is used. However, data points are available on business days instead of calendar days. This is due to the fact that interest rates are only published on business days, and in such cases, it is recommended to not include such dates into data set (Janabi, 2018). As all of the time series used in this study are following the US holiday schedule, the pattern of missing data points is the same across all variables, and thus, is not causing issues in this study.

1.3 Structure of the study

Following the introduction, Section 2 defines the theoretical background, giving an introduction to LIBOR and SOFR together with an overview of prior literature and existing research carried out on the topic. Section 3 describes the data and presents the chosen variables, and is followed by introduction to methodology in Section 4. The empirical results gathered by using the predefined methodology are presented in Section 5. Finally, in Section 6, the implications of results together with their limitations are being discussed, and the discussion is followed by concluding remarks.

2. Theoretical background

Due to the short period of existence of SOFR, the literature on the relationship between the US dollar LIBOR and SOFR is relatively scarce, and studies addressing SOFR are mainly focusing on developing its term structure and adapting SOFR in derivatives pricing (e.g. Andersen & Bang, 2020; Jarrow & Siguang, 2021; Skov & Skovmand, 2021). Nevertheless, the interbank dynamics is not a new area of interest, and especially the 2008 financial crisis highlighted the importance of the interest rate spreads as an indicator of the prevailing market conditions, sparking curiosity among researchers about the determinants of interbank spreads. As the aim is to understand dynamics of LIBOR and SOFR, and the factors driving the spread between them, the sections first introduces the methodology behind each of the rates, and then provides an overview of previous studies done of the roles of credit and liquidity risk components in interbank market.

2.1 London Interbank Borrowing Rate (LIBOR)

London Interbank Offered Rate, better known as LIBOR, is a set of benchmarks reflecting the average interest rate of interbank borrowing. Its purpose is to produce an average rate which represents the rates at which the leading banks could obtain wholesale, unsecured funding in their market environment in specific currencies and for certain periods of time. Currently, the LIBOR rate is available for five currencies: USD, GBP, EUR, CHF and JPY. With respect to each of these currencies, there are available seven tenors: Overnight, One Week, One Month, Two Months, Three Months, Six Months, and 12 Months. This leads to publication of 35 individual rates on each London business day. Each LIBOR rate is calculated based on input data from LIBOR panel banks. For US dollar LIBOR, the panel is formed by 16 large banks, and each of the panel banks contributes to all seven US dollar LIBOR tenors. The submitted rate should be based the banks’ unsecured funding transactions to the greatest extent possible, and the published rate is an arithmetic mean of the submissions after four highest and four lowest values are left out. Therefore, in the US, the published rate is average of eight rate submissions. (IBA, 2021)

One reason why suitability of Libor as a reference rate has been questioned is the LIBOR manipulation scandals. LIBOR is a judgement-based estimate of the rate at which Libor panel banks could borrow money on interbank market. In the past, this feature has exposed LIBOR for the possibility of manipulation by panel banks, and according to court rulings, this vulnerability has not been left unused by some of the panel banks. There are a few reasons why a panel bank would be tempted to distort the rate it reports. Reporting lower rate can be appealing as it would signal positively about the credit worthiness of reporting bank. In addition to the reputational benefits, the moves of LIBOR to one way or to another can make the business more profitable depending on the trading positions the bank holds. (Abrantes-Metz et al. 2012)

LIBOR manipulation during financial crisis has been examined by various researches, and the majority of these studies have provided evidence of the existence of manipulation, and this is also indicated by the legal actions. The extent of manipulation has been more difficult to expose, and there is no conclusive evidence in regard to the magnitude of the effects caused by the manipulation. (Mollenkamp & Whitehouse, 2008; Abrantes-Metz et al., 2012) Nonetheless, there is also empirical evidence of manipulation in terms of better trading gains which is consistent with what is reported by officials (Snider & Youle, 2014). Youle (2014) has estimated an average effect of manipulation to be around minus eight basis points, where as other authors have provided evidence about more extensive manipulation, around -30 to -40 basis points during the peak of financial crisis (Poskitt & Dassanyake, 2015; Bonaldi, 2017; King & Lewis, 2019) suggesting that the spread between LIBOR and other interest rates should have been even higher.

Since the manipulation was uncovered in 2012, the ICE Benchmark Association have worked on returning the creditability of LIBOR, and since March 2019, the Waterfall Methodology underlying LIBOR has required the contributor banks to base their submissions to actual unsecured funding transactions to the degree possible (IBA, 2021). However, the LIBOR manipulation is not only issue of LIBOR. Ideally, the reference rate should derive from active and liquid markets, and therefore, diminishing liquidity in the interbank market has increased concerns about the representativeness of LIBOR (e.g. Fed 2021d). This shift has been driven by changed regulatory environment. As an example, banks have to fulfil a high-quality liquid asset requirement, Liquidity Coverage Ratio (LCR), which incentives to deposit extra cash to central banks for overnight instead of lending it in interbank markets. Net Stable Funding Ratio (NSFR) is another liquidity standard set by the regulators, and it obliges banks to prefer longer-term liabilities which reduces the demand in the interbank market. To reflect higher balance sheet costs caused by firmer risk management and new regulatory standards, the banks have had to reprice the risks linked to unsecured interbank lending (Kim et al, 2018). Therefore, it is seen unlikely that interbank markets would recover much and obtain the required level of market activity (Kim et al. 2018; ARRC 2021).

2.2 Secured Overnight Financing Rate (SOFR)

Secured Overnight Financing Rate (SOFR) is based on US Treasury repo market and it is published by the New York Fed each business day (Fed, 2021c). SOFR has an underlying market with daily transactions of over $700 billion compared to less than $1 billion for LIBOR, and this large volume of transactions makes it more representative of funding costs banks are facing. (Congressional Research Service, 2021)(Smith 2019)(Fed 2013) In addition, the fact that SOFR is transaction based makes it less vulnerable for manipulation. However, it is necessary to understand how the behaviour of SOFR can differ quite significantly from what have been witnessed in the past in terms of LIBOR. During its short period of existence, the volatility of SOFR has been a major concern, and the magnitude of its daily swings have been as high as 282 basis points. As the SOFR relies entirely on transaction data, it is prone to be more volatile than expert-judgement based LIBOR.

Currently, the New York Fed is only publishing one SOFR rate based on overnight transactions and three average rates, compared to 35 different LIBOR rates being published. SOFR is a secured rate, and as an overnight rate it is repriced on a daily basis. Therefore, unlike LIBOR, it does not bear credit risk, and therefore, SOFR does not reveal the level of stress in global funding markets, which might be problematic especially for smaller banks lacking access to the lending in secured repo markets. In fact, risk free reference rates based on secured rates, such as SOFR, can move in opposite direction to unsecured rates, such as LIBOR or EFFR (Schrimpf & Susko, 2019).

The SOFR rate was first published on the 2nd of April 2018 and it is a calculated as a volume-weighted median of transaction level tri-party repo data. The cumulative sum of volumes of transactions, ordered from lowest to highest rate, is taken, and then a rate associated with the trades at 50th percentile of volume is identified, and rounded to the nearest basis point at publication. (New York Fed 2021). In March 2020, the New York Federal Reserve started publishing backward-looking SOFR averages for 30-day, 90- day and 180-day periods. SOFR was announced to be the replacement for LIBOR in 2017 by Alternative Reference Rate Committee (ARRC) which was established earlier by the Fed.

Unlike LIBOR, SOFR is a backward looking rate meaning that it is measurable only at the end of the term, whereas, with LIBOR, the rate is known at the beginning of the term. In practise, this means that, for example, with 3-month LIBOR the interest is known three months beforehand whereas with SOFR, the interest would be known when the 3-month period comes to its end. The movements of SOFR seem to be following the fed funds rate suggesting that the Fed Funds target rate has also an effect on SOFR. (Gellert & Schlögl 2019) As the Federal Reserve uses purchase of repos as tool to control the effective fed funds rate (EFFR), its monetary policy has a direct effect on SOFR due to its close connection to the US Treasury repo market. However, SOFR is significantly more volatile compared to both LIBOR and EFFR, and one of its special features is the end of month spikes which becomes more prominent in quarter- and year-ends. These spikes are result of increased month-end activity in repo markets: As regulatory agencies focus more of their supervision on the month-end figures, it creates an incentive to better manage the balance sheet exposures around reporting dates (Schcrimpf & Sushko 2019).

2.3.1 Transition to SOFR

U.S. regulators have stated that no new LIBOR-linked financial contracts should be made after end of 2021 (Fed 2020), and therefore, the final steps in the New York Fed's phased transition plan should be taken sooner rather than later.

In October 2020, the largest central counterparties (CCPs), CME Group and LCH Group, made a major transition from Fed Funds to SOFR discounting and Price Alignment Interest (PAI) in accordance to New York Fed's paced transition plan. The CCP discounting conversion was expected to build up liquidity in SOFR products: as discounting risk of market participants' portfolios changed from EFFR to SOFR it also generated a need for hedging it, and therefore, increased the trading activity of SOFR derivatives, ultimately supporting transition from USD LIBOR to SOFR. According to Bloomberg (2020), although this expectation realized and activity in SOFR-linked interest rate swaps surged in October 2020 right after discount rate conversion, the progress in the liquidity of SOFR has remained modest.

LCH transitioned over one million contracts with a total notional value of $120 trillion, and the scope of the first part of the transition included cleared interest rate swaps, cross-currency swaps and deliverable and non-deliverable forwards and options. For resulting valuation changes, LCH made compensation payments and provided risk-based compensation in a form of SOFR/Fed Funds basis swaps for all members with relevant interest rate contracts allowing them to reduce the impact of discounting change. Participants were able to choose to have the compensation only in cash if they did not wish to receive basis swaps. (LCH 2020)

Scope for the transition in October 2020 for CME included USD OTC cleared swaps excluding SOFR index swaps which were already using SOFR discounting and price alignment. According to Bloomberg (2020), the notional value of the swaps was $7.2 trillion. CME generated the NPV for all trades under SOFR discounting and calculated and processed corresponding cash adjustment amounts for accounting and neutralizing the effect of discounting conversion.

CME also booked mandatory series of EFFR/SOFR basis swaps to participants' accounts to take the portfolios of the participants back to the original discounting risk profile. Booking of basis swaps was required to reduce re-hedging costs for the participants, but as it might also expose them to risk that they were not willing to take, CME conducted an auction where participants could unwind the swaps. To compute the cash compensation, they constructed an end-of-day SOFR curve by using SOFR futures contracts in the short end and Fed Funds-SOFR basis swaps for the rest of the curve. (CME 2020)

The only step pending in Fed's paced transition plan is the creation of a forward-looking term reference rate based on SOFR derivatives market during the first half of 2021. However, the challenges in increasing the liquidity of SOFR derivatives could delay the ARRC's ability to development of the rate. (Marcus Burnett, SOFR Academy) In May 2021, ARRC issued an update on SOFR term rates announcing CME Group to be administrator for the developed term rate, ones the market indicators are met. The indicators require deep and liquid SOFR derivatives and cash markets, which is essential for having robust and stable SOFR term rate.

2.4 Rates in previous research

Although SOFR has existed only a short period of time, the LIBOR's relation to other overnight rates has been widely researched. McAndrews et al. (2017) defines a term interbank rate, such as US Dollar LIBOR, to be a combination of four main components: expected average of the overnight interest rate, the term premium, credit risk premium, and funding liquidity risk premium. As a secured overnight rate, SOFR is lacking both term premium and credit risk premium, and instead of time-to-time unstable interbank market with diminishing activity, its liquidity risk is based on highly active repo market.

2.4.1 Measuring Liquidity and credit risk in unsecured interbank market

A large amount of research have concentrated on explaining the LIBOR-OIS spread, which helps understanding the components that may influence LIBOR. Majority of studies have decomposed the LIBOR-OIS spread into credit risk and liquidity risk components (E.g. Michaud et al, 2008; McAndrews et al, 2008; Frank & Hesse, 2009), and to large extent, the research period has included the 2008 financial crisis when the spreads increased significantly. Prior to financial crisis, the LIBOR was used for discounting, but due to the widening of the spreads the market participants moved to OIS discounting utilizing EFFR.

Based on previous research, two main components of term interbank rate are aforementioned credit risk premium and funding liquidity risk premium, first one being the compensation for risk of default and the latter one being combination of funding structure of banks, the liquidity of their assets, and the expected liquidity conditions (McAndrews et al. 2017). In this context, liquidity can be defined as a bank's ability to raise funding swiftly and with decent transaction costs. Credit risk can be defined as a risk that counterparty defaults, a chance that the counterparty is unable to pay its debt as the transactions are uncollateralized. The liquidity and credit risk components of LIBOR are the required premia for accepting these risks.

In the U.S., LIBOR-OIS spread has been widely used as a proxy for money market liquidity (Chalamandaris & Pagratis, 2019), but it has also been argued that the spread can be used to evaluate risk of lending to other banks. The OIS, overnight index swap, rate is the difference between the term OIS rate, which is the market expectations for the overnight rate for the period, and the average of overnight rate over the contract period. In the U.S. the overnight rate is effective federal funds (EFFR) rate. As OIS contracts are secured and at the time of maturity, only net cash flows are exchanged, the OIS rates include only two of the four main components of term interbank rate described by McAndrews et al. (2017): the expected average of the overnight interest rate and the term premium. Therefore, the LIBOR-OIS spread mainly consists of liquidity and credit risk premia. (McAndrews et al., 2017).

During the 2008 financial crisis, the LIBOR-OIS spread increased significantly due to mistrust in the interbank market, causing market participants to be reluctant to lend money. Between these two components, research has shown more evidence of liquidity being the main driver in the dramatic swings during the 2008 financial crisis. However, there is a clear intertwined relationship between credit risk and liquidity components of LIBOR and therefore, the dynamics are not that explicit. Increased spread reveals distress in the banking industry, and Alan Greenspan, a former Chairman of Federal Reserve, has said LIBOR-OIS to be a barometer of fears in bank insolvency. (Thornton, 2009)

It is evident, that the distinction between the credit risk and liquidity component in LIBOR-OIS spread is difficult to make, and this relationship might fluctuate over time. Most of the research has examined the roles of liquidity and credit risk components in LIBOR-OIS spread during global financial crisis when the spread dilated considerably. The previous research has not been able to find consensus on relative roles of both components: The liquidity component has been widely seen as a main driver in the interbank markets (Hui et al., 2011; Gefang et al. 2011; Christensen et al. 2014; King & Lewis, 2015; Schwarz, 2017). But, there is also contradictory evidence, and for example, Taylor & Williams (2009) provide evidence that the widening in LIBOR-OIS spreads during the financial crisis were mainly a reflection of increased credit risk premia and were not much affected by the Fed's actions to provide more liquidity to the economy. Angelini et al. (2011) also identifies credit risk component to be the main driver.

According to Aotken and Comerton-Forde (2003), the liquidity measures can be either trade-based or order-based. The number of trades would be an example of trade-based measure whereas bid-ask spread would be an example of trade-based measure. (Aotken and Comerton-Forde, 2003) However, this kind of order book data is hard to obtain, and for that reason, in many studies, liquidity component has been calculated based on credit risk: As LIBOR-OIS spread is seen to consist mainly from credit and liquidity risk components, and as latter one is rather difficult to calculate, Bank of England (2008) has suggested decomposing spread based on Credit Default Swap (CDS) spreads of LIBOR panel banks. CDS premiums are insurance for bonds issued by the panel banks, and the size of the spread reflects the probability that banks might default on their debt. After removing the calculated credit risk component from the spread, the remaining part is the liquidity component. This approach has been taken, for example, by Frank & Hesse (2009) and Michaud et al. (2011). Among research focusing on liquidity aspect of the spread, a popular approach has been to use the LIBOR-OIS spread as a liquidity risk component and include a credit risk component made of CDS premia of panel banks as a control variable (McAndrews et al. 2008; Hui et al.,2011; McAndrews et al. 2017).

In previous research, the credit default swap (CDS) spreads of the LIBOR panel banks have been used as a proxy for credit risk component of Libor (Taylor & Williams, 2009; Kwan, 2009; Michaud et al, 2008). Kwan (2009) examined the relationship between Libor-OIS spread and CDS spreads of the panel banks, and was able to explain around 44% of the variation of the spread concluding the effect of counterparty risk as a driving force of Libor. When researching the spread between LIBOR and OIS, Michaud et al. (2008) constructs the risk premium via credit risk, funding liquidity of the borrowing bank, uncertainty about the trend of expected overnight rates, market liquidity, and the microstructure of the market. As funding liquidity and microstructure of the market was difficult to measure, they were treated as unobserved variable appearing into the residual after other variables were taken into consideration. However, this might have caused credit risk variable to be influenced by the funding liquidity.

Michaud et al (2008) and Taylor & Williams (2009) measures banks' risk of default by using the spread between unsecured and secured interbank rates together with the CDS premium referencing the debt held by borrowing banks. However, they do not take into consideration the liquidity aspect: the spread between the rates is affected by liquidity premia via both unsecured and secured market conditions, and in the market where underlying collateral is trading. With CDS spreads, Michaud et al (2008) used maturity of five years, thus having a large maturity mismatch. Authors present evidence from euro, USD, and sterling markets suggesting that credit factor may only influence long-term movements in Libor-OIS spreads and do not have an effect on day-to-day fluctuations of the rate. During financial crisis, there was a low degree of diffusion of Libor quotes submitted by the panel banks compared to the behaviour of theirs CDS premia which suggests that during the crisis, the interbank market hardly reflected the risk of default. As a consequence, the explanatory power of CDS premia was low. (Michaud et al. 2008) Besides CDS premia, LIBOR-Repo spreads have also been used as a proxy for counterparty credit risk (E.g. Taylor & Williams, 2009).

An OLS regression model has been widely used to explain the spread between US dollar LIBOR-OIS spread. In Taylor & Williams' (2009) version, they estimated and OLS regression model in levels form to explain the LIBOR-OIS spread but they noted that due to the presence of unit root, the first differences could be more suitable solution (e.g. McAndrews et al., 2008)

2.4.2 Liquidity and calendar effects in secured repo market

Due to the presence of collateral, the credit risk in secured repo market is minimal. However, the liquidity is one of the main components also in repo market. Repo is an agreement of a sale of security with a commitment to repurchase the security at a certain date (Fed, 2021). For the borrower of cash, the transaction is repo, and for the lending counterparty, the transaction is called reverse repo. The repo market is one of the largest money markets in the world, and many times larger than unsecured interbank markets (Bech et al., 2010; Fed, 2021). The repo rates are determined based on the quality of the collateral: with a liquid collateral the borrower pays low interest for the overnight loan. Repo market is also a tool for monetary policy implementation used by Federal Reserve.

Calendar effects can be observed from the historical behaviour by looking into the surges in SOFR during month-ends. This effect in repo rates in general is also shown by Happ (1986) and Fleming et al (2008). This is largely caused by banks' balance sheet optimization, window dressing activities, which increases the demand for reserves driving the rates up. Additional reason reported by Bech et al. (2010) is the issuance of Treasury coupon securities on these dates.

2.4.4 The effect of interest rate expectations

The interbank term rates incorporate a term premium which accounts for the uncertainty about the development of expected overnight funding rates. The expectations hypothesis of interest rates suggests that as term deposits and overnight deposits are substitutes, the term interest rates should move closely together with expected overnight rates over the same period (Michaud et al. 2008).

OIS has been used to measure overnight interest rate expectations as there is a minor, almost none, counterparty risk associated to OIS contracts, and as the contracts do not require any initial cash flows, the liquidity premia should be small. (Michaud et al, 2008) As shown by Sundaresan et al. (2008), OIS rate consists both interest rate expectation and a small interest rate risk premium for the uncertainty of future average EFFR. Authors also provide strong evidence that the OIS rates carry almost no liquidity or credit risk premium. Prior studies on interest rate term structure are consistent with their findings (Longstaff, 1989; Longstaff 1990; 2000; Corte et al. 2008).

The expectations hypothesis, the relationship between term rates and expected overnight rates, is affected by the presence of credit risk, liquidity factors, and the premium paid for uncertainty about future development of short rates. Due to these factors, the relationship may not hold perfectly, and the spread between the rates may fluctuate over time. (Michaud et al. 2008)

3. Variables and data

This section provides justification for the choice of data and variables used in this study together with a descriptive statistics. First the variables are introduced and their construction is explained. In the second part of the chapter, the data is described.

3.1 Variables

The variables used in this study are chosen based on previous research and they are constructed based on data from public sources. In this study, the focus is in the spread between SOFR and LIBOR, and the purpose is to understand the shift in the behaviour of reference rate the market participants encounter when replacing LIBOR with SOFR. In following subchapters, the variables used in the empirical part of the study are being introduced, and later on, the data used in the study will be examined.

LIBOR-SOFR spread (*Spread*)

For empirical part of this research, the daily historical data about 3-month US dollar LIBOR and overnight Secured Overnight Financing Rate (SOFR) is collected. The 3-month tenor is chosen as it is used as a reference rate for the most US dollar denominated interest rate swaps together with other interest rate derivatives (Duffie et al. 2013; Yoldas & Senyuyz, 2018). Even though SOFR was first published in April 2018, the Federal Reserve Bank of New York has retroactively published daily indicative SOFR with a starting point of August 2014, which will also serve as a beginning of the analysis period. Historical rates of SOFR can be extracted either from the website of Federal Reserve Bank of New York or DataStream (2021) by Thomson Reuters. DataStream is also the source used for the historical USD LIBOR rates.

At the moment, SOFR does not have term rates as the SOFR derivatives market is lacking sufficient amount of liquidity. According to ARRC, there are some specific productive use cases for term rates but they are not required and thus, market participants should not wait for forward-looking term rates in order to transition from LIBOR to SOFR (Fed, 2021a). In this study, a 90-day average for SOFR is calculated based on the overnight rate. There are a few different ways to calculate SOFR average for a certain period of time. The Federal Reserve Bank of New York (2021a) has stated that the market participants need to consider whether to use simple or compounded average to calculate SOFR for an interest period, and whether to use in arrears or in advance structure. With simple interest, the daily rate of interest is applied to the principal, and at the end of the period the payments is the sum of those daily amounts. With compounded interest, the interest is also calculated for the accumulated interest that is not yet paid. In this study, a compounded interest is calculated and used as it is more accurate in terms of time value of money, allowing hedging, and better market functioning. For calculating SOFR, ISDA's formula for Compound Annualized Interest is being used:

$$SOFR\ Average = \left[\prod_{i=1}^{d_b}\left(1+\frac{SOFR_i \times n_i}{360}\right)-1\right] \times \frac{360}{d_c} \qquad (1)$$

Where d_b is the number of business days in the interest period, d_c is number of calendar days in the interest period, $SOFR_i$ is the interest rate of the business day b, n_i is the number of calendar days in the calculation period for which $SOFR_i$ applies. In practise, on Fridays the r_b will be 3, and otherwise it is usually 1. 360 is used as a money market convention for the number of days in year which is 360 in the United States, and i represents each business day within the period.

The choice between in advance and in arrears structure is about determining the time period over which the average of SOFR observations is calculated. Average of SOFR in advance is operationally easier to implement, and it is also easier to sell for the customers as the interest is known at the beginning of the period. Currently, most of the contacts referencing LIBOR set the floating rate at the beginning of the interest period. However, it does not reflect what is actually happening in the interest rates. In arrears structure uses the observations of SOFR during the actual interest period, but as the average rate is known only at the end of the period, it can be challenging as it does not give much notice before, for example, the coupon payments are due. In advance and in arrears structures are used also with overnight rates. (Fed 2021a) At the beginning of March 2020, Federal Reserve Bank of New York started to publish three daily compounded averages of SOFR rate for 30-day, 60-day, and 90-day periods.

The basis spreads of the two rates with different maturities is expressed in basis points, and will be denoted as $Spread_t$ in levels and $\Delta Spread_t$ in first differences. The rates are not published during weekends and holidays which causes missing data points. However, it is not recommended to include such dates when interest rates are not published (Janabi, 2018), and therefore a daily data on business days instead of calendar days is used.

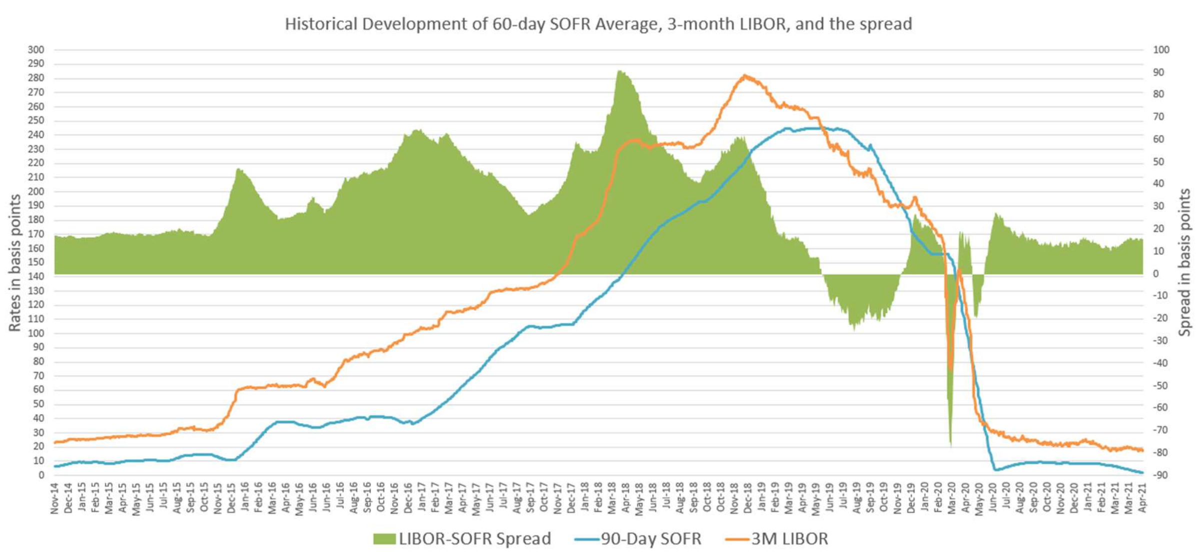

Figure 1. Historical development of 90-day compounded SOFR Average in arrears versus 3-month USD Libor.

The historical development of 90-day compounded SOFR Average in arrears, 3-month USD LIBOR, and the spread between the rates are plotted into Figure 1. The LIBOR-SOFR spread was calculated by subtracting the value of 90 day SOFR Average from the 3-month USD LIBOR value at time t. From the picture, it can be seen how both rates follow the same trend but LIBOR is trading usually above SOFR, and SOFR seems to follow LIBOR with a lag. In 2019, this trend reversed, as the interest rates in the US were inverted, meaning the short-term rates were higher than longer tenors. It is important to remember that LIBOR is a forward-looking rate and based on markets' overlook for the 3-months period, whereas SOFR is based on actual transactions that took place within that period. As can be observed from the Figure 1, there was a large decline in 3-month US dollar LIBOR in March 2020, when markets reacted to the Covid-19 pandemic, and the Fed increased its repo operations by $2 trillion. During the pandemic, the interest rates have decreased significantly due to the extensive amount of monetary stimulus in the U.S. resulting in a huge amount of excess cash in the economy.

Credit and liquidity risk ($Cred_t$ and Liq_t)

In this study, 3-month LIBOR-OIS spread is used as a combined credit risk and funding liquidity risk component in unsecured interbank market (e.g. Hui et al. 2010; McAndrews et al. 2008; Michaud & Upper, 2008), and it is assumed that the spread is fully explained by these components. The spread is decomposed into credit and liquidity risk components based on credit risk component which is calculated based on the CDS premia of panel banks, and using the residual as the liquidity component. Hence, it is assumed that liquidity and credit risks are independent and the CDS premia of panel banks provide a fair probability of default. Previously, a similar approach has been taken, for example, by Frank & Hesse (2009) and Poskitt (2011), and the method is recommended by Bank of England (2007).

In previous studies, the most widely used proxy for interbank credit risk has been CDS premia of LIBOR panel banks. In this study, this approach is also used and credit risk component is constructed based on CDS premia of banks contributing US LIBOR with 40% recovery rate. In DataStream, the shortest maturity for CDS premia is six months. To avoid maturity mismatch, the approximation for three month CDS premia is calculated by dividing the 6-month premia by two. Credit risk component is built by collecting this calculated 3-month premia from 12 panel banks out of 16 banks in total (IBA, 2021), and calculating the median premia. The median is used instead of mean as the mean of the CDS premia seem to overestimate the size of credit risk component due to the presence of extreme values of individual banks. Also, the LIBOR is calculated by leaving out the highest and the lowest submissions, which also supports the decision of the use of median. Same approach for measuring interbank credit risk has been taken, for example, by Taylor & Williams (2008). Remaining four banks out of 16 are left out due to unavailability or low frequency of CDS data. A table of panel banks can be found in appendix. The calculation of liquidity component can be written as follows:

$$(3M\ LIBOR - 3M\ OIS)_t = Liq_t + Crd_t \qquad (2)$$

$$Liq_t = (3M\ LIBOR - 3M\ OIS)_t - Crd_t$$

where Crd_t is a value of calculated median CDS premia of panel banks at time t which is used as a proxy for credit risk, and Liq_t is the remaining part of the basis spread between LIBOR and OIS after the credit risk component has been removed. All variables are expressed in basis points. Both credit risk and liquidity risk components are expected to have a positive effect on the spread between LIBOR and SOFR.

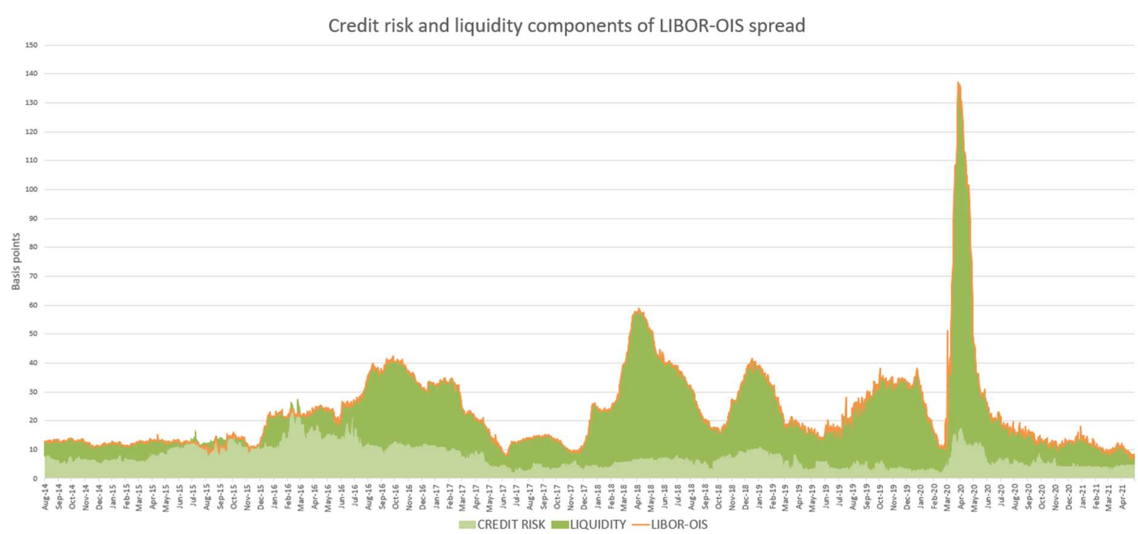

Figure 2. Decomposition of US Dollar LIBOR-OIS spread into credit risk and liquidity components.

In figure 2, the outcome of the decomposition of the LIBOR-OIS spread can be observed. The credit risk component, which was constructed based on CDS spreads of panel banks, follows the shape of LIBOR-OIS spread to some extent. In the spring 2016, there was a spike in credit risk component which caused it to exceed the LIBOR-OIS spread, and therefore the liquidity component is slightly negative. This indicates that the CDS premia proxy might exaggerate the role of credit risk. The increase of the credit risk component in 2016 was lead by Deutsche Bank due to the uncertainty caused by the investigation related to its role in 2008 financial crisis. In spring 2018 and at the end of 2019, the increase of the spread seem to be largely due to the liquidity component. Overall, liquidity component is more volatile than credit risk factor which is consistent with findings from previous studies (E.g. Gefang et al., 2011)

Future Expectations (*FwdExp*$_t$)

As SOFR average is based on an overnight rate, it does not contain future expectations unlike 3-month LIBOR. For this reason, the spread between the two contain term premia. Due to the absence of liquid SOFR-linked overnight index swap market for the research period, the future expectations component is measured as a difference between 3-month OIS rate and overnight effective federal funds (EFFR) rate, and can be written as follows:

$$FwdExp_t = 3M\ OIS_t - EFFR\ _t \qquad (3)$$

where $FwdExp_t$ accounts for future expectations and is a difference between 3-month OIS rate and EFFR rate at time t.

EFFR reflects short term funding costs and it serves as a fixing rate for certain swaps and futures. The US financial institutions that are licensed to hold deposits have a regulatory requirement to hold a certain percentage of the deposits in the Federal Reserve accounts. The excess reserve balances, the amount exceeding the required level, and operational cash flows are managed by the institutions by lending and borrowing the overnight funds to one another at a rate called federal funds rate. A volume weighted median of the federal funds rate of the day, EFFR, is published following morning. The future expectations are expected to have a positive effect on the LIBOR-SOFR spread.

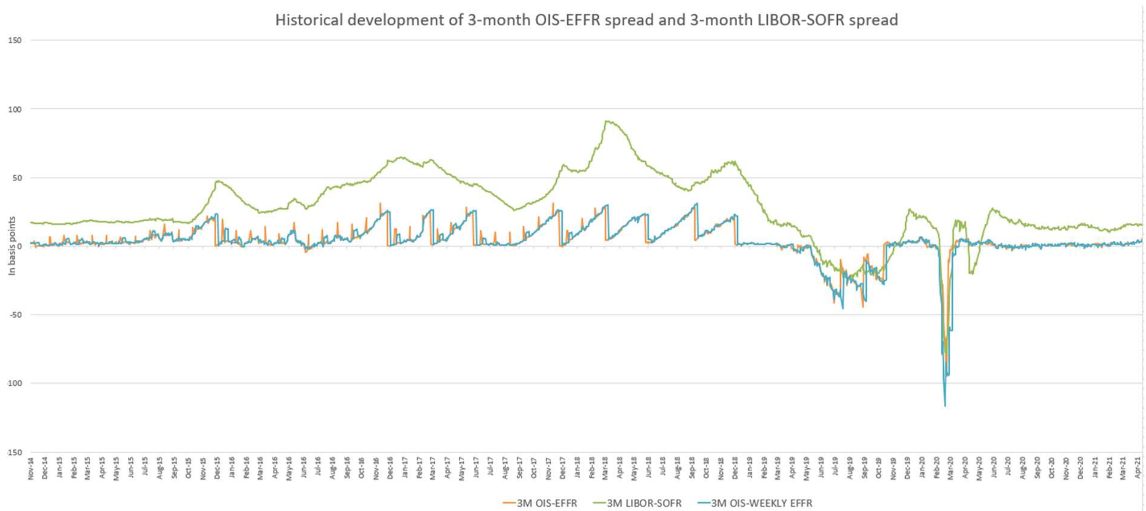

Figure 3. The historical development of spread between 3-month OIS and overnight EFFR and spread between 3-month LIBOR and 90-day SOFR average.

The Figure 3 describes the historical development of the spread between 3-month OIS and EFFR rate, which is used as a proxy for future expectations, and the spread between 3-month LIBOR and 90-day SOFR average. There are some seasonal drifts in the behaviour of fed funds rate, and it often trades lower at month-end’s. Until spring 2018, month-end spikes in EFFR can be easily detected from the graph, but they even out until to the end of the period. Due to these significant spikes in month-ends, spread between 3-month OIS and weekly average EFFR is incorporated. The weekly figure is calculated by taking an average of seven calendar days ending on Wednesday of the current week (DataStream, 2021). The weekly spread evens out the month-end volatility significantly, but it reacts to the market events with a small delay compared to the raw overnight EFFR. The changes in the Fed’s target rate can be easily detected from the figure as a sharp declines in the spread. The volatility of both spreads decreases significantly at the end of period, which is most likely caused by the monetary policy during the Covid-19 pandemic, which has exploded the amount of money supply in the economy and it has made the Fed to cut its target rate to zero. Performance of both variables,

$FwdExp_t$ and $FwdExpW_t$, in explaining the LIBOR-SOFR spread will be evaluated in the empirical part of the study.

Volume of repo market (*RepoVol*$_t$)

To reflect the liquidity conditions in the secured repo market, a daily volume of repo market underlying SOFR, $RepoVol_t$ is incorporated. The volume data is provided by the Federal Reserve. On the first day of 2021, there was a large spike in the volume – the day-to-day change in the volume was 1,046 $billion. This outlier was cleaned by taking the average of the previous and following day of this outlier. Appendix 2 shows the original time series of repo market volume, and the cleaned $RepoVol_t$ variable. Repo rates are also affected by the liquidity conditions of the market underlying the collateral. However, due to difficulties in measuring such liquidity conditions, the risk associated with collateral markets is left out from this study. Increase in the repo market volume is expected to decrease the spread between LIBOR and SOFR, since an increased repo market demand is expected to increase the SOFR rate.

Dummy for end-of-quarter volatility (*EoQ*$_t$)

As discussed in previous section, the repo market activity during the reporting periods has resulted in large spikes in overnight SOFR. Therefore, a dummy variable for the quarter-ends is also included. The value of one is placed one day after the end-of-quarter date due to the fact that a value date of SOFR average is always one business day later than the value data of the final SOFR observation included, meaning that the effect of quarter-end spike would be included into the average of the first business day after the end-of-quarter date. Other dates have a value of zero. The end of month-volatility is not included into model as the data used for SOFR is a 90-day average, and the month-end volatility has been relatively modest compared to the quarter-ends. The end-of-quarter dummy is expected to have a negative effect on the spread since it is expected to increase the SOFR rate.

3.2 Data and descriptive statistics

The data sources used in this research are Federal Reserve Bank of New York and DataStream by Thomson Reuters which is a global platform providing financial and macroeconomic data. The first possible data point of SOFR is from August 22, 2014. Therefore, the 90-day compounded average by arrears can be calculated starting from November 20, 2014 and this date serves as a starting point of the analysis period. Time series of 3-month US dollar LIBOR, overnight SOFR, 3-month OIS, EFFR, and CDS spreads of panel banks are collected from DataStream, and repo market volume is provided by the Fed. All data series include observations between November 20, 2014 and April 30, 2021, thus, a total count of observations for data in levels and first differences being 1,682 and 1,681 respectively. In Table 1 below, descriptive statistics for all variables are presented.

Table 1. Descriptive statistics for all variables in levels and first differences.

	Mean	***Median***	***Max***	***Min***	***Std.Dev.***	***Skewness***	***Kurtosis***	***JB***
$\boldsymbol{Spread_t}$	28.76	25.45	91.290	-78.40	24.33	-0.25	0.92	76.88***
$\boldsymbol{\Delta Spread_t}$	-0.0009	-0.00800	17.67800	-31.47300	1.65016	-4.65927	110.29542	858144.55***
$\boldsymbol{Cred_t}$	8.15	6.90	27.42	2.01	4.17	1.11	1.31	463.03***
$\boldsymbol{\Delta Cred_t}$	-0.0011	0.00000	6.82500	-3.49501	0.62507	0.92428	16.70999	19796.64***
$\boldsymbol{Liq_t}$	15.77	11.08	121.71	-5.26	15.62	2.88	13.05	14264.2***
$\boldsymbol{\Delta Liq_t}$	-0.0011	-0.02500	42.45500	-32.50700	2.15964	3.08029	126.67042	1126504.6***
$\boldsymbol{FwdExp_t}$	3.64	2.60	31.20	-94.70	11.44	-2.22	13.47	14080.1***
$\boldsymbol{\Delta FwdExp_t}$	0.00178	0.10000	81.90000	-35.30000	4.01540	5.09879	131.27198	1214265.0***
$\boldsymbol{FwdExpW_t}$	3.67	2.90	31.50	-116.30	13.86	-2.90	17.14	22946.9***
$\boldsymbol{\Delta FwdExpW_t}$	0.00059	0.10000	57.10000	-35.30000	3.22845	1.91526	99.03527	687995.28***
$\boldsymbol{RepoVol_t}$	822.88	787.00	1358.00	505.00	180.75	0.56	-0.59	113.73***
$\boldsymbol{\Delta RepoVol_t}$	0.19274	-1.00000	179.0000	-100.0000	29.30833	0.60990	2.84511	671.18***

Note: *** indicates 1% level of significance for Jarque-Bera test.

All variables in Table 1 except RepoVol are presented in basis points. The spread gets values between -78.4 and 91.3 basis points and has a standard deviation of 24.3 which describes the fluctuating volatility of the spread. In average, daily changes in the variables are very small, but have also a larger swings such as maximum of -31.5 basis point day-to-day drop in the spread. Liquidity component has had a large spike 42.5 basis point day-to-day change, and the deep drop in future expectations at the beginning of Corona pandemic has led to impressive -116.3 basis points drop at the day-to-day change. This magnitude of this drop can be easily detected from Figure 4 where historical development of LIBOR-SOFR spread, future expectations, credit, and liquidity components are expressed. In levels form, future expectations is relatively stable based on standard deviation. However, it seem to be much more volatile in its day-to-day fluctuations compared to liquidity. This is most likely due to the fact that the future expectations build by utilizing an overnight EFFR rate whereas both liquidity and credit risk are based on term rates which reduces the day-to-day volatility in the latter rates.

Table 1 also presents skewness and kurtosis for all variables together with Jarque-Bera (JB) test statistic. Spread is negatively skewed in first differences and the same goes for future expectations in first differences. Otherwise variables are positively skewed, except Spread in levels, and RepoVol in both levels and first differences, are quite close to normality. Results can be expected with time series data, and most of the variables have a positive excess kurtosis indicating large outliers, which can easily be detected from the other statistics, and Figure 4. The Spread in levels form and Cred, however, have a negative excess kurtosis indicating flat tails. Jarque-Bera (JB) test is used as a goodness-of-fit test to evaluate whether the skewness and kurtosis in data is matching normal distribution. For all variables, there is large statistics value for JB test statistic, and the null hypothesis for normality of the data will be rejected in 1% significance level. Thus, the variables do not follow normal distribution.

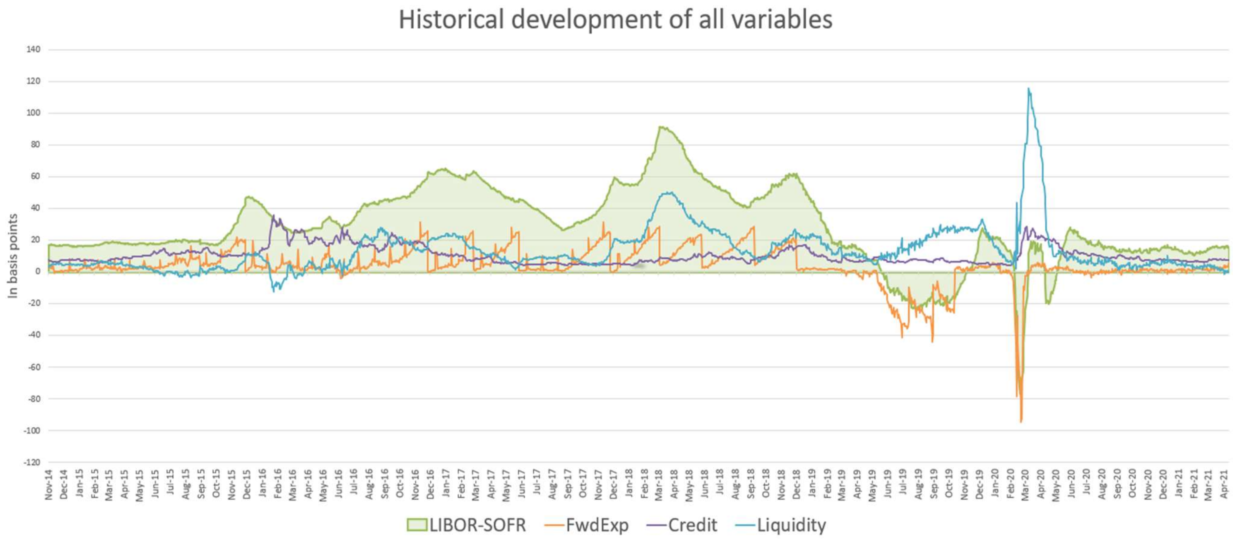

Figure 4. Historical development of 3-month LIBOR-SOFR spread, Future Expectations as FwdExp, Credit, and Liquidity components during the analysis period.

From Figure 4, the historical development of all variables can be observed. The spike of liquidity component during the first days of global Covid-19 pandemic especially stands out from the graph. It is also noticeable, how the relationship between Liquidity component and LIBOR-SOFR spread seems to turn from positive into negative already in spring 2019. At the beginning of 2019, the interest rate curves in the U.S. were inverted which drove the LIBOR-SOFR spread to go negative. This is also well reflected in future expectations, FwdExp, component. In Table 2 in below describes the correlation between variables in levels form.

Table 2. Pearson correlation of variables in levels form.

	Spread	*Cred*	*Liq*	*FwdExp*	*FwdExpW*	*RepoVol*
Spread	1.0000	0.1238	0.1397	0.7129	0.7498	-0.5074
Cred	0.1238	1.0000	0.0269	0.1164	0.0688	-0.4285
Liq	0.1397	0.0269	1.0000	-0.0428	-0.1322	0.4380
FwdExp	0.7129	0.1164	-0.0428	1.0000	0.8771	-0.4845
FwdExpW	0.7498	0.0688	-0.1322	0.8771	1.0000	-0.5099
RepoVol	-0.5074	-0.4285	0.4380	-0.4845	-0.5099	1.0000

The correlation between spread and explanatory variables seem reasonable and the signs are as anticipated. The correlation between future expectations and the spread stands out from the results being much stronger than the correlation with credit risk and liquidity components. There is a relatively strong negative correlation between the repo market volume and the spread. The correlation of the spread with liquidity and credit risk is surprisingly small within the whole sample. The correlation between the explanatory variables do not indicate presence of multicollinearity, as FwdExp and FwdExpW are not included into models simultaneously. FwdExpW has slightly stronger correlation with the Spread. In Table 3, the correlation results for the same variables in first differences are presented.

Table 3. Correlation of variables in first differences.

	ΔSpread	*ΔCred*	*ΔLiq*	*ΔFwdExp*	*ΔFwdExpW*	*ΔRepoVol*
ΔSpread	1.0000	-0.0292	0.5661	-0.0357	0.1237	-0.0724
ΔCred	-0.0292	1.0000	-0.2703	0.0076	-0.0131	0.0622
ΔLiq	0.5661	-0.2703	1.0000	-0.3187	-0.2306	-0.0488
ΔFwdExp	-0.0357	0.0076	-0.3187	1.0000	0.1656	-0.0779
ΔFwdExpW	0.1237	-0.0131	-0.2306	0.1656	1.0000	-0.0116
ΔRepoVol	-0.0724	0.0622	-0.0488	-0.0779	-0.0116	1.0000

The change in liquidity is most correlated with the change in spread. However, the use of data in first differences seem to revert the relationships of spread and credit risk and one of the future expectations variables. The correlation between *FwdExpW* and *Spread* is still relatively significant but much lower than the correlation between *Liq* and *Spread*. The correlation between explanatory variables remain relatively low.

4. Empirical framework

In this section, the statistical methods used in this study are being introduced. Because the global pandemic hit the worlds' economy during the research period, the market conditions differ a lot between November, 20 2014 and April 30, 2021. Therefore, to model the rates more accurately, and to apprehend the distinctions in the determination of them under different market conditions, the data is divided into two sub-periods. First period, from November 2014 to end of February 2020, is considered to correspond to normal market conditions, as stock market crash and the Fed's emergency rate cut did not take place until March 2020 (Mazur et al., 2021; Fed, 2020). The period from March 2020 to April 2021, the period of massive stimulus to fight against financial consequences of the pandemic, has been a period of abnormal market activities which has its effect to the rates. The whole sample contains observations from the period between November 20, 2014 and April 30, 2021.

The relationships described in hypotheses at the end of Section 2 are examined by applying linear regression to data in order to explain the spread between 3-month LIBOR and SOFR, Vector Autoregression (VAR) models, impulse responses, and variance decomposition analyses are used to deepen the understanding of the relationship between identified components. VAR models with Granger-causality test is used to confirm the existence of relationship between the LIBOR-SOFR spread and other variables. Appendix 3 presents the signs of anticipated relationship between the spread and identified factors based on theoretical background. In addition to researching the hypotheses, the one of the goals is also find a dynamic spread adjustment with help of linear regression.

4.1 Linear Regression

As was observed from Figure 1 in pervious chapter, there is a significant spread between 3-month US dollar LIBOR and 90-day SOFR average. To investigate the determinants of LIBOR-

SOFR spread, a linear ordinary least squares (OLS) regression model is applied. The approach has been popular among previous research of interbank dynamics (e.g. McAndrews et al. 2008, Hui et al. 2011, McAndrews et al. 2017).

Linear regression analysis can used to analyse the relationship between dependent variable and independent variables, and aiming to explain movements in dependent variable with respect to movements of independent variables. OLS is a method for estimating the parameters that aims to minimize the sum of squared distances between the dependent and independent variables. The sum of squared distances, known also as residual sum of squares (RSS), is given by minimising RSS with respect to all elements of β:

$$RSS = \hat{u}'\hat{u} = [\hat{u}_1 \hat{u}_2 \dots \hat{u}_T] \begin{bmatrix} \hat{u}_1 \\ \hat{u}_2 \\ \vdots \\ \hat{u}_T \end{bmatrix} = \hat{u}_1^2 + \hat{u}_2^2 + \cdots \hat{u}_T^2 = \sum \hat{u}_t^2 \qquad (4)$$

Where $\hat{u}$ is a vector of residuals. The coefficients estimates are given by:

$$\hat{\beta} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_k \end{bmatrix} = (X'X)^{-1}X'y \qquad (5)$$

Where X is a T × k matrix of T observations of the independent variables $x_1 - x_k$, and y is a vector of T observation of dependent variable $y_1 - y_T$. The idea is to find parameters $\hat{\beta}$ for which the error term $\hat{u}$ is minimised. (Brooks, 2008)

To avoid biased estimation results, and to choose a suitable estimation method, a series of tests is conducted to detect violations of assumptions. The first assumption requires the average value of errors to be zero, $E(u_t) = 0$. In this study, a constant is used in model, which assures that this assumption will not be violated. Assumption of constant variance of errors, $var(u_t) = \sigma^2 < \infty$, however, needs to be tested as when violation is left unnoticed and OLS is used as an estimation method, it can lead to wrong interpretation of results, as the standard errors could be wrong. In this study, White's (1980) test is used for test heteroscedasticity in models. (Brooks, 2008) Like McAndrews et al. (2007) & King et al. (2019), in this study, the detected heteroscedasticity is taken into account by employing Newey-West approach which adjusts standard error estimates for heteroscedasticity.

Third assumption of uncorrelated errors, $cov(u_i, u_j) = 0 \text{ for } i \neq j$, can have similar implications as heteroscedasticity in case of unnoticed or ignored violation. In this study, the autocorrelation was detected by using graphical inspection, Durbin-Watson (DW) test, and Breusch-Godfrey test. (Durbin & Watson, 1951) All conducted tests provided evidence of presence of autocorrelation which influences estimation results – the coefficient estimates are no longer BLUE. If heteroscedasticity or autocorrelation is present, the efficiency of the OLS estimator is disrupted, and the standard errors could be biased even though the coefficient estimates are still valid. Thus, Newey-West approach is used to reduce the impact of heteroscedasticity and autocorrelation, which will also improve the accuracy of t-values. The approach has been popular in the context of unsecured and secured interest rates (e.g. McAndrews et al., 2007; King et. al (2019)).

OLS estimator is consistent and unbiased when independent variables are not correlated with the disturbance term. If such correlation exists, the explanatory power of variables can be falsely inflated. The fifth assumption is that the residuals are normally distributed, $u_t \sim N(0, \sigma^2)$. This can be tested by using Jarque-Bera (JB) test, which checks the normality based on skewness and kurtosis. Although, the JB test provides evidence for non-normality due to presence of outliers, in general, there is no theoretical justification for removing the outliers. The correlation between variables were examined in Section 3, and there is no closely related explanatory variables that would affect the regression estimates or R^2. Additionally, in this study, Augmented Dickey-Fuller, Phillips-Perron, and KPSS were used to test variables for stationarity. As the tests provided evidence of non-stationary, the estimations were also done by using variables in first differences form.

4.1.2 Dynamic spread adjustment

One of the targets of this research is the creation of a dynamic spread adjustment, which mimics the spread between LIBOR and SOFR. The created spread adjustment can be used when transforming financial contracts from LIBOR to SOFR. The formula of the adjustment can be written as follows:

$$SpreadAdj_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \cdots + \beta_k x_{kt} \qquad (6)$$

Where β_1 is the constant term, $x_{2t} - x_{kt}$ are the identified spread determinants, credit risk, interbank liquidity, future expectations, and repo market liquidity in levels form. $\beta_2 - \beta_k$ are the coefficients of the spread determinants. Linear regression analysis with the OLS estimation method is first applied to identify the spread determinants, $x_{2t} - x_{kt}$, that are statistically significant in explaining the spread. The performance between different models in different data samples is evaluated based on R^2 and adjusted R^2 statistics. The significant spread determinants are then included into the final model where the intercept and the coefficients $\beta_2 - \beta_k$ of the spread determinants are calculated.

The estimated intercept and coefficients can be then used out of sample to calculate the spread between LIBOR and SOFR, when the values of the spread determinants are known. This adjustment could then be implemented into contracts currently referencing LIBOR when implementing the ARRC's proposed fallback language. The purpose of the spread adjustment is to help converting cash products referencing US dollar LIBOR. The adjustment should make the spread-adjusted version of SOFR comparable with US dollar LIBOR, and it should minimize the changes in value caused by the transition (ARRC, 2021b). For example, a financial contract that is currently linked to LIBOR could be converted to SOFR by adding a developed spread adjustment on top of SOFR rate to avoid unwanted value transfer between counterparties of the contract. After the adjustment model is defined, it is then added on top of the 90-day SOFR average. Finally, in this study, the historical performance against the recommended adjustment (ARRC, 2021; ISDA, 2021), 5-year median spread between LIBOR and SOFR, added on top of SOFR rate, and their performance against historical 3-month LIBOR rate is evaluated.

4.2 Vector Autoregression (VAR)

In previous studies, the interest rates are often reported to be persistent. Thus, in regard to possible lagged relationship, a vector autoregression (VAR) is applied to inspect the interplay of variables further. First order positive autocorrelation is discovered from most of the variables and therefore, to capture and inspect the effect that past values have on the interest rate dynamics, a vector autoregressive model is applied. Previously, for example, Bech et al. (2010) and Frank & Hesse (2009), have utilized vector autoregression to inspect the basis between unsecured and secured interest rates. The VAR models are estimated with two different orders of variables by reversing the order for the second estimation in order to inspect the effect of the order on the results.

In VAR system, current values of each of the variables depend on combinations of the previous values of all variables and error terms. In case of two variables in the system with k lags of each variable, the VAR equation can be written as follows:

$$\underset{g \times 1}{y_t} = \underset{g \times 1}{\beta_0} + \underset{g \times g}{\beta_1}\underset{g \times 1}{y_{t-1}} + \underset{g \times g}{\beta_2}\underset{g \times 1}{y_{t-2}} + \dots + \underset{g \times g}{\beta_k}\underset{g \times 1}{y_{t-k}} + \underset{g \times 1}{u_t} \qquad (7)$$

Where g is the number of variables considered in the VAR system. For each equation, the βs can be estimated by using OLS. To ensure the stationarity of the variables used, the series of unit root and stationarity tests are applied to the variables in levels form, and based on the findings, the estimations were done by using first differences. (Brooks, 2008) However, as argued by Brooks (2008), the differencing reduces the information on long-term relationships between the time series, and therefore, the estimations are also done by using the data in levels form.

VAR can be used to investigate relations between the variables in the VAR system. In this study, Granger-causality, impulse responses, and variance decompositions analyses are applied within VAR framework. Granger- causality test is used to analyse whether the past values of variable x can significantly explain the present values of y – whether variable x "Granger-causes" variable y. For Granger-causality test, the null hypothesis is: *"Lags of variable y_{1t} do not explain current y_{2t}"* for each equations in VAR system. F-test is used in testing hypothesis to examine the joint significance of lags of a certain variable within the VAR system to detect Granger-Causality (Granger, 1969; Brooks, 2008; Luetkepohl, 2011). The number of lags for VAR is chosen based on graphical inspection, and Akaike's and Bayesian information criteria (AIC and BIC).

Granger-causality tests can only help analysing whether variables have significant impacts on the other variables in the system. Impulse responses can reveal the signs of those relationships, and how long the effect of a variable will remain in VAR system. Therefore, to deepen the understanding of the system dynamics, the orthogonalized impulse responses are calculated for the estimated model to examine the responsiveness of a variable to each of the variables within the system. Variable decompositions help further examining the system dynamics by determining to what extent the movements in a variable are caused by its own shocks, and what proportion can be explained by the shocks to other variables. For both variance decompositions and impulse responses the ordering of the variables is important, especially if residuals are highly correlated. (Sims, 1980; Brooks, 2008).

5. Results

First, all variables were tested for stationarity by using Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. All tests provide evidence for most of the variables being non-stationary in levels form, whereas all variables in first differences were stationary. Non-stationary variables can lead to spurious regression which causes misleading estimates for statistical significance. As in previous research, the unsecured-secured rate relationships have been examined both in levels and first differences form, the same approach is taken in this study. However, as the OLS estimates in levels form will most likely be biased due to non-stationary variables, the results gained from the estimation in levels form will be only used for creation of the dynamic spread adjustment.

Due to recent market dislocations caused by Covid-19, testing the whole sample period might have an effect on the results. Therefore, the dataset is divided into aforementioned sub periods; Whole sample is the period from November 20, 2014 until April 30, 2021. Normal period is the period from November 20, 2014 until February 29, 2020. Crisis period is starting from the 1st of March 2020, which is an approximation for a starting point of the global pandemic, and the period ends April 30, 2021.

5.1 Linear regression estimates

First, a simple linear regression is used to estimate the relationship between the LIBOR-SOFR spread, and the independent variables, including credit risk, liquidity risk, future expectations, repo market volume, and end of quarter volatility. The results of analysis done by using data in first differences are first presented. At the end of the chapter, the performance of the spread adjustment created by using data in levels form is compared to actual 3-month US dollar LIBOR rate and the recommended spread adjustment (ARRC 2021; ISDA 2021)

5.1.1 Estimation results in first differences

One econometric issue common when working with time series data is the non-stationarity, which can lead to spurious results. The all variables were tested with series of unit root and stationarity tests, and Spread was proven to be non-stationary with a high probability. Also Cred, Liq, and RepoVol show some evidence of non-stationarity. The first differences of all variables were already stationary, and therefore the estimations are calculated by using the first differences of the time series variables. The models estimated were the same for all three periods. First model aim to explain the change in Spread with change in Cred, Liq, FwdExpW, RepoVol, and EoQ, and can be written as follows:

$$\Delta Spread_t = \beta_1 + \beta_2 \Delta Cred_t + \beta_3 \Delta Liq_t + \beta_4 \Delta FwdExp_t + \beta_5 \Delta RepoVol_t + \beta_6 EoQ_{t-1} + u_t \quad (8)$$

where $\Delta Spread_t$ is the change in the spread between 3-month US dollar LIBOR and 90-day SOFR average at time t, $\Delta Cred_t$ is change in credit risk component, ΔLiq_t is change in liquidity component, $\Delta FwdExp_t$ measures change in future expectations at time t, $\Delta RepoVol_t$ is the volume of repo market underlying SOFR measuring repo market liquidity, and EoQ_{t-1} is a dummy which accounts for end of quarter volatility of overnight SOFR. The EoQ_{t-1} is EoQ_t lagged by one day so that the quarter-end dummy gets value of 1 on the day when quarter-end effect should be visible in $\Delta Spread_t$. $\beta_1, \dots, \beta_6$ are coefficients of explanatory variables and intercept.

Estimated models are written in Table 4 in below, and the estimation results are presented in Table 5.

Table 4. Estimated regression models.

Model 1	$\Delta Spread = \beta_1 + \beta_2 \Delta Cred + \beta_3 \Delta Liq + \beta_4 \Delta FwdExpW + \beta_5 \Delta RepoVol + \beta_6 EoQ$
Model 2	$\Delta Spread = \beta_1 + \beta_2 \Delta Cred + \beta_3 \Delta Liq + \beta_4 \Delta FwdExpW + \beta_5 \Delta RepoVol$
Model 3	$\Delta Spread = \beta_1 + \beta_2 \Delta Cred + \beta_3 \Delta Liq + \beta_4 \Delta FwdExp + \beta_5 \Delta RepoVol$

Table 5. Regression results. Whole period in first differences.

	Model 1			Model 2			Model 3		
Obs.: 1682	Coeff	T-stat	Signif	Coeff	T-stat	Signif	Coeff	T-Stat	Signif
Intercept	0.00054	0.0097		0.00052	0.0094		0.00034	0.0056	
ΔCred	0.41882	6.2387	***	0.41923	6.2414	***	0.39582	5.1089	***
ΔLiq	0.51279	10.807	***	0.51295	10.807	***	0.50365	9.7264	***
ΔFwdExp							0.07005	3.7021	***
ΔFwdExpW	0.14309	2.7370	***	0.14315	2.7373	***			
ΔRepoVol	-0.0027	-1.7474	*	-0.00261	-1.7422	*	-0.00204	-1.3256	
EoQ	0.08329	0.7329 0							
R^2	0.413			0.413			0.365		
Adjusted R^2	0.412			0.412			0.364		
F-Statistic	236			295			241		
Significance	***			***			***		

Note: Regression t-values are adjusted by using Newey-West estimator. *, **, *** describes 10%, 5%, and 1% significance level, respectively.

As ΔEoQ is not significant it is excluded from the second model. All other variables are significant in 1% significance level except ΔRepoVol which is significant only in 10% level of significance. The signs of all variables are as expected. Based on R^2 and adjusted R^2, the explanatory power is quite small which was expected when using first differences. When excluding ΔEoQ, the F-statistic increases but the explanatory power of the model remains the same according to R^2 and adjusted R^2. Third model replaces $\Delta FwdExpW$ with $\Delta FwdExp$ to compare the performance of the variables. The first one seem to have more explanatory power over the ΔSpread when comparing the coefficient estimates. $\Delta FwdExpW$ is used to limit the disturbance compared to $\Delta FwdExp$ which is caused by seasonal volatility in EFFR. The intercept is insignificant in all models. In Table 6. the same equations are applied for the period before the pandemic, the Normal period.

Table 6. Regression results. Normal period in first differences.

	Model 1			Model 2			Model 3		
Obs.: 1376	Coeff	T-stat	Signif	Coeff	T-stat	Signif	Coeff	T-Stat	Signif
Intercept	-0.02860	-0.7799		-0.02867	-0.7815		-0.03128	-0.7998	
ΔCred	0.34084	4.3927	***	0.34114	4.3877	***	0.30736	4.0270	***
ΔLiq	0.48263	5.6188	***	0.48251	5.6156	***	0.44171	5.3871	***
ΔFwdExp							0.05525	1.7493	*
ΔFwdExpW	0.12093	2.4387	**	0.12097	2.4368	*			
ΔRepoVol	-0.00376	-1.5275		-0.0036	-1.5171		-0.00265	-1.2383	
EoQ	0.12490	0.8882							
R^2	0.303			0.303			0.246		
Adjusted R^2	0.300			0.301			0.244		
F-Statistic	119			149			112		
Significance	***			***			***		

Note: Regression t-values are adjusted by using Newey-West estimator. *, **, *** describes 10%, 5%, and 1% significance level, respectively.

The estimation results for the normal period tells very similar story as the results for whole sample, except the significance of ΔRepoVol disappears, and also ΔFwdExpW and ΔFwdExp are insignificant in Model 2 and Model 3. Coefficient for ΔCred is slightly smaller. Model 2 is again the best according R^2 and adjusted R^2 but overall the models performed worse than within the whole sample. The crisis period is much shorter including only 305 observations. The results for the third data sample are presented in Table 7 in below.

Table 7. Regression results. Crisis period in first differences.

	Model 1			Model 2			Model 3		
Obs.: 305	Coeff	T-stat	Signif	Coeff	T-stat	Signif	Coeff	T-Stat	Signif
Intercept	0.0831	0.3677		0.0831	0.3684		0.0914	0.3716	
ΔCred	0.6301	2.1313	**	0.6302	2.1337	**	0.5071	2.3092	**
ΔLiq	0.5591	7.5530	***	0.5592	7.5748	***	0.5777	8.3150	***
ΔFwdExp							0.1137	2.0537	**
ΔFwdExpW	0.1919	1.6966	*	0.1919	1.6992	*			
ΔRepoVol	-0.0038	-1.1086		-0.0038	-1.1434		-0.0047	-1.2622	
EoQ	0.0241	0.1144							
R^2	0.50			0.50			0.458		
Adjusted R^2	0.491			0.493			0.451		
F-Statistic	59.7			74.9			63.5		
Significance	***			***			***		

Note: Regression t-values are adjusted by using Newey-West estimator. *, **, *** describes 10%, 5%, and 1% significance level, respectively.

The third estimation period does not provide significant swings in the estimation results. The ΔCred is now significant only 5% level and ΔRepoVol and ΔEoQ remain unsignificant. Based on R^2 and Adjusted R^2, the models were able to explain a larger portion of the movements of the Spread during the crisis period, although the significance of individual variables decreased. During the crisis period, the interest rates have remained very close to zero due to the extensive stimulus, so there is also less spread to be explained. Overall, based on the estimation results, the ΔCred and ΔLiq seem to have a relatively large effect on the change of LIBOR-SOFR spread as the mean change of ΔSpread is 0.63 and 0.56 given one unit change of ΔLiq and ΔCred respectively. The future expectations component seems to also explain the change in the spread. However, based on this regression analysis, it cannot say that volume of the repo market or end-of-quarter volatility of SOFR would have a significant effect on the spread.

5.1.2 Estimation in levels and spread adjustment

As discussed earlier, the linear regression analysis was conducted also for data in levels form, and the results can be found in Appendix 4. However, due to the non-stationarity, the estimates are likely to be biased. Same models formatted based on theoretical background are applied as when using data in first differences. The models are presented in Table 4 in previous chapter. First model aims to regress the Spread on Cred, Liq, FwdExpW, RepoVol, and EoQ, and the estimated model takes form:

$$Spread_t = \beta_1 + \beta_2 Cred_t + \beta_3 Liq_t + \beta_4 FwdExpW_t + \beta_5 RepoVol + \beta_6 EoQ_{t-1} + u_t \quad (9)$$

The results are presented in Appendix 4. The estimations were again applied for three samples, whole sample period, normal sample period, and crisis sample period, referring to Covid-19 pandemic. As can be expected, compared to the previous estimation results using first differences, the explanatory power is much higher in all models and in all samples. All variables have expected signs in all models and all data samples, except Cred has interestingly a negative sign when applying data for whole sample, and for crisis period. This could be explained an increased financial uncertainty caused by Covid-19, which was not realized in interest rates due to the massive economic stimulus that was pushing down the interest rates, and thus there is seemingly negative relationship between the credit risk component and the spread. In normal period, Cred is not significant. RepoVol remained significant through all samples, but has only a slightly negative impact on the spread. Model 2, without *EoQ* variable, is again performing the best among all data samples based on adjusted R^2 statistics, and is therefore used as an alternative spread adjustment. The spread adjustment can be written as follows:

$$\mathrm{SpreadAdj_t} = \beta_1 + \beta_2 \mathrm{Cred_t} + \beta_3 \mathrm{Liq_t} + \beta_4 \mathrm{FwdExpW_t} + \beta_5 \mathrm{RepoVol}$$

The coefficient estimates for the model are presented in Appendix 4.

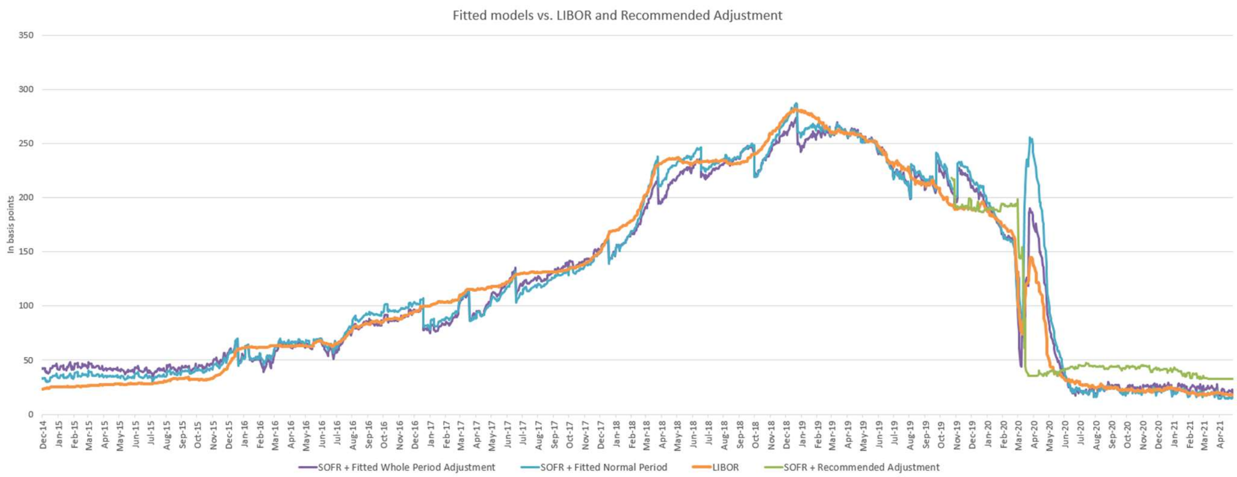

Figure 5. Comparison of fitted models, LIBOR, and adjustment recommended by ARRC and ISDA.

In Figure 5, the performance of Model 2 fitted for the whole period and Model 2 fitted for normal period is presented together with actual 3-month LIBOR rate and 5-year median adjustment recommended by ARRC and ISDA. Due to the short period of existence of SOFR, the recommended adjustment can only be calculated for the last 396 observations, and it is presented as a green line in Figure 5. In the fitted models, the Fed's interest rate cuts and increases can be easily seen, and it is causing noise into the time series. At the beginning of period, the model fitted for normal period (blue line) tracks better the movements of LIBOR whereas at the end of period, when it is used out-of-sample, it performs slightly worse. Both fitted values also overestimate the sharp increase in LIBOR in spring 2020 whereas the adjustment recommended adjustment does not react to it. At the end of the period, the adjustment is over 20 basis points higher than LIBOR whereas fitted adjustments track the LIBOR rather well.

The purpose of the spread adjustment is to help changing cash products referencing US dollar LIBOR to use SOFR as reference rate, and it should make the spread-adjusted version of SOFR comparable with US dollar LIBOR (ARRC, 2021b). As the models introduced in this chapter are tracking the actual LIBOR rate better, it seems like the dynamic adjustments would better mimic the movements of LIBOR when adjusting for interest rate reform for LIBOR-pegged cash products. The results of regression analysis reveal that there is a relationship between change of LIBOR-SOFR spread, and the change of liquidity, credit risk, and future expectations. However, the relationship between repo market volume and the spread, or between the end-of-quarter volatility and the spread, cannot be confirmed. In next chapter, these relationship are further examined with Granger-causality, impulse responses, and variance decomposition analyses.

5.2 Vector Autoregression

To further analyse the interaction of the variables with one another and their past values, VAR model was fitted to data in order to test Granger-causality between variables and to conduct analysis on impulse responses and variance decomposition to further examine the effect of credit risk, liquidity, future expectations, and repo market volume on the spread between LIBOR and SOFR. The estimation was done for the whole sample and for the pre-Covid-19 sample. The data sample from the crisis period does not contain enough observations for VAR, and thus was left out. As variables were detected to be non-stationary in levels form, the VAR models were estimated by using variables in first differences. The Granger-causality was tested by using data also in levels form to ensure that the results are aligned.

5.2.1 Granger-causality

With data in first differences, BIC is minimised with 8 lags whereas AIC suggests a much larger model. As also graphical inspection supports 8 lags, a VAR(8) model is fitted. In table 8 in below, the results for F-test of the joint significance of the lags of a certain variable in given equation. To compare the results, same models were fitted for normal period, and the whole period. Based BIC, the VAR(9) model was fitted to the data in levels form. The p-values for Granger-causality are presented in Table 8 in below.

Table 8. P-values of F-test results for the joint significance of lags of each variable.

	Cred	Liq	FwdExp	RepoVol
ΔNormal Period	0.0000	0.0000	0.0006	0.1300
ΔWhole period	0.0000	0.0000	0.0000	0.2346
Normal Period	0.0000	0.0000	0.0000	0.1479
Whole period	0.0000	0.0000	0.0000	0.3310

In Table 8 above, the rows contain the p-values of tests for different data samples, normal period and whole period, and the delta (**Δ**) describes the use of variables in first differences. The last two rows of the table contain the test results when using data in levels form. Columns describe the variable of which significance in explaining the values of Spread is tested. The results are telling one truth: lagged and present values of liquidity, credit risk, and future expectations are significant in explaining the LIBOR-SOFR spread whereas volume of the repo market is not. The result is same in levels and in first differences for both periods, normal period and the whole period.

The findings provide evidence of the effect of interbank liquidity and credit risk components, and the results are in line with previous research about the determinants of the spread between LIBOR and other secured interest rates (e.g. McAndrews et al, 2008; Frank & Hesse, 2009). The term risk component seem to affect the spread between term LIBOR and SOFR, which is expected due to the methodological differences between the two rates, LIBOR being a term rate while SOFR is an overnight rate. However, against the expectations, the repo market volume cannot significantly explain the spread between 3-month LIBOR and 90-day SOFR average. This is likely due to the market underlying SOFR being highly-liquid, and the fluctuations of that market do not seem to influence the 90-day SOFR average more than they influence the 3-month LIBOR.

5.2.2 Impulse Responses

As with Granger-causality test one can only examine the existence of significant explanatory power of a variable to another variable, the impulse responses analysis is conducted to better understand the relationship. First impulse responses were calculated for whole period and then for the normal period ending prior to the beginning of Covid -19 pandemic. Crisis period was left out from the analysis due to small number of observations. The data is in first differences. The impulse responses were observed for LIBOR-OIS spread, credit risk, liquidity risk, future expectations, and repo market volume. Future expectations component calculated with daily average EFFR rate, FwdExp, was chosen to be incorporated into the final model instead of FwdExpW based on information criteria.

Whole period

All figures presenting separate unit shocks to each of the variable and their effect on a certain variable can be found from Appendix 5. As can be seen in Figure 6 in below, the shock introduced to change in LIBOR-SOFR spread had the largest effect to its own values. A shock in liquidity had a significant negative impact on following day, and it did not turn into positive until T+8. The shocks introduced to credit risk and repo market volume seem not to have much effect on the spread. A shock in future expectations has a positive effect on the spread which does not stabilize until T+9. When observing the impulse responses of liquidity in Figure 7, the largest effects are caused by shocks in liquidity itself, the spread, and the repo market volume. Similar to the impulse responses of the spread, shocks in liquidity have a negative effect on liquidity T+1. A shock in repo market volume has a significant positive effect on the liquidity component T+1, which makes sense as it can be expected that the liquidity shocks in the repo market are connected to the liquidity risk of the interbank market. Other shocks than the shock introduced to liquidity component seem to stabilize quite quickly. In Figure 8, the orthogonalized impulse responses for future expectations are presented. Liquidity shock has a significant negative effect on the future expectations at time T, which then turns into positive at time T+1. Innovation in spread has also a positive effect on future expectations at

T+1. The shocks introduced into the system do not stabilize until T+10. As can be observed in Figure 9, the credit risk is mainly affected by the shocks in liquidity, repo market volume, and the credit risk itself. Repo market volume seems to be only affected by the shocks in future expectations and its own shocks, as presented in Figure 10 in below.

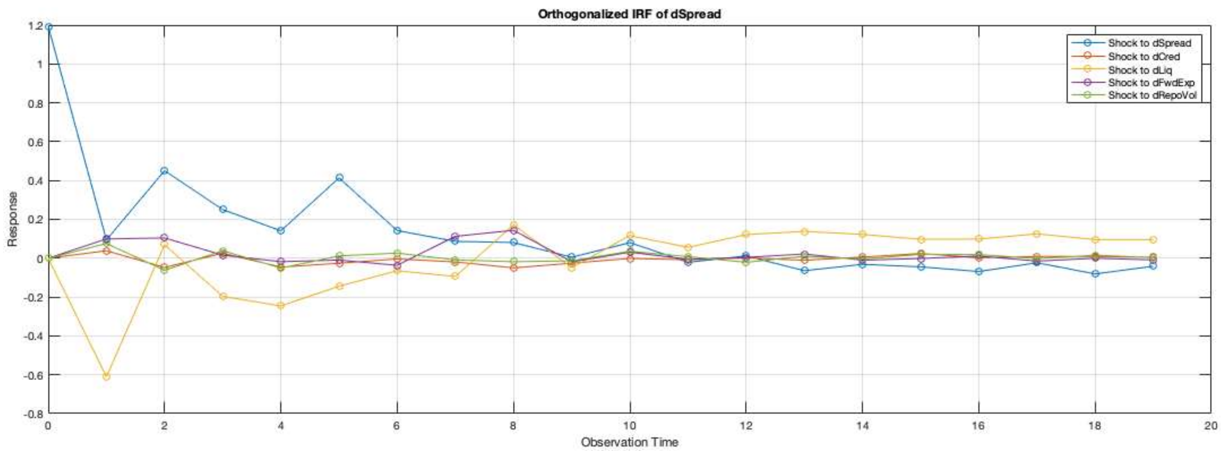

Figure 6. Impulse responses. Orthogonalized IRF of Spread. Whole period.

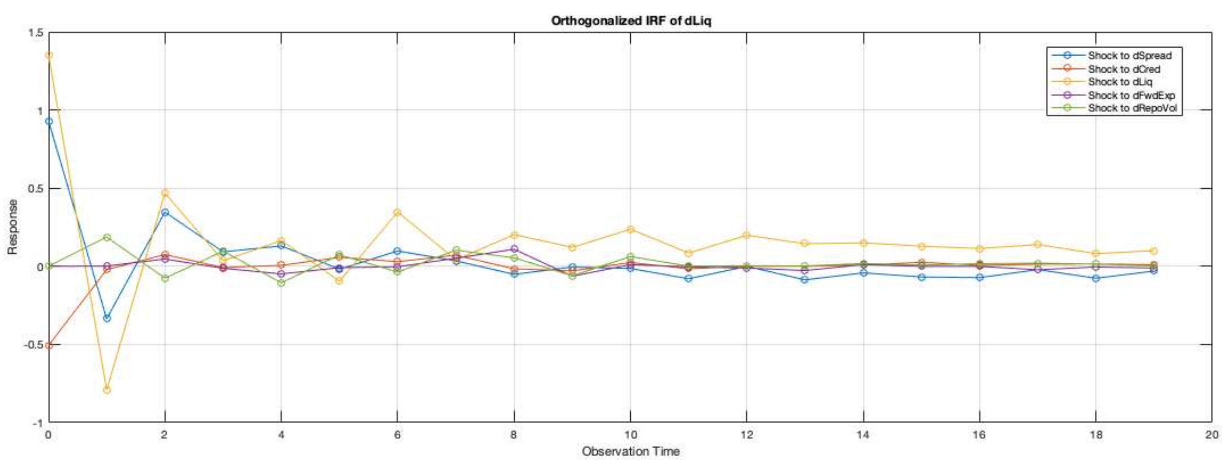

Figure 7. Impulse responses. Orthogonalized IRF of Liquidity. Whole period.

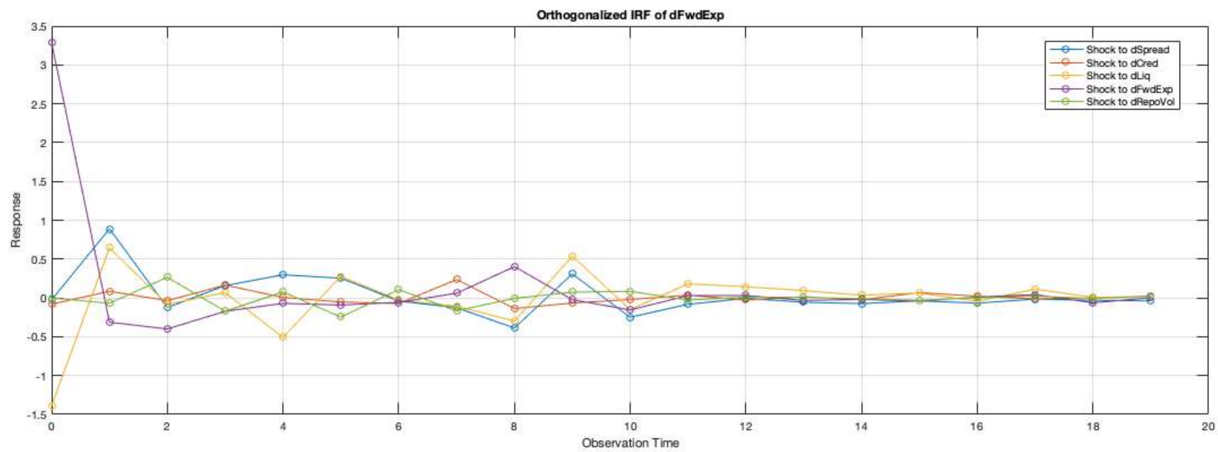

Figure 8. Impulse responses. Orthogonalized IRF of Future Expectations. Whole period.

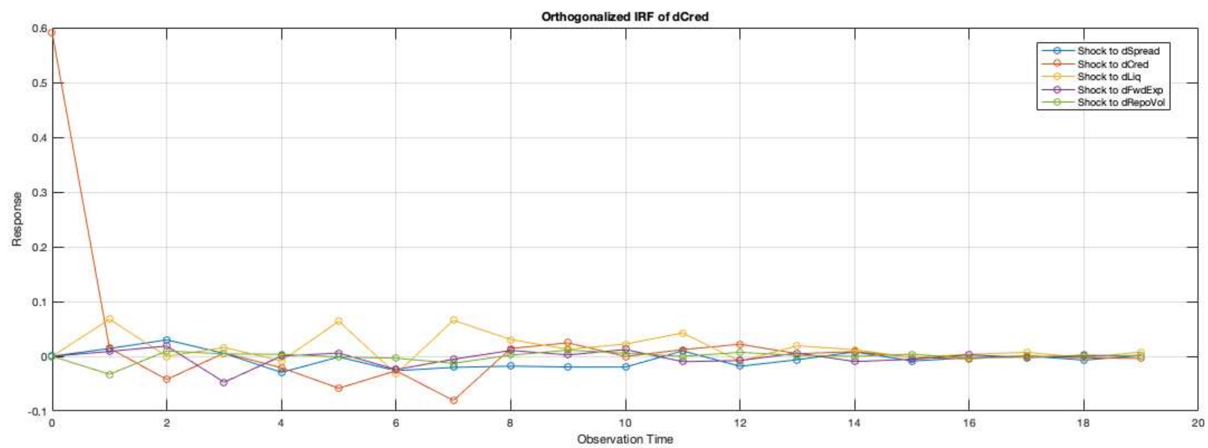

Figure 9. Impulse responses. Orthogonalized IRF of Credit. Whole period.

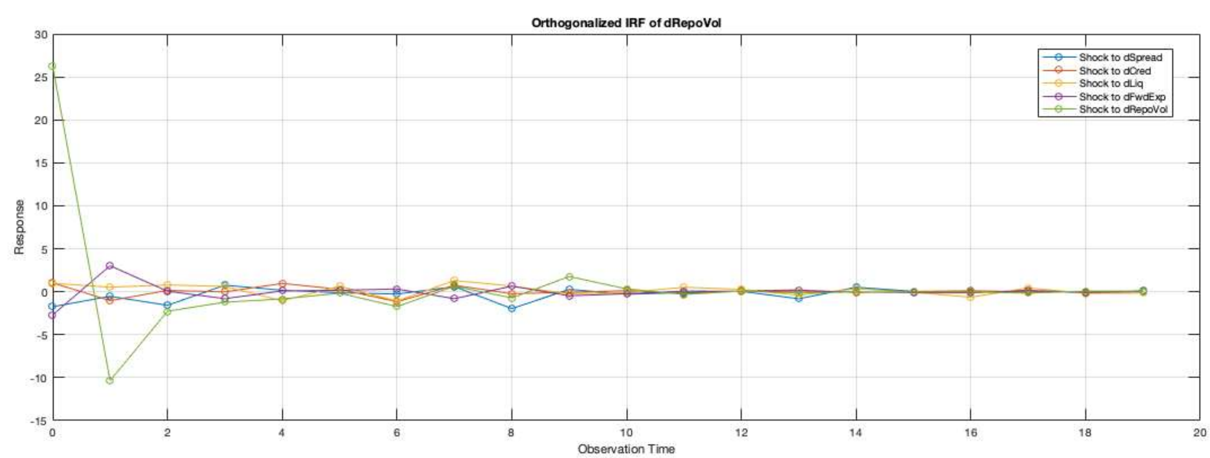

Figure 10. Impulse responses. Orthogonalized IRF of Repo Market Volume. Whole period.

All the shocks appear to move out from the system rather quickly, except the effect of the shock introduced by liquidity to the liquidity and spread components. The impulse response analysis done for the whole period for first differences suggests that the relationship between the spread, credit risk, liquidity risk, future expectations and repo market volume components is more complex and the present values are not enough when explaining the change in the spread. Based on analysis, especially the 2^{nd} and 5^{th} lag of Spread, the 1^{st} and 2^{nd} lag of liquidity, and the 1^{st} and 2^{nd} lag of future expectations would be important in explaining the spread. However, the impact of the shocks does not seem to last long, implying that the effect of changes in values of liquidity, future expectations, and the spread itself are affecting also future values of the Spread, but this effect does not seem to be long-lasting.

Normal period

The impulse response analysis was conducted also for the period before the pandemic to observe the relationship under more normal market conditions. The illustrations for impulse responses between all variables in the system can be found in Appendix 6. For the normal period the same VAR(8) model was applied.

As seen in Figure 11 in below, a positive shock introduced to the spread has again a significant, long-lasting positive effect to its later values. Similar to the whole period, shock in liquidity has a negative effect on the spread at T+1, but it seem to stabilize swiftly. In line with the impulse response analysis for the whole period, the spread is positively affected by the shock in the future expectations, and the shocks in credit risk and repo market volume do not seem to have much effect on the spread. Based on the analysis, the spread is the most affected by its own shocks, but shocks introduced in liquidity have also a significant impact on the spread.

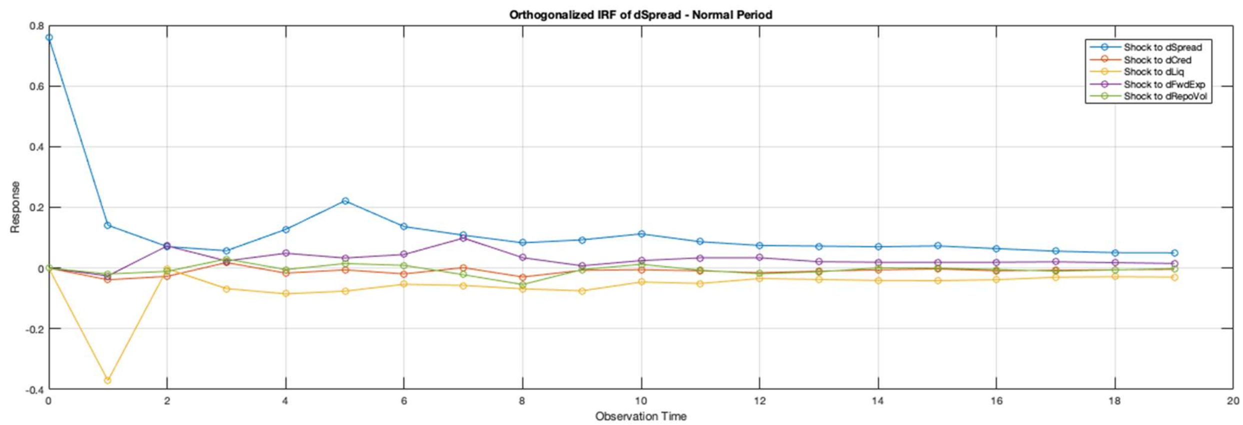

Figure 11. Impulse responses. Orthogonalized IRF of Spread. Normal period.

When comparing results from the whole period with the normal period, it can be observed that including the period of Covid-19 into the dataset adds complexity to the relationship between the variables. However, it does not drastically change the dynamics between the variables.

5.2.3 Variance decomposition analysis

By analysing variance decompositions, one can observe how much an orthogonal shock to one variable in the system affects to variance of the forecast error in another. Variance decompositions were calculated for two periods, the whole data sample and the pre corona sample. The data used was in first differences, and the estimation was done with model of order 8. Table 8 gives variance decompositions for the LIBOR-SOFR spread for 1, 2, 3, 4, 5, 7, 10, 14, and 20 days ahead for two orders of variables:

Order I: ΔSpread, Cred, Liq, FwdExp, RepoVol

Order II: RepoVol, FwdExp, Liq, Cred, Spread

Two opposite orderings are applied to examine the sensitivity of the results for the order of the variables. Corresponding figures for variance decompositions are available in Appendix 7.

Table 9. Variance decomposition (%) for LIBOR-SOFR spread residuals of two orderings (I, II). Whole period.

	Explained by innovations in									
Days ahead	**ΔSpread**		**ΔCred**		**ΔLiq**		**ΔFwdExp**		**ΔRepoVol**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**
1	100.0	64.2	0.0	3.6	0.0	31.8	0.0	0.0	0.0	0.4
2	78.6	58.6	0.0	3.1	20.4	31.7	1.0	6.1	0.3	0.4
3	80.0	56.5	0.2	3.0	18.4	34.1	1.0	6.0	0.5	0.9
4	79.0	58.1	0.2	2.9	19.3	32.4	1.0	5.7	0.5	0.8
5	76.9	58.7	0.3	3.0	21.3	31.5	1.0	5.7	0.6	1.0
7	77.8	61.5	0.3	2.8	20.4	29.5	0.9	5.3	0.6	1.0
10	75.5	59.8	0.4	2.8	21.3	30.4	2.2	6.0	0.6	1.0
14	74.0	59.2	0.4	2.8	22.7	31.0	2.2	6.0	0.7	1.0
20	72.3	59.4	0.4	2.9	24.5	30.5	2.2	6.3	0.7	1.1

Table 9 presents the effect of shocks in each variable on the LIBOR-SOFR spread variation. The results are presented for two aforementioned orderings of variables. As presented in Table 9, shocks to liquidity account for over 20 % of the variation of the interest rate spread in Order I, and over 30 % for Order II. The results are highly sensitive for the ordering of the variables, but the liquidity still has the largest effect on the spread after the innovations in the spread itself. Future expectations account for 1 – 6 % whereas credit and repo market volume account less than 3 %. According to variance decompositions, the innovations in spread itself have the largest effect on the spread. In table 9 in below, the variance decomposition results for normal period can be observed.

Table 10. Variance decomposition (%) for LIBOR-SOFR spread residuals of two orderings (I, II). Normal Period.

	Explained by innovations in									
Days ahead	**ΔSpread**		**ΔCred**		**ΔLiq**		**ΔFwdExp**		**ΔRepoVol**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**
1	100.0	89.6	0.0	1.0	0.0	8.6	0.0	0.5	0.0	0.2
2	81.0	77.8	0.2	4.9	18.6	15.4	0.1	1.4	0.1	0.5
3	80.5	77.0	0.3	4.8	18.4	15.4	0.8	2.2	0.1	0.6
4	79.9	76.7	0.3	4.8	18.7	15.5	0.9	2.4	0.2	0.6
5	79.3	76.5	0.4	4.7	19.0	15.0	1.1	3.2	0.2	0.7
7	79.8	77.5	0.4	4.3	18.3	13.7	1.4	4.0	0.2	0.6
10	77.9	76.0	0.5	4.3	18.6	12.9	2.5	5.6	0.6	1.3
14	77.6	76.0	0.5	4.2	18.6	12.4	2.7	6.1	0.6	1.4
20	77.4	76.0	0.5	4.1	18.7	12.0	2.9	6.5	0.6	1.4

The results presented in Table 10 are aligned with the variance decomposition for whole period, except the role of liquidity in both orderings has decreased and it now accounts only for 13 –19 %. However, the effect of liquidity is still larger than combined effect of credit risk, future expectations, and repo market volume. In normal period, the role of the innovations in spread itself has increased which indicates that other components have less effect on the LIBOR-SOFR spread during normal market conditions.

Based on both impulse responses and variance decomposition analysis, the incorporation of the crisis period overestimates the effect of liquidity risk component in the change of LIBOR-SOFR spread. However, the liquidity component still has a relatively significant role in the determination of LIBOR-SOFR spread, and it has the most explanatory power among all variables investigated in this study.

6. Conclusions and discussion

In this paper, the dynamics of the spread between 3-month US Dollar LIBOR and 90-day SOFR Average during period between November 20, 2014 and April 30, 2021 is examined in order to gain knowledge on how the methodological differences between the two rates affect the spread. The spread between the two rates describes the change in the risk that market participants face as the interest rate reform progresses. Therefore, it is important to understand what is incorporated into that risk. By examining existing literature and by looking into the methodology behind the two rates, a set of anticipated rate determinants – interbank credit and liquidity risk, future expectations, and repo market liquidity – have been identified. In Section 5, the relationship between the spread and these determinants are examined with linear regression, Granger-causality, impulse responses, and variance decomposition analyses.

The first research question focuses on the relationship between the spread and interbank credit risk and liquidity factors. Based on the results of linear regression and Granger-causality analyses, credit and liquidity risk components are significant in explaining the spread, which is consistent with the previous research where the spread between LIBOR and other secured interest rates, i.e. OIS rate, is examined (e.g. E.g. Michaud et al, 2008; McAndrews et al, 2008). However, the importance of the credit risk component in the spread determination seem to be relatively small compared to the findings made during 2008 financial crisis. Despite of the seemingly small effect of the credit risk component, U.S. banks have suggested creation of a dynamic credit spread index which could be added to SOFR. In addition, new credit sensitive alternatives are being introduced into the market, which could be utilized in transition from LIBOR to SOFR. This includes Bloomberg's short term bank index (BSBY) and American Interbank Offered Rate (AMERIBOR).

In reality, the distinction between credit risk and liquidity risk is challenging to make as the two risks are closely related. In addition, neither the possibly illiquid CDS market nor misreported LIBOR submissions are taken into consideration in this study. Credit sensitivity of interest rates seem to be important under market disturbances caused by credit crisis, such as 2008 financial crisis. Although the credit risk appears to be less relevant in today's abnormal market conditions caused by the Covid-19 pandemic, incorporating credit risk components into interest rates will better reflect the funding conditions especially for those who are less active in secured repo markets, i.e. for smaller banks.

Goal of the second research question is to provide insight whether the methodological differences between term LIBOR and SOFR can explain the spread between them. As the SOFR is secured overnight rate, it does not incorporate credit risk or term risk components. On the contrary, term LIBOR is unsecured term rate. Thus, the credit and term risk components should exist in the spread between the two rates. In addition, the rates have different underlying market, and therefore the liquidity components of the two rates differ from one another. In linear regression analysis conducted in this study, the changes of the identified components were able to explain 30–50 % of the changes of the spread, meaning that the identified methodological differences were able to partially explain the spread, but a larger part of the changes of the spread was left unexplained. Based on the impulse responses, the relationship between the variables is more complex, and the present values of the variables can influence the future values of the spread. On the basis of Granger-causality analysis, all of the identified components are significant in explaining the spread, except repo market liquidity which is measured by repo market volume.

Although the quarter-end volatility of SOFR has caused concern among market participants, its influence becomes insignificant when using 90-day rolling-average SOFR rate. As the evidence for the explanatory power of the repo market volume was weak, the relationship between the repo market demand and the spread cannot be confirmed. The weak explanatory power of repo market liquidity components, measured by the end of quarter dummy and repo market volume, might be partially influenced by the inverted interest rate curves. In September 2019, there was a large day-to-day jump of 282 basis points in overnight SOFR, when at the same time the interest rate curve in the U.S. were inverted. This caused the 90-day SOFR average to be above the 3-month LIBOR. Due to this, the relationship between the explanatory variables and the spread was temporarily reversed. Which in turn could decrease the overall detected explanatory power.

The third research question aims to pinpoint the most significant driver of the spread among the identified factors. In line with the results from linear regression estimations, impulse response and variance decomposition analyses also confirm the significant role of the interbank liquidity risk dynamics in determining the spread in short horizon. The results suggest the interbank liquidity risk to have the most explanatory power over the spread among identified spread determinants. Thus, it can be concluded that among identified factors, the interbank liquidity risk has the most explanatory power over term LIBOR-SOFR spread. Nonetheless, borrowing in the interbank market has become increasingly unpopular (Fed, 2021d), being one of the triggers behind the interest rate reform. Therefore, one could argue that the liquidity risk in the unsecured interbank market should not be so relevant to the banks' funding costs.

Additional goal of this study was a creation of dynamic adjustment to account for the difference between LIBOR and SOFR. ARRC (2021) and ISDA (2021) have suggested the use of 5-year median spread between LIBOR and SOFR to adjust for interest rate reform in cash products. Based on findings of this study, an alternative model for the recommended spread adjustment was created. This adjustment can be used to account for the structural differences when converting US dollar LIBOR linked contracts to SOFR. As shown in chapter 5.1, the recommended spread adjustment, five-year median of historical spread between US Dollar LIBOR and SOFR, fails to accurately reflect the financial conditions during abnormal market conditions. The alternative spread constructed in this study is more precisely able to reflect market conditions during more volatile periods. However, dynamic spreads have their own challenges: they are harder to communicate to relevant counterparties, the methodology is harder to implement, and they do not have support from relevant regulators (i.e. ARRC and ISDA).

This thesis contributes to the literature in several ways. Firstly, it studies the spread between LIBOR and SOFR and the spread determinants, providing insight about the dynamics affecting the spread, and shedding light on the embedded structural differences. To the knowledge of the author, so far the previous research has focused on the spread between LIBOR and other secured interest rates, leaving SOFR out of the scope. This is likely due to the short period of existence of SOFR. The study examines the behaviour of the spread during its whole period of existence and helps to understand the realized effect of the methodological differences and the interplay of the identified spread determinants. This may help market participants to prepare for the interest rate reform and to identify the key risks they encounter when implementing the ARRC's proposed fallback language. The developed dynamic spread adjustment can be used as a tool that provides support in the transition as it accounts for the structural differences between the rates: It helps adjusting SOFR for credit risk, term risk, and liquidity risk – the risks that are present in term LIBOR.

In addition, the research sheds light on the interest rates dynamics during global pandemic. The Covid-19 pandemic was included into the research period, and it can be observed how it is quite different in nature compared to the 2008 great financial crisis. The observed interest rate dynamics clearly changed at beginning of Covid-19 pandemic in March 2020. This can most likely be explained by an enormous amount of stimulus that has been injected into the economy. During March 2020 alone, the Fed excessively expanded its repo operations by $2 trillion to ensure sufficient level of liquidity in the money markets. Moreover, during the same month, the Fed cut the federal funds rate first by 0.5% followed by a cut of 1.0%. During the pandemic the level of liquidity in the economy has been exceptional, which well explains the abnormal behavior of the spread components. This highlights the difficulty of finding an appropriate adjustment for the spread during extraordinary market conditions. At the time of writing, the effect of Covid-19 pandemic is still very much present in the world's economy, and despite the improved situation in the U.S., especially the effect that the excess cash has on the interest rates is yet to be observed when the world reaches its post-Covid equilibrium.

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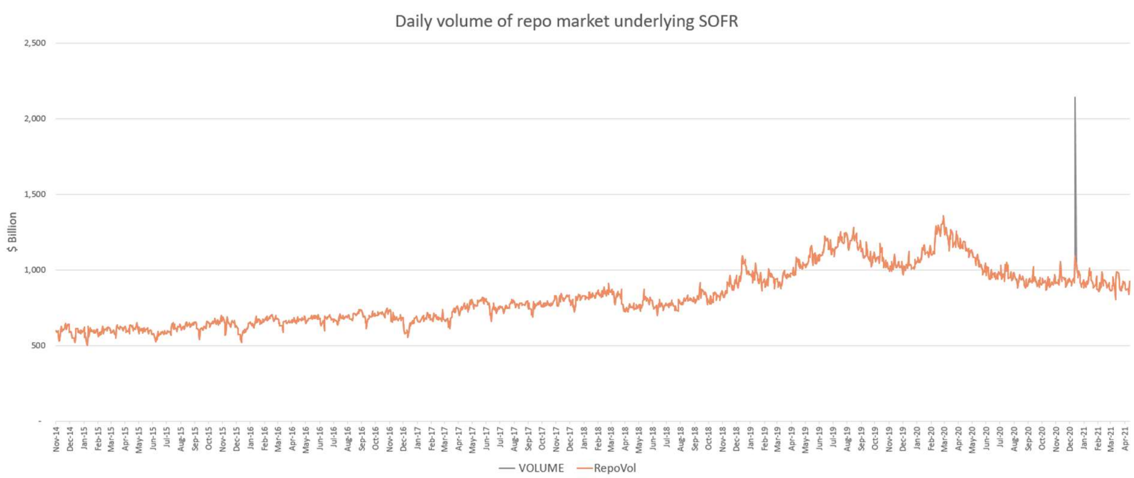
Appendices

APPENDIX 1: US LIBOR PANEL BANKS IN STUDY.

Bank	**CDS Data**
Bank of America N.A.	Incorporated
Barclays Bank plc	Incorporated
Citibank N.A.	Missing
Cooperative Rabobank U.A.	Incorporated
Crédit Agricole Corporate & Investment Bank	Incorporated
Credit Suisse AG	Incorporated
Deutsche Bank AG	Incorporated
HSBC Bank plc	Incorporated
JPMorgan Chase Bank, N.A.	Incorporated
Lloyds Bank plc	Incorporated
MUFG Bank, Ltd	Incorporated
National Westminster Bank plc	Missing
Royal Bank of Canada	Missing
SMBC Bank International plc	Incorporated
The Norinchukin Bank	Missing
UBS AG	Incorporated

APPENDIX 2: DAILY VOLUME OF REPO MARKET UNDERLYING SOFR AND REPOVOL VARIABLE IN $ BILLIONS.



APPENDIX 3. EXPLANATORY VARIABLES AND EXPECTED SIGNS OF COEFFICIENTS

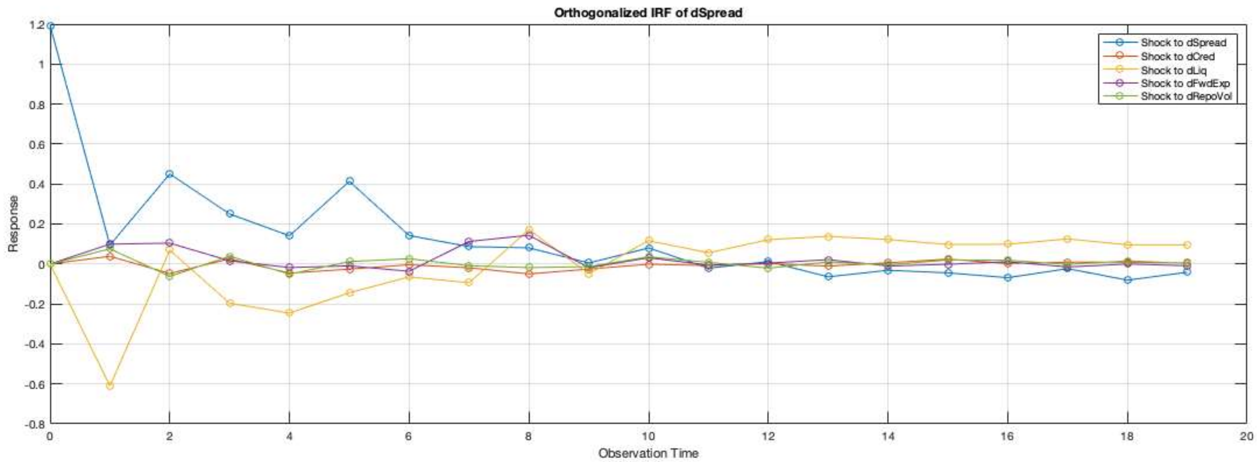
Variable	***Description***	***Predicted Sign***
$\boldsymbol{Cred_t}$	Interbank credit risk	+
$\boldsymbol{\Delta Cred_t}$	Change in interbank credit risk	+
$\boldsymbol{Liq_t}$	Interbank liquidity risk	+
$\boldsymbol{\Delta Liq_t}$	Change in interbank liquidity risk	+
$\boldsymbol{FwdExp_t}$	Future expectations of interest rates	+
$\boldsymbol{\Delta FwdExp_t}$	Change in future expectations of interest rates	+
$\boldsymbol{FwdExpW_t}$	Future expectations, using averaged EFFR	+
$\boldsymbol{\Delta FwdExpW_t}$	Change in future expectations of interest rates, using averaged EFFR	+
$\boldsymbol{RepoVol_t}$	Volatility of repo market	-
$\boldsymbol{\Delta RepoVol_t}$	Change in repo market volatility	-
$\boldsymbol{EoQ_t}$	End of quarter dummy variable	-

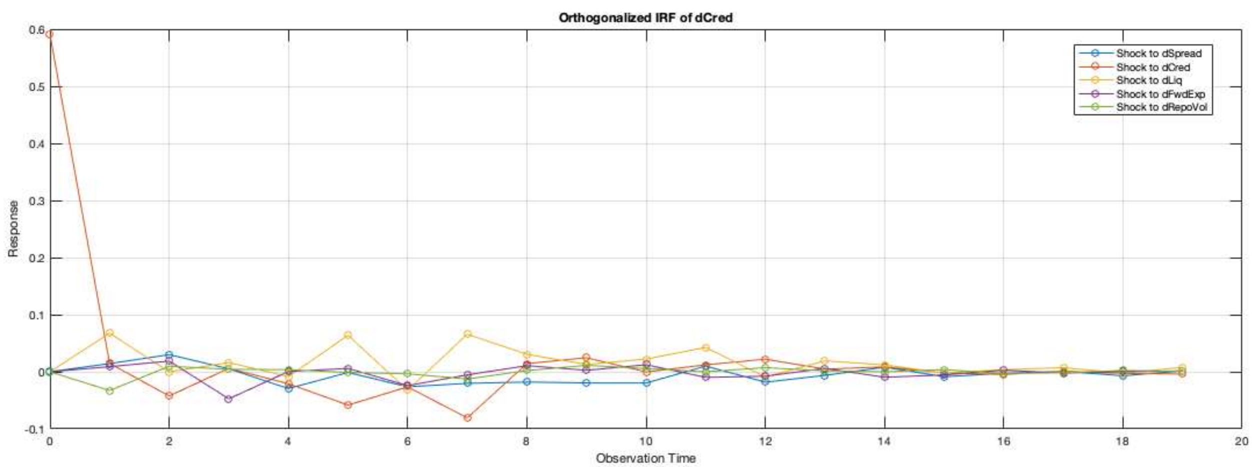
APPENDIX 4. ESTIMATION RESULTS FOR DATA IN LEVELS.

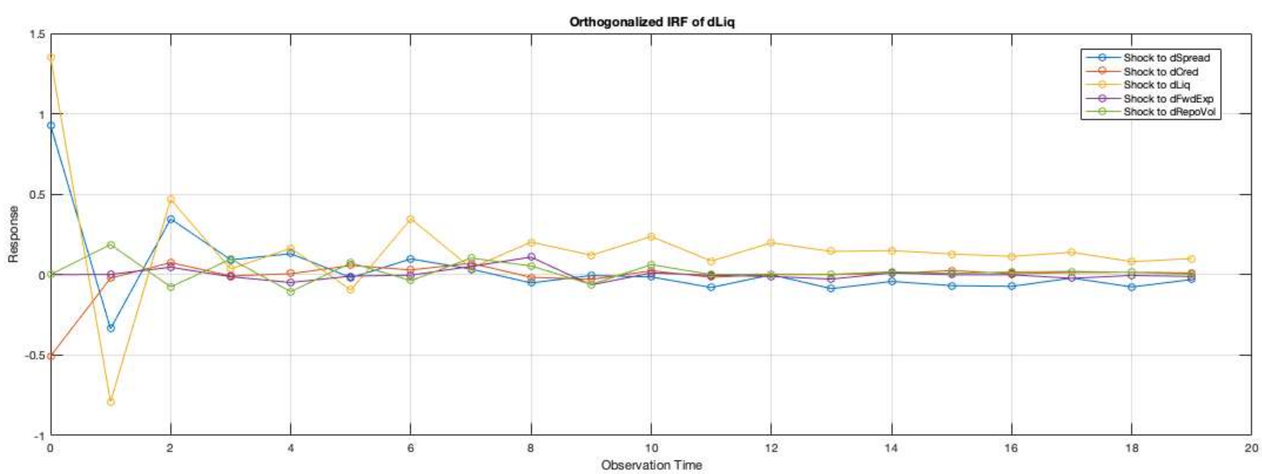
Whole sample	**Model 1**			**Model 2**			**Model 3**		
Obs: 1682	**Beta**	**t-stat**	**signif.**	**Beta**	**t-stat**	**signif.**	**Beta**	**t-stat**	**signif.**
Intercept	68.636	7.0504	***	68.644	7.0461	***	78.162	7.5916	***
Cred	-0.67233	-2.2447	**	-0.66941	-2.2371	**	-0.92701	-2.8549	***
Liq	0.64082	5.2739	***	0.64139	5.2825	***	0.59784	4.6659	***
FwdExp							1.0766	13.3373	***
FwdExpW	1.0352	12.0233	***	1.0348	12.0561	***			
RepoVol	-0.058766	-6.482	***	-0.058739	-6.4717	***	-0.067078	-6.943	***
EoQ	3.989	1.3711							
R^2	0.707			0.707			0.648		
Adjusted R^2	0.706			0.706			0.647		
F-Statistic	810			1010			771		
Significance	***			***			***		
Normal period	**Model 1**			**Model 2**			**Model 3**		
Obs: 1377	**Beta**	**t-stat**	**signif.**	**Beta**	**t-stat**	**signif.**	**Beta**	**t-stat**	**signif.**
Intercept	41.609	6.2053	***	41.693	6.1997	***	47.497	6.3196	***
Cred	0.23901	1.1467		0.24101	1.156		0.17814	0.7926	
Liq	1.0793	14.2341	***	1.0803	14.1817	***	1.1251	13.9023	***
FwdExp							1.1385	14.2087	***
FwdExpW	1.1766	16.4439	***	1.1747	16.398	***			
RepoVol	-0.042105	-6.1585	***	-0.042161	-6.151	***	-0.048727	-6.2904	***
EoQ	4.1127	1.5238							
R^2	0.775			0.775			0.729		
Adjusted R^2	0.775			0.774			0.728		
F-Statistic	947			1180			921		
Significance	***			***			***		
Crisis period	**Model 1**			**Model 2**			**Model 3**		
Obs: 306	**Beta**	**t-stat**	**signif.**	**Beta**	**t-stat**	**signif.**	**Beta**	**t-stat**	**signif.**
Intercept	69.672	4.8393	***	67.958	4.7169	***	85.256	5.068	***
Cred	-1.7146	-3.0397	***	-1.7347	-2.9942	***	-1.94	5.068	***
Liq	0.31592	4.3009	***	0.31484	4.1593	***	0.30722	4.3743	***
FwdExp							0.77366	9.2198	***
FwdExpW	0.61529	8.4895	***	0.62244	8.6457	***			
RepoVol	-0.052611	-3.4746	***	-0.050563	-3.3479	***	-0.067656	-3.5923	***
EoQ	8.3313	3.7024	***						
R^2	0.843			0.839			0.774		
Adjusted R^2	0.84			0.837			0.771		
F-Statistic	322			392			257		
Significance	***			***			***		

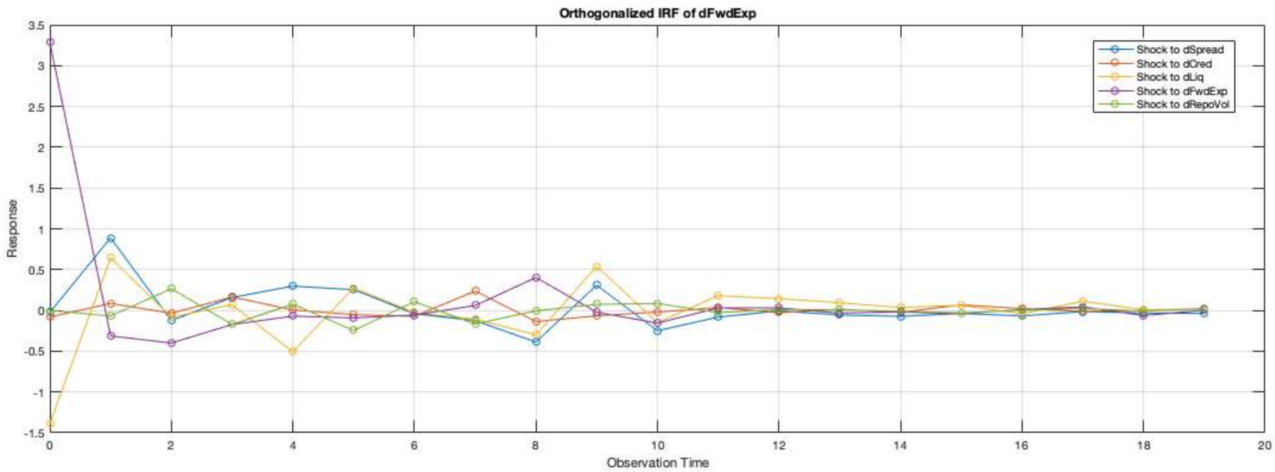
Note: Regression t-values are adjusted by using Newey-West estimator. *, **, *** describes 10%, 5%, and 1% significance level, respectively.

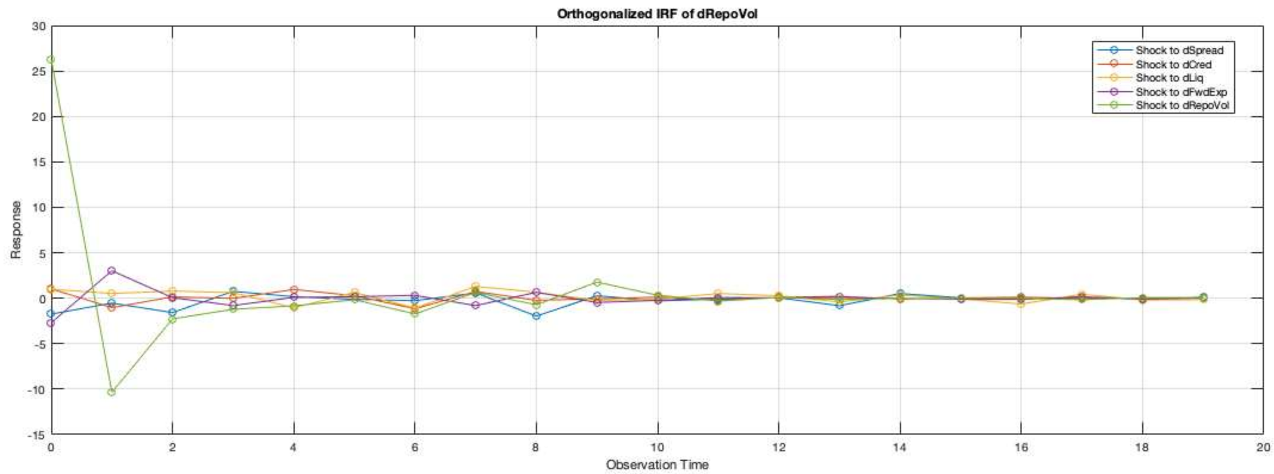
APPENDIX 5. IMPULSE RESPONSES IN FIRST DIFFERENCES. WHOLE SAMPLE.



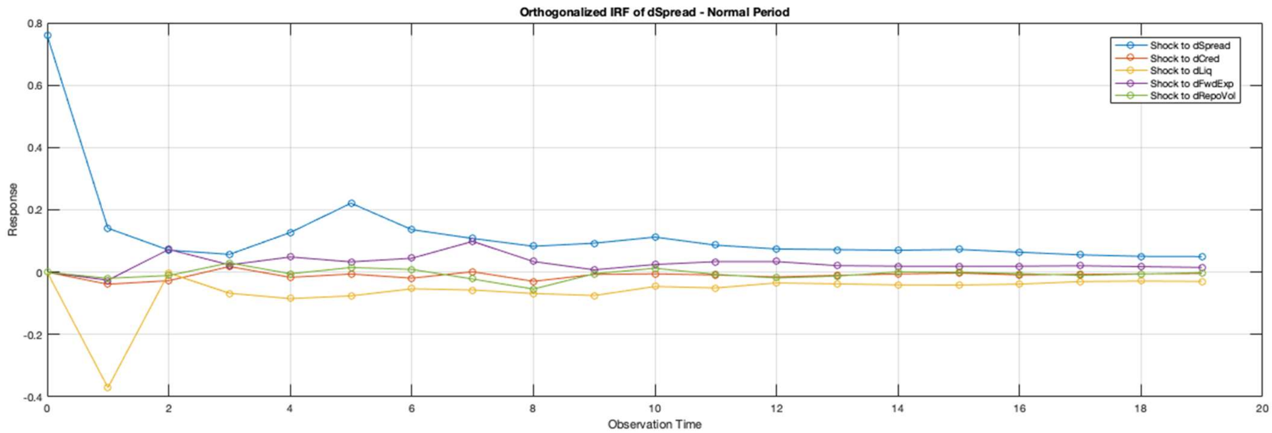


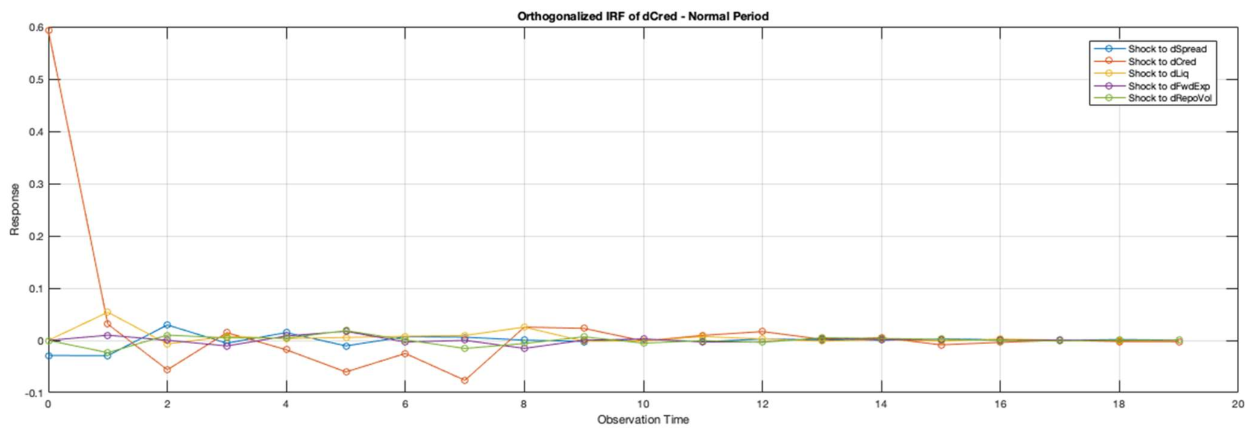


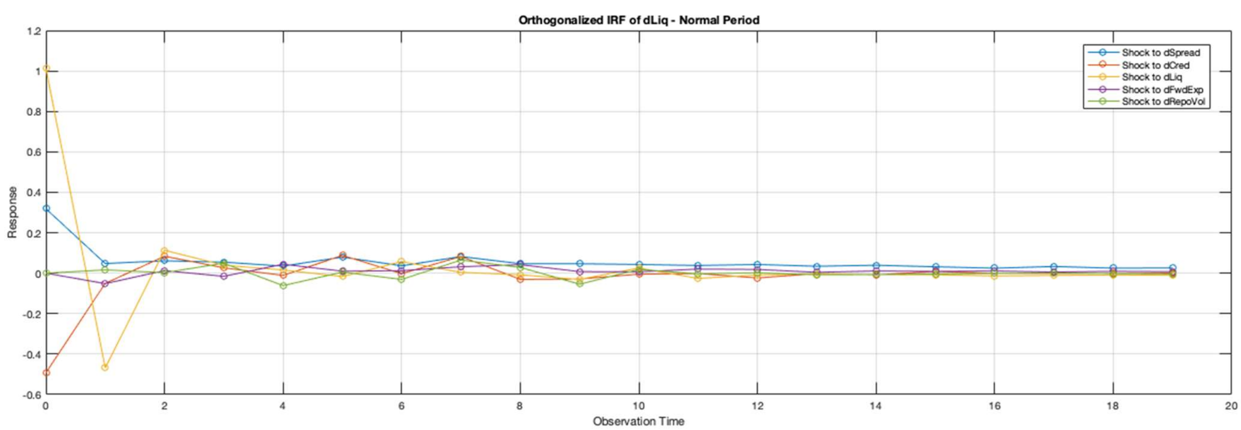

Orthogonalized IRF of dFwdExp
Response
Observation Time
Shock to dSpread
Shock to dCred
Shock to dLiq
Shock to dFwdExp
Shock to dRepoVol

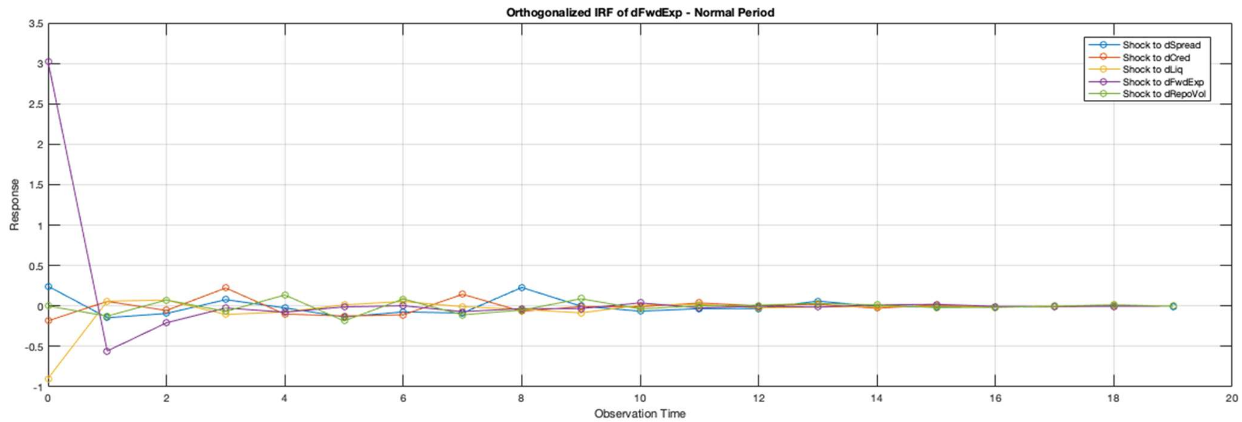

Orthogonalized IRF of dRepoVol
Response
Observation Time
Shock to dSpread
Shock to dCred
Shock to dLiq
Shock to dFwdExp
Shock to dRepoVol

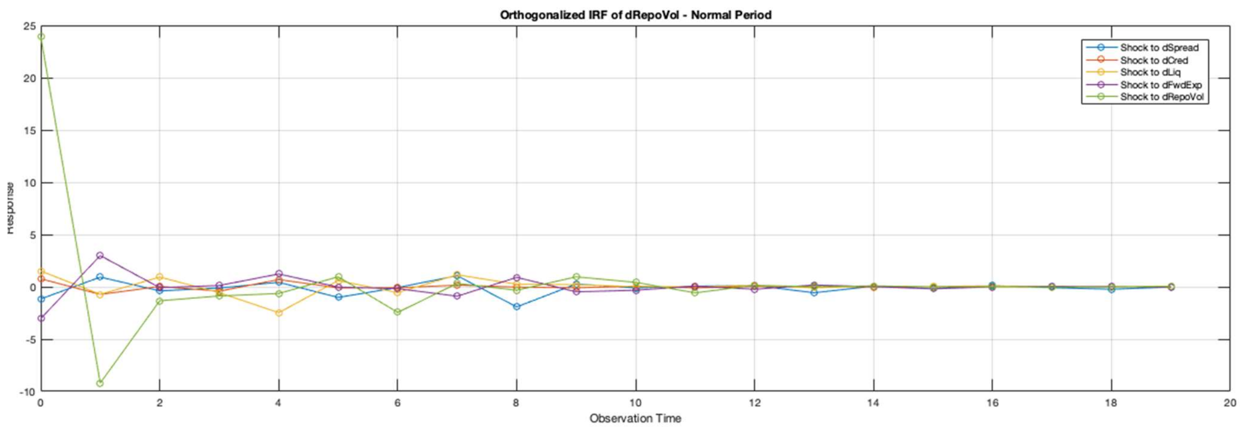
APPENDIX 6. IMPULSE RESPONSES IN FIRST DIFFERENCES. NORMAL PERIOD



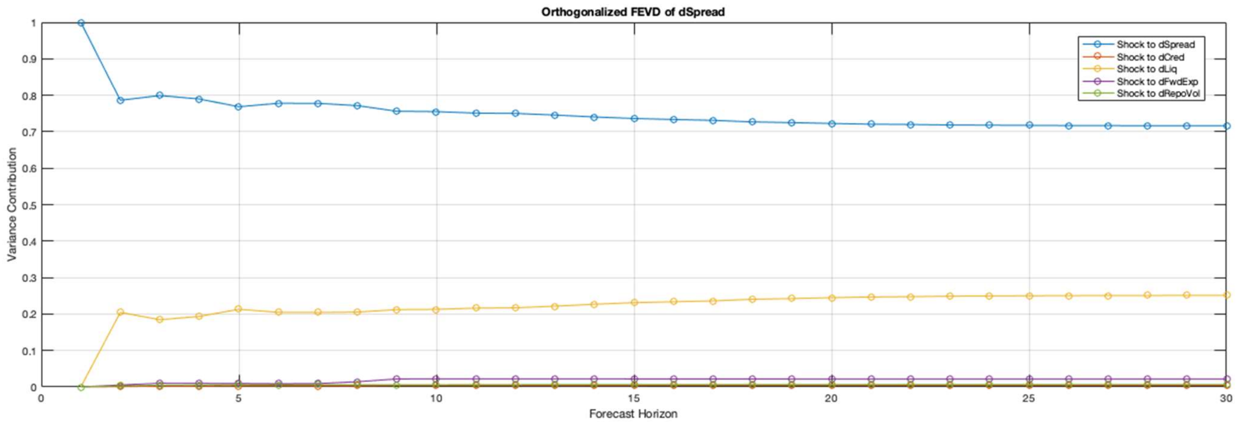


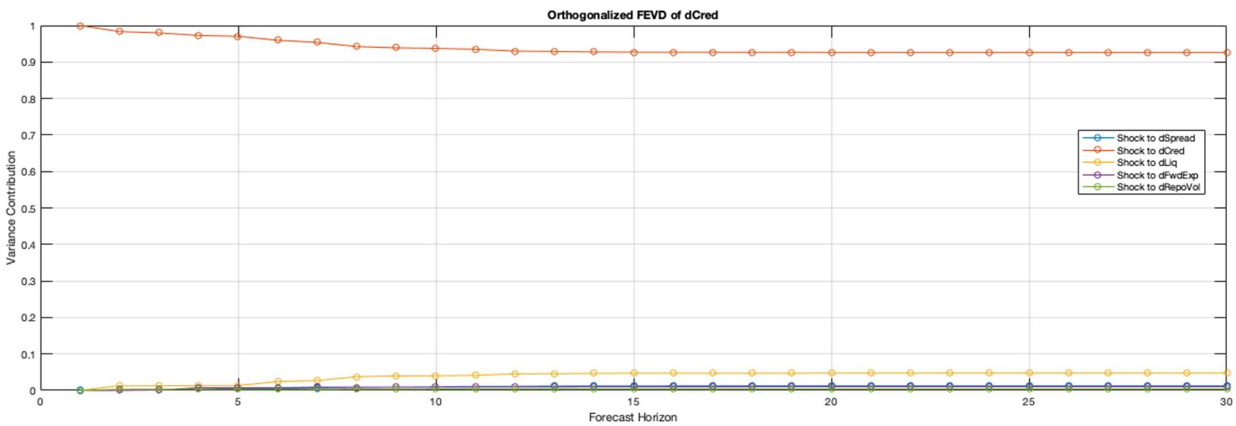


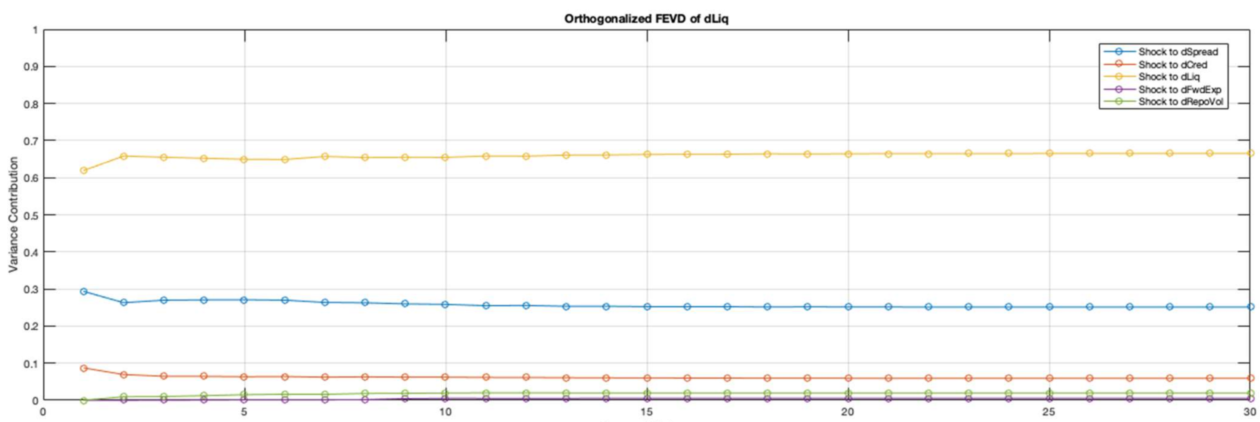

Orthogonalized IRF of dFwdExp - Normal Period
Shock to dSpread
Shock to dCred
Shock to dLiq
Shock to dFwdExp
Shock to dRepoVol
Response
Observation Time

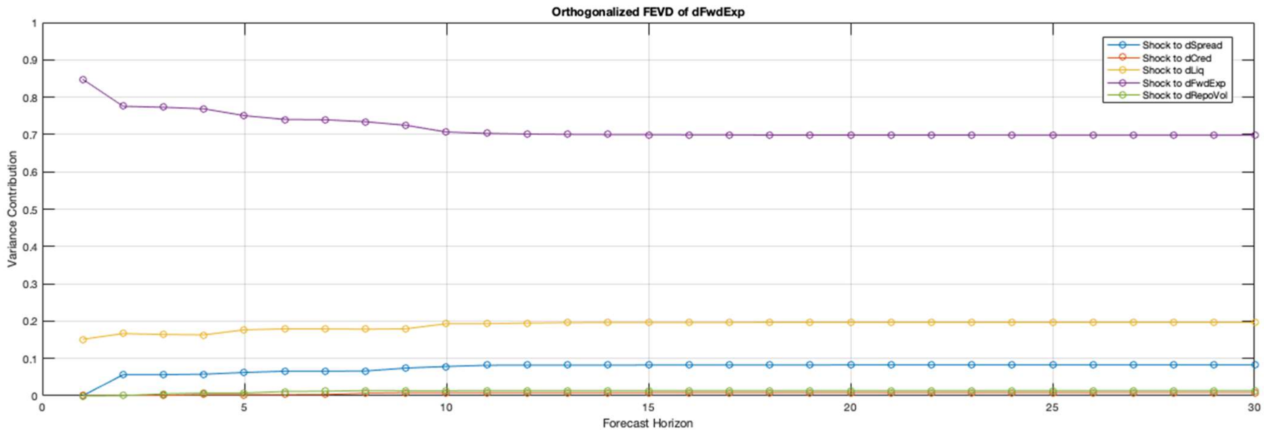

Orthogonalized IRF of dRepoVol - Normal Period
Shock to dSpread
Shock to dCred
Shock to dLiq
Shock to dFwdExp
Shock to dRepoVol
Response
Observation Time

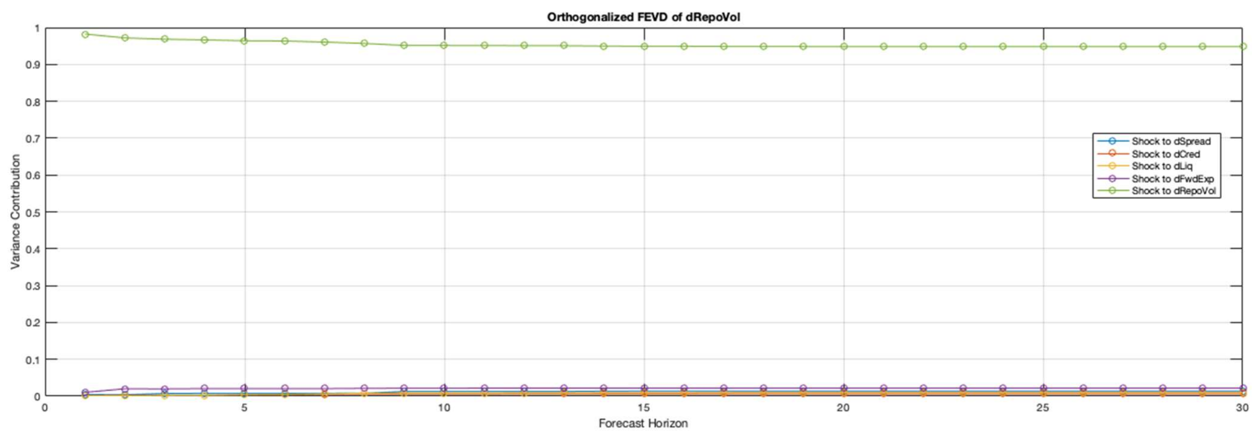
APPENDIX 7. VARIANCE DECOMPOSITIONS IN FIRST DIFFERENCES. WHOLE PERIOD.








Orthogonalized FEVD of dFwdExp
Variance Contribution
Forecast Horizon
Shock to dSpread
Shock to dCred
Shock to dLiq
Shock to dFwdExp
Shock to dRepoVol


Orthogonalized FEVD of dRepoVol
Variance Contribution
Forecast Horizon
Shock to dSpread
Shock to dCred
Shock to dLiq
Shock to dFwdExp
Shock to dRepoVol