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Swiss Sight Deposit Exemption Thresholds and the SARON

Bachelor Thesis in Business and Finance

Thomas Meier

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Abstract

Since the introduction of negative interest rates, several major central banks have used reserve tiering systems to lower the profitability pressure on banks. This study empirically investigates the effect of exemption threshold changes on the Swiss Average Rate Overnight (SARON), using a segmented regression approach, paired with an autoregressive integrated moving average (ARIMA) model. The study examines two unique exemption threshold changes in 2019 and 2020 using an intraday SARON time series combined with daily trading volumes on the Swiss secured money market. The main results of this study consist of a significant positive relation found between an exemption threshold change and the SARON. Additionally, an exemption threshold change seems to trigger a rebalancing process, which in turn results in a significantly higher trading volume compared to the pre-change-period. Thus, by adjusting the exemption threshold, the SNB can influence the SARON and stimulate the liquidity on the secured money market.

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Acronyms

ACF Autocorrelation Function. 23, 24, 28, 30, 36, 38

ADF Augmented Dickey–Fuller. 27

AR Autoregressive. 22

ARIMA Autoregressice Integrated Moving Average. 2, 4, 19, 22, I

BIC Bayesian Information Criterion. 24, 28, 36

bp Basis Points. 8, 26

ET Exemption Threshold. 1, 25

KPSS Kwiatkowski–Phillips–Schmidt–Shin. 27

LIBOR London Interbank Offered Rate. 1, 7

MA Moving Average. 22

NPR Negative Policy Rate. 11

PACF Partial Autocorrelation Function. 23, 24, 28, 30, 36, 38

repo Repurchase Agreement. 5, 43

SARON Swiss Average Rate Overnight. 1, 4, 7, 12, I

SIX Swiss Infrastructure and Exchange. 2, 14

SNB Swiss National Bank. 1, 12, 33

Chapter 1

Introduction

Interbank market rates serve as a benchmark for a wide array of financial contracts, including derivatives, securities and loans worth trillions of dollars in the global economy (Fuhrer et al., 2021). In Switzerland, the most meaningful interbank rate is the Swiss Average Rate Overnight (SARON). As the successor of the London Interbank Offered Rate (LIBOR), the SARON has established itself as the major short-term reference interest rate in the Swiss financial market (Jordan, 2020). As of September 2019, the NWG, 2019 reports the contract volume linked to the SARON at over 400 billion Swiss Francs. Further, on the 13th June 2019 the Swiss National Bank (SNB) declared keeping the SARON close to the SNB policy rate a main objective in their monetary policy implementation strategy (SNB, 2019d).

In 2015, the SNB implemented a negative interest rate policy combined with a reserve tiering system. The reserve tiering system is a key component of the monetary policy in negative territory for a number of central banks, including the European Central Bank, the Bank of Japan, the Swedish Riksbank, Danmarks Nationalbank and the Swiss National Bank (Boutros & Witmer, 2020). Applying a reserve tiering system means that banks' reserve holdings at the central bank above a certain threshold are remunerated at an upper interest rate (typically negative), while reserves below the threshold are remunerated at a lower interest rate (typically zero) (Fuhrer et al., 2021). Since in Switzerland the lower interest rate is indeed zero, the threshold is called exemption threshold (ET) (SNB, 2014).

Despite being a center piece in the Swiss monetary policy implementation, the role of the exemption threshold is not yet well understood in the academic literature (Fuhrer et al., 2021). This paper contributes to this chasm by providing an empirical analysis to answer the question, how exemption threshold changes affect the SARON. Thus, the objective of this study is to analyse and quantify the effect of an exemption threshold change on the SARON by using two unique policy events in 2019 and 2020.

In order to analyse the ET-change effect in these two policy events, this study uses two different event study approaches. First, a segmented regression methodology is used to measure the SARON level shift (Healey, 2004). Second, an autoregressive integrated moving average (ARIMA) model approach is used to measure the same effect in order to add more robustness to the results (Box & Tiao, 1975). Third, a segmented regression model examines level differences in the SARON trade volume. For the analysis of this policy events, this paper uses confidential intraday SARON data and daily SARON trade volumes obtained directly from the Swiss Exchange (SIX). This data set is then complemented with ET-factor data extracted from the SNB's annual reports.

As the main contribution, this study finds a significant positive correlation between exemption threshold changes and a subsequent change in the SARON. The magnitude of the measured effect, varies depending on the ET-change event and the methodology applied. The bandwidth of the measured SARON effect reaches from 0.0285 bp - 0.3624 bp per 1% ET-increase. In view of the rebalancing process elaborated in section 2.1.1, the demand effect of banks, with reserves below the ET seems to outweigh the supply effect of banks with reserves above the ET.

The trade volume analysis finds empirical evidence of an increased trading volume level in the period after the ET-change, with an effect magnitude measured at 2.14% and 6.05% per 1% ET-increase. Another results is that, the trade volume analysis finds no significant level difference from the period between the announcement date and the effective ET-change, compared to the pre-announcement-period. Finally, the sustained heightened trade volume level in the post-change-period infers that the rebalancing process is ongoing for at least another one and a half months after the effective ET-change.

The work of this paper relates to the growing literature about negative interest rate transmission.

Berentsen et al., 2020 and Danthine, 2018 analyse the long-term impact of negative interest rate policies and exemption thresholds. They conclude that ET are an effective remedy against declining bank profits, by lowering the profitability pressure induced by the negative interest rate policy. At the same time, Berentsen et al., 2020 find that the transmission of negative interest rates to money market interest rates is not affected by the exemption threshold.

Another relatively new strand of literature has looked at the role and impact of reserve tiering and exemption thresholds specifically. While some studies shed light on the ET-change effect on a bank-behavior-level, e.g. less risk taking (Fuster et al., 2021), this paper provides a first link of the ET-change effect on the SARON rate. Further, Basten and Mariathasan, 2018 examine the direct effect of the negative interest rate policy on the behavior of Swiss banks, when it was introduced for the first time. They find that banks with SNB reserves over their exemption threshold moved liquidity away from the central bank accounts and towards the interbank market. Therefore, Basten and Mariathasan, 2018 find a first indication for the existence of the described supply effect in the rebalancing process following an ET-change. Fuhrer et al., 2021 and Boutros and Witmer, 2020 both investigate the monetary policy implementation via reserve tiering, deriving their conclusions from a theoretical model based on the traditional Poole, 1968 model of reserve demand. Additionally, Fuhrer et al., 2021 complements their theoretical model with an empirical analysis of bank-level data. Both studies find that reserve tiering helps to maintain sufficient activity in the interbank market. Fuhrer et al., 2021 further adds frictions into the model and finds that due these frictions such as collateral constraints, trading costs, etc. not only the aggregate level of reserves but also the reserve distribution matters. These findings support this paper's line of reasoning that interbank market participants actively optimize their reserve distribution and in the process of doing that could affect the SARON. Fuster et al., 2021 conduct an empirical analysis to examine the effect of a change in the exemption threshold on the bank behavior. They find that banks with high collateral holdings use the interbank market to increase their sight deposits at the SNB. In the mean time, banks with low collateral holdings use less interbank borrowing, but instead grow their customer deposits. Thus, Fuster et al., 2021 not only provide evidence for the existence of the mentioned demand effect, but also illustrate an important constraint for rebalancing its sight deposits following an exemption threshold change.

The remainder of this paper is structured as follows. The next section provides a theoretical introduction into some of the key concepts used in this paper, a background on the Swiss money market, the Swiss average rate over night SARON and its calculation methodology and finally the exemption threshold and its calculation methodology. Section 3 describes the data sources, the reasoning behind the time frame selection and provides some descriptive statistics of the data set. Section 4 gives an overview of the two empirical methodologies used in this paper, the segmented regression and the autoregressive integrated moving average ARIMA model. Section 5 summarizes the results of the SARON and the trade volume analysis, thereby sheding light on the empirically measured effects of exemption threshold changes. Next, section 6 discusses the findings, implications and limitations. Finally, section 7 summarizes the implications and provides a lookout for further research.

Chapter 2

Theoretical Concepts

The following concepts are intended to introduce the reader to some of the key concepts, in order to understand the empirical analysis and its derived implications. The remainder of this chapter is structured as follows: First the Swiss money market is introduced, together with the rebalancing process following an ET-change. Second, light is shed on the background and calculation methodology of the SARON. Third, the exemption threshold concept and its implication on the marginal and average deposit rate is explained.

2.1 Background on the Swiss Money Market

This subsection provides a short introduction of the Swiss money market[1]. Interbank market participants can trade reserves in the secured or unsecured segment of the money market (Guggenheim et al., 2011). However, since the financial crisis the secured money market[2] is the predominant market to trade reserves (Guggenheim et al., 2011). Transactions and binding quotes in the secured overnight market are used to calculate the Swiss Average Rate Overnight (SARON), which in turn plays an important role for monetary policy implementation (Fuhrer et al., 2021).

The bargaining power of banks is little and the variation in interest rates on the repurchase agreement (repo) market is low (Fuhrer, 2018). The trading in the secured money market takes

[1] Refer to Kraenzlin and von Scarpatetti, 2011 for a more detailed overview of the money market.
[2] This paper uses the terms secured money market and repo market interchangeably.

place on the CO:RE trading platform, which is a non-anonymous electronic trading platform with bilateral trade relationships (SIX, 2022a). Quote-based trading is the predominant form of trading and the trading fees are low (Fuhrer et al., 2021).

The majority of the repo market trading is done overnight against the so-called SNB general collateral (GC) basket, which then are called general collateral transactions (SIX, 2022a). These general collateral transactions are cash-driven and the borrower is allowed to deliver any security that is part of the SNB GC basket as collateral (SIX, 2022c). Due to the stringent requirements of the GC basket in regard to credit rating and liquidity, these SNB eligible securities are considered low risk (BIS, 2019). This stringent collateral requirements lead to collateral constraints in the secured money market, preventing some banks from executing certain repo transactions (Fuhrer et al., 2021). Given, that this study analysis the rebalancing process of sight deposits at the SNB after an exemption threshold change, this collateral constraints could be a factor preventing banks from participating in this rebalancing process and thus bias the analysis (Fuhrer et al., 2021).

Finally, in order to access the repo market, market participants need to hold a reserve account at the SNB (SIX, 2022c). Therefore, there is no market segmentation in the sense that a few market participants have access to the SNB and are exposed to negative interest rates whereas others do not (Veyrassat, 2004).

2.1.1 Rebalancing Process

In a system with an exemption threshold on sight deposits, banks are per definition either above or below their individual threshold. Through the repo market[3], banks can adjust their sight deposits by trading with the SNB or between each other and thus in- or decrease their sight deposits at the SNB to their desired level[4]. Over time, the banks therefore optimize their reserves by e.g. filling up their exemption threshold or by withdrawing and lending their reserves above the ET on the interbank market (Fuster et al., 2021). If the SNB now changes the exemption threshold, this whole rebalancing process starts once again, or if it is still ongoing it gets intensified (Maechler & Moser, 2020).

[3] Strictly speaking, they can also allocate their reserves over the unsecured money market, however trading activity on this market segment has been very low since the financial crisis (Fuhrer et al., 2021)

[4] Typically banks manage their sight deposits in the overnight secured market(Fuhrer et al., 2021)

In a repo transaction, there always exists a cash borrower and a cash lender[5], which therefore leads to a classical supply-demand dynamic (SIX, 2022a). On one side, the banks, who have sight deposits exceeding their exemption threshold have an incentive to sell them of via the repo market[6], thus they are the *cash lenders*. On the other side, the banks, who have sight deposits below their exemption threshold have an incentive to fill up their exemption threshold via the interbank market[7], thus they are the *cash takers* (Maechler & Moser, 2020). Hence, in this rebalancing process the cash takers increase the liquidity demand on the interbank market and thereby put upwards pressure on the SARON - *demand effect*. Respectively, the cash lenders increase the liquidity supply on the interbank market and thereby put downwards pressure on the SARON - *supply effect*.

2.2 Swiss Average Rate Overnight

Since 1989, the London Interbank Offered Rate LIBOR is being fixed daily in London, by the British Bankers' Association on the basis of reports from 12 international banks (Jordan, 2009). The LIBOR is a reflection of the conditions on the unsecured money market, and contains a credit risk along with a liquidity premium (Kenyon & Stamm, 2012). For decades the LIBOR has been playing a central role in financial markets, as it was often used as a benchmark in financial contracts (Monticini & Thornton, 2013). However, after the financial crisis, the LIBOR came under scrutiny, because it became evident, that several banks manipulated the LIBOR-Rates through under-reporting (Monticini & Thornton, 2013). This led central banks around the world to come up with a new tamper-proof successor for the LIBOR (Graf, 2021). As a result, in 2009 the SNB presented their new invention the so called "Swiss average rate over night" SARON, to fill the void left by the retiring LIBOR (Jordan, 2009).

On the 13th June 2019, the SNB introduced the SNB policy rate, replacing the target range for the three-month CHF LIBOR in the implementation strategy of its monetary policy (SNB, 2019d). Simultaneously, the SNB declared keeping the SARON close to the SNB policy rate a main objective

[5] The cash borrower, borrows cash and sells collateral and the cash lender lends cash, buys collateral and gets interest rate in the end called the repo rate, which is used to calculate the SARON (SIX, 2022a). However, practically speaking, when the repo rate is negative it is the other way round and the cash taker receives an interest payment.

[6] Because the SARON is generally higher then the SNB policy rate applied to the sight deposits above the ET (Maechler & Moser, 2020).

[7] The reason being, that the banks can make a profit due to the zero interest rate below the exemption threshold and the negative SARON rate.

in their monetary policy strategy (SNB, 2019d). As per the end of 2021, the LIBOR got officially abandoned and replaced by the SARON in Switzerland (Glanzmann et al., 2021). And as of early 2021 the SARON is the central reference interest rate used as a benchmark for secured loans, and a host of different financial instruments such as swaps, futures and forwards (SNB, 2021).

The main difference between the SARON and the LIBOR is that the former is based on actual transactions and only factors in collaterized interbank transactions (Jordan, 2009). These characteristics are expected to prevent commercial banks from being able to manipulate the reference rate (Glanzmann et al., 2021). Considering, that the SARON only reflects the secured money market, along with the fact that the SNB can only operate in the secured money market, the SARON represents a clearer image of the impact of the SNB's repo transactions (Jordan, 2009). This switch implies that the SNB will now use the SARON as the reference rate for its monetary policy strategy and thus pays great attention to keeping it close to its SNB policy rate (Glanzmann et al., 2021).

2.2.1 Calculation of the SARON

The average rate is calculated on a reference price (R_q), that is based on binding quotes [8], or on the basis of concluded trades (T_p). Thus, the average rate is recalculated every time a new quote is issued or a trade has been concluded, providing that they meet the following specifications (SIX, 2021b).

2.2.1.1 Trades

The index calculation is fed directly with the price (P_n) and volume (V_n) of a trade, provided that the price is within the trade filter of 50 basis points (bp). Thus, all trades that fulfill equation 1 are taken into account for the average rate calculation.

$$P_{n-1} - 50\,bp <= T_p <= P_{n-1} + 50\,bp \tag{1}$$

[8] Generally speaking, a quote is an offer sent to selected participants as specified by the participant to buy or sell a security at the quoted price (SIX, 2022a). A quote remains in the order book until it is executed, overwritten or deleted (SIX, n.d.).

The trade filter does not limit the trade volumes taken into account and the average rate is not corrected if a trade is reversed (SIX, 2021b). Considering all the restrictions mentioned above, the average rate (AR_n) is calculated following equation 2.

$$AR_n = \frac{AR_{n-1} \cdot \sum_{j=1}^{n-1} v_j + p_n \cdot v_n}{\sum_{j=1}^{n} v_j} \tag{2}$$

Thus, disregarding the quotes and assuming the trades meet the mentioned conditions, one can see in equation 2 that the average rate is an ever updating volume-weighted average of the repo trades. Therefore, if the money market participants start to rebalance their reserves as a consequence of an exemption threshold change, one should see an increase in concluded trades. This in turn would lead to a quickly updating SARON and interest rate differences in the repo trades should become visible. The definition of the trade filter also reveals, that there exists no volume limit on the trades included to calculate the SARON (SIX, 2022b). Thus, hefty repo transactions volumes by the big players influence the SARON more strongly than small ones.

2.2.1.2 Quotes

The reference price (R_q) is calculated based on the available quotes in the order book, providing they lie within the quote filter. The starting point for the quote filter is the mid price (m) [9] The quote spread (q_n) is measured at the mid price and is rounded to five decimal points (SIX, 2022b). Thus, the SIX, 2021b defines its quote spread as in equation 3

$$m - 3\,bp \leq q_n \leq m + 3\,bp \tag{3}$$

This calculation takes into account both quotes that correspond exactly to the marginal value and those which are only available to a selection of participants. Furthermore, the volume of quotes is restricted to CHF 100 million (SIX, 2022b). Multiple identical quotes on each side of the order get accumulated and capped at CHF 100 million as well (SIX, 2022b). This procedure is intended to reduce manipulation risk (SIX, 2021b). Thus, once a quote gets issued that meets the quote spread

[9] The mid price (m) is the price which lies halfway between the bid and ask price. It is a volume-weighted average of the best buy and sell quotes.

criteria from equation 3, it is taken into account to recalculate the reference price (R_q) following equation 4

$$R_q = \frac{\sum_{j=1}^{n} q_j \cdot v_j}{\sum_{j=1}^{n} v_j} \tag{4}$$

In order to get from the reference price to the average rate, one has to simply divide the reference price by the average quotes volume (V_q)[10].

$$AR_n = \frac{R_q}{V_q} \tag{5}$$

Both the trade and quote filter reveal that manipulations of the SARON are much harder compared to the LIBOR. Further, the existence of the quote filter improves the quality of the link between the repo trades triggered by the exemption threshold change and the SARON. The reason being, that the SARON is less likely to be influenced by pure speculation quotes which would contort the analysis of this study, which solely focuses on repo trades intended for reserve rebalancing.

2.2.1.3 Calculation Interval, Publication Times and Fixings

The average rate is published at 08:30 for the first time and for the last time at the end of the trading day (SIX, 2022b). The average rates are being calculated in real time but are only published every ten minutes. Additionally, the market value of the average rate is published three times a day at 12:00, 16:00 and 18:00[11]. The 18:00 fixing serves as the reference reading for various derivative financial products (e.g. mortgages) and the valuation of financial assets (SIX, 2021a).

2.2.1.4 Compounded SARON

The SARON is an overnight rate that applies to the upcoming overnight period and is based on the Day-Count convention ACT/360 (SIX, 2022b). To support market participants which are generally engaged in long-term contracts, SARON Compound Rates and Indices for pre-defined time periods in arrears beyond the overnight tenor are supplied (SIX, 2021a). These Indices and SARON Compound

10 $V_q = \frac{\sum_{j=1}^{n} v_q}{n}$

11 These three rates are also referred to as fixed rates or fixings.

Rates play an important role for benchmarking in financial products like mortgages, deposits, bonds, swaps, futures and many more (SIX, 2021a).

2.3 Exemption Threshold

Since the financial crisis, central banks have introduced negative policy rates supported by tiered reserve remuneration approaches (Fuster et al., 2021). Reserve tiering means that banks' reserve holdings below a certain exemption threshold are remunerated at a different interest rate than reserves above the threshold (Fuhrer et al., 2021). In the example of Switzerland, this means that bank's reserves below the threshold are remunerated at zero percent interest rate and therefore at no cost (SNB, 2019a). However, the residual reserves above the threshold are remunerated at the current SNB policy rate, which is negative and thereby results in costs for the banks (Baeriswyl et al., 2021). Basten and Mariathasan, 2020 have shown, that banks tend to not pass through the negative interest rates to depositors. Thus, negative interest rates in the last decade diminished the passive margins and dampened banks' profitability (Maechler & Moser, 2020). Hence, the original idea of the exemption threshold was to alleviate the profitability pressure on the banks, without interfering with the monetary policy (Danthine, 2018).

The reserve tiering system allows the SNB to pursue a negative policy rate NPR, without harming the banks' profitability to much, by applying the NPR only to the reserves above the threshold. Figure 1 provides a simplified example of this concept and shows the significant difference between the average and marginal interest rate on sight deposits.

In figure 1, the $Average\,interest\,rate = \frac{(X*Interest free\,rate)+(Y*SNB\,policy\,rate)}{X+Y} = -0.3\%$, whereas the marginal interest rate is simply the SNB policy rate = -0.75%. This simplified example shows how the exemption threshold helps the SNB to enforce its policy rate, while simultaneously being able to flexibly change the average interest rate on its sight deposits. Maechler and Moser, 2020 state that during the introduction of the negative SNB policy rate in 2015, the average interest rate charged on the sight deposits has indeed only been -0.25% instead of the -0.75% marginal interest rate, without the exemption threshold. This in turn implies that about two-thirds of the total sight deposits were exempt from negative interest, which highlights the importance of the ET. Danthine, 2018 comes to the same conclusion that the SNB is able to guide financial markets with the marginal policy rate, while drastically reducing the pressure on the banks with the use of the large exemption thresholds.

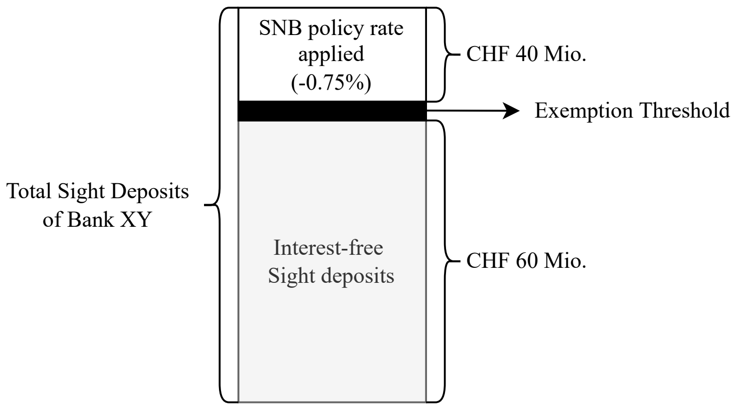

Figure 1 – Schematic illustration of the difference between marginal and average interest rate on SNB sight deposits

2.3.1 Calculation of the Exemption Threshold

The reserve tiered remuneration system poses the question, about the height of the total exemption threshold amount. In order for the system to work, in aggregate, the sum of all exemption thresholds must be lower than the sum of all sight deposits (Maechler & Moser, 2020). Otherwise the banks would carry out money market transactions in order to avoid being subject to the negative interest rate on sight deposits (Jordan, 2009). This in turn lead to money market rates close to zero. Historically, this necessary conditional must have been met, because the SARON trajectory has indeed been close to the SNB policy rate (Maechler & Moser, 2020). Nevertheless, the amount of sight deposits exempt from the negative interest on sight deposits has been substantial in the past[12].

The SNB knows two different methods for calculating the exemption threshold, one for the domestic bank group with reserves at the SNB and another for the foreign banks without reserves at the SNB [13].

[12] E.g. at the end of December 2019 the total amount of sight deposits at the SNB was CHF 566 bn. while the total sum of exemption thresholds amounted to 409 bn (SNB, 2019a). This translates to around 72% of the sight deposits being exempt from the negative policy rate.

[13] Apart from the calculation method, the minimum exemption threshold for each individual sight deposit account holder is at least CHF 10 Million (SNB, 2019d).

2.3.1.1 Minimum Reserve-Based Threshold Method

All sight deposit account holders, which are subject to minimum reserve requirements (domestic banks), are subject to this first calculation method (SNB, 2019c). The exemption threshold is calculated in two steps, firstly a basis component is computed and secondly the cash holdings get subtracted. The basis component is computed using the moving average of the banks' minimum reserve requirements over the preceding 36 reference periods (SNB, 2019c) [14]. A reference period corresponds to 30 days and always starts at the 20th calendar day (SNB, 2019c). The moving average of the bank's minimum reserve requirements is then multiplied by the current applicable ET-factor. This applicable threshold factor can be changed by the SNB at any time, however the condition of higher aggregate sight deposits than the sum of exemption threshold still holds. Lastly, the cash holdings get subtracted from the basic component, the reason being that otherwise banks could escape the NPR by hoarding cash (SNB, 2019c). Note, that following this definition, exemption thresholds differ between banks and more importantly between bank categories [15], which is intended by the SNB.

2.3.1.2 Fixed Threshold Method

For all the other sight deposit account holders, which do not fulfil the requirements for the first method, the SNB sets an arbitrarily fixed threshold (SNB, 2019c). Note that the exemption threshold effect analysis of this paper is based on the exemption threshold factor and therefore is not fully expressive for the reaction of the foreign bank group.

[14] Note that on the first November 2019 the SNB switched from a static reference period calculation, where they used the reference period from November 2014 for all the subsequent years, to a new dynamic moving average model, which is mentioned here in this paper (SNB, 2019a). This calculation method change coincides with the ET-change date and thus could distort the ET-change effect analysis, because now banks are theoretically able to increase their exemption threshold by adjusting their balance sheet in order to have more assets counting to their minimum reserve requirements.Fuhrer et al., 2021 indeed find some evidence on banks reallocating their deposits to categories that count more to the minimum reserve requirements. However, they also find that this asset reallocation process needs time and does not immediately take effect due to the moving average calculation method (SNB, 2019c). Thus the bias is expected to be minor.

[15] The exemption threshold of a bank is calculated as a multiple of its minimum reserve requirements, which itself is a function of its short-term liabilities. Therefore, banks with higher stock of short-term, safe assets relative to their short-term liabilities receive relatively lower exemption thresholds as a share of their short-term, safe assets (Maechler & Moser, 2020).

Chapter 3

Description of Data

This chapter is structured into three parts. First the data sources are specified, together with a short outline of all the variables used in the empirical analysis. Second, the reasoning behind the time frame selections is explained and finally descriptive statistics for the data set are provided.

3.1 Data Sources

For the empirical analysis, this paper uses confidential information about intraday [16] SARON fixings and daily SARON trade volumes obtained directly from the Swiss Infrastructure and Exchange Group (SIX)[17]. This data set is then extended by merging the SARON data with the SNB data on the exemption threshold factor, which is extracted from the annual reports of the SNB[18]. Table 1 provides an outline of all the variables used in the empirical analysis, complemented with their available frequency and units.

[16] The SARON gets fixed three times a day, at 12:00, at 16:00 and at 18:00 (SIX, 2022b)
[17] The SIX is officially commissioned by the SNB to calculate the SARON, precise to six digits (SIX, 2022b)
[18] For the analysis, SNB, 2019a

Variable	Description	Unit	Frequency
$SARON_t$	Swiss average rate overnight, short-term interest rate on the Swiss repo market	percentage	intraday (12:00, 16:00, 18:00)
ETD_t	Dummy for exemption threshold change at time t, coded one at and after exemption threshold change, zero else	binary	intraday (12:00, 16:00, 18:00)
ETD_t^*	Dummy for announcement date of exemption threshold change at time t, coded one at and after announcement date, zero else	binary	intraday (12:00, 16:00, 18:00)
MO_t	Measurement occasion variable, counter starting from one at beginning of each time frame	integer	intraday (12:00, 16:00, 18:00)
BOD_t	Beginning of the day dummy, coded one for every 12:00 fixing, zero else	binary	intraday (12:00, 16:00, 18:00)
MOD_t	Middle of the day dummy, coded one for every 16:00 fixing, zero else	binary	intraday (12:00, 16:00, 18:00)
EOD_t	End of the day dummy, coded one for every 18:00 fixing, zero else	binary	intraday (12:00, 16:00, 18:00)
$WKND_t$	Weekend dummy, coded one for every 18:00 fixing before the weekend or bank holidays, zero else	binary	intraday (12:00, 16:00, 18:00)
ET_t	Exemption threshold factor set by the SNB	integer	intraday (12:00, 16:00, 18:00)
MO_t	Measurement Occasion, counter starting from one in each time frame	integer	intraday / daily
AN_t	Announcement period dummy, coded one for time period between ET-change announcement date and the actual ET-change date, zero else	binary	daily
TV_t	Trade Volume of concluded trades on the Swiss repo market	CHF Millions	daily

Table 1 – Overview of the most important variables used in the empirical analysis

3.2 Time Frame Selection

In order to analyze the two exemption threshold changes, the time series is first divided into two separate time frames called time frame one and time frame two. Subsequently these two time frames are each divided into a pre- and post-change-period, with the exemption threshold being the break point. Additionally, for the trade volume analysis, the time frame is split into three periods in order to measure the announcement effect between the announcement date and the effective ET-change. In the next paragraphs, the reasoning behind the time frame cut-off dates is provided.

For the first exemption threshold change, which occurred on the first November 2019, the time frame is selected from the 13th June 2019 until the 11th December 2019[19]. The 13th June 2019 is chosen, because it represents the date of the second quarterly monetary policy assessment 2019 of the SNB. In this presentation, the SNB officially introduces the SNB policy rate, which effective immediately replaces the target range of the three-month LIBOR as the guideline for its monetary policy (SNB, 2019d). Accompanying this policy change is the SNB's new objective of keeping the SARON close to the SNB policy rate (SNB, 2019d). Thus, it seems reasonable to start the analysis at the date where keeping the SARON close to the SNB policy rate is recorded as an official objective of the monetary policy of the SNB. Since the quarterly monetary policy assessments are always published at 09:30 a.m. the 13th June 2019 is included in the time frame (SNB, 2022a). The end point of the first time frame is given as one day before the quarterly monetary policy assessment on the 12th December 2019. This cut-off date is selected because in line with the parsimony principle, the effects of the reaction to the last quarter monetary policy assessment are excluded in order to limit biases attributed to effects other than the exemption threshold change.

Following the reasoning for the end point of the first time frame excluding the monetary policy assessment of December, the start point of the second time frame is set on the start of February 2020[20]. Monetary policy statements always go hand in hand with certain expectations of the interbank market participants and this December monetary policy statement is no exception (Demiralp & Jorda, 1999). Central banks' monetary policy announcements always contain a certain surprise

[19] Note that for intraday SARON data, the start (end) date always refers to the first (last) fixing of the respective date. E.g. for the end date on the 11.12.2019 this would be the 18:00 p.m. fixing.

[20] Because the first and second February 2020 fall on a weekend, the time series starts at the 3rd February 2020.

component, which results in short-term interbank market turbulences as has been shown by (Demiralp & Jorda, 1999). Hence, in order to limit the contortion due to such turbulences, believed to be stemming from the December monetary policy assessment, these short-term turbulences are cut out by leaving this period out of the analysis. The end point of the second time frame is set on the 17th June 2020, which is one day before the SNB's second quarterly monetary policy assessment of 2020 (SNB, 2020b). This date is chosen with the same line of argument about the surprise effect of monetary policy statements. However, the SNB states in its annual report, starting by the end of June, it complemented its fine tuning operations with an additional extensive long-term repo program to inject more liquidity[21] into the interbank market and thereby lowering the upwards pressure of the SARON (SNB, 2020a). Thus, this period can not be claimed to be representative for the ET-change effect of the 1st April 2020, without controlling for these large long-term repo program [22].Hence, in order to cut out this disturbances, the period after the 17th June 2020 is excluded.

3.3 Descriptive Statistics

Since the SARON gets fixed three times a day at 12:00, 16:00 and 18:00, a regular work week consists of 15 data points. For the first time frame, from the 13th June 2019 until the 12th December 2019, this amounts to 387 observations. For the second time frame, from the 3rd of February 2020[23] until the 17th June 2020, this amounts to 279 observations.

Table 2 shows the disaggregated descriptive statistics for the pre-and post-change-periods. Table 2 illustrates the difference in mean of the four periods. Noticeable is the increase in mean from the pre-change-period to the post-change-period in both time frames. Additionally, note that the standard deviation in the first time frame increases almost five-fold, whereas the standard deviation in the second time frame nearly halves. The implications of this volatility difference, will be discussed further in the empirical analysis chapter. The maximum of the pre-change-period in the first time frame is close to the pre-change-period mean, whereas the pre-change-period maximum of the second time

[21] The SNB claims in its annual report, that the liquidity on the interbank market decreased due to big interbank market trying to fill up their now higher exemption threshold at the SNB (SNB, 2020a)

[22] In order to control for this specific distortion, one needs transaction-level data, which is not available to the author of this study.

[23] Since, the 1st of February is a Saturday, the time series starts at the 3th February.

SARON	Time frame 1		Time frame 2	
	Pre-Change	Post-Change	Pre-Change	Post-Change
# Obs.	300	87	126	153
Mean	-0.738285	-0.689420	-0.705771	-0.658891
Std. Dev.	0.004113	0.022812	0.01515	0.000858
Min.	-0.753029	-0.710987	-0.717987	-0.661322
Max.	-0.730256	-0.624696	-0.666065	-0.656535

Table 2 – Descriptive summary statistics for the intraday SARON data for the respective time frames

frame is closer to the post-change-period mean. This finding can be attributed to the announcement effect in the second time frame, discussed in section 5.2.

The trade volume variable consists of daily observations, thus leading to three times less observations in the data set compared to the SARON time series. Hence, the time frame one from the 13th June 2019 to the 12th December 2019, amounts to 129 observations and time frame two from the 3rd February 2020 to the 17th June amounts to 93 observations. Table 3 shows the disaggregated data descriptive statistics for the daily trade volume on the Swiss repo market. Similar to the SARON time series, the trade volume time series shows significant mean differences between the pre- and post-change-periods. Additionally, the means between the two time frames in general are different with the second time frame exhibiting a much higher mean trading level volume in both periods.

Trade Volume	Time frame 1		Time frame 2	
	Pre-Change	Post-Change	Pre-Change	Post-Change
# Obs.	100	29	42	51
Mean	2590.8	6511.7	7828.4	11174.4
Std. Dev.	772.9	1263.2	1267.6	1378.9
Min.	1258.0	4590.0	4662.0	7785.0
Max.	5831.0	9387.0	11039.0	13620.0

Table 3 – Descriptive summary statistics for the daily trade volume on the Swiss repo market for the respective time frames

Chapter 4

Empirical Methodology

This paper uses two different intervention analysis approaches to estimate the effect of an exemption threshold change. First, an introduction to the segmented regression methodology is provided. Second, the autoregressive integrated moving average ARIMA model approach is introduced.

4.1 Segmented Regression Analysis

Segmented regression is a method, in the family of regression analysis, in which the independent variable gets split into separate intervals at so called break points (Pickup, 2014). In a time series analysis these breakpoints are specific dates or time points. Afterwards, a separate regression line is fit to each interval. Finally, the separate regressions can be compared two draw conclusions about differences between each other (Healey, 2004).

The question one is attempting to answer dictates the specific form of the design matrix of the segmented regression model (Huitema & Mckean, 2000). Since this paper is only interested in the level change and not the slope change the model proposed by Pickup, 2014 is applied. Thus, no slope change is measured, but the pre-change-period slope is taken into account and simultaneously controls for any linear trend present.

For the SARON analysis a two-phase intervention model is applied, meaning that it includes only one break point per time frame. For the trade volume analysis a three-phase segmented regression is used, which conceptually works the same, just with two breakpoints, to account for three different periods instead of two[24].

For the two-phase segmented regression, each of the two time frames gets split into a pre-change-period and a post-change-period through a respective step function[25]. The conceptual design matrix for the two-phase segmented regressions is illustrated in table 4. Note that this notation is consistent with the assumption of persistent and immediate change beginning at time t_1+1 (Huitema & Mckean, 2000). Therefore, the pre-change-period consists of t_1 observations, whereas the post-change-period consists of t_2 observations. The total number of observation in the model is $(t_1 + t_2) = T$. Hence, the Values entered in the first column are 1 through T. Accordingly, the dependent variable values in the last column are identified as $Y_1, Y_2, Y_3, ..., Y_T$. The independent variable in the second column is the step function, that contains the value zero for all observations in the pre-change-period and 1 for all observations in the post-change-period. Hence, this column consists of t_1 zeros and t_2 ones.

Measurement Occasion *MO*	Step Function *ETD*	Dependent Variable *Y*
1	0	Y_1
2	0	Y_2
3	0	Y_3
.	.	.
.	.	.
.	.	.
t_1	0	Y_{t1}
$t_1 + 1$	1	$Y_{t1} + 1$
$t_1 + 2$	1	$Y_{t1} + 2$
$t_1 + 3$	1	$Y_{t1} + 3$
.	.	.
.	.	.
.	.	.
$t_1 + t_2 = T$	1	$Y_{t_1+t_2} = Y_T$

Table 4 – Own illustration of the design matrix for a two-phase segmented regression model for time series adapted from Huitema and Mckean, 2000

The corresponding regression equation of the dependent variable Y on the two independent variables

24 Since, the models are so similar, only the two-phase model is explained in detail.

25 This paper uses a step function, in order to measure for an immediate persistent effect. However, different transfer functions can be used to search for different effects, e.g. a pulse function to account for an additive outlier(Pickup, 2014)

MO and ETD reads as follows

$$Y_t = \beta_0 + \beta_1 \times MO_t + \beta_2 \times ETD_t + \varepsilon_t \quad with\, t = 1, ..., T \tag{6}$$

The three parameter estimates can be interpreted as follows:

β_0 = the pre-change-period level estimate

β_1 = the pre-change-period slope estimate

β_2 = the level change estimate

This study's main interest lies in the last coefficient, because it allows to give a description of the level change between the pre- and post-change-period. While the β_1 coefficient estimates the pre-change-period slope, it mainly serves as a control variable for linear trends. The segmented regression used in this paper employs the ordinary least squares method. In order for the ordinary least square estimation to yield unbiased, consistent and efficient parameter estimates, the Gauss-Markov assumptions need to be met (Huitema & Mckean, 2000). The three Gauss-Markov assumptions can be summarized as follows (Theil, 1971):

1. **No correlation**. The error terms are uncorrelated from each other.[26]
2. **Homoscedasticity**. The variance of the error terms is finite and constant over time.
3. **Zero mean**. The expected value for all error terms is zero.

Like in most time series studies the first two Gauss-Markov assumptions are not met in the empirical analysis part of this paper (Pickup, 2014). Thus, this paper employs the Newey West estimator[27], which is used to overcome autocorrelation and heteroscedasticity (Newey & West, 1986). The third assumption, zero mean of the error terms, is often more easily met with a fitting regression (Theil, 1971). This paper poses no exception with the zero mean assumption being met in all the regressions applied.

[26] For time series models, it is assumed that the errors before and after the error at time t contain no information, which could be useful in predicting the error at time t - No Serial Correlation (Huitema & Mckean, 2000).

[27] For a detailed documentation of the Newey-West Estimator, refer to Pickup, 2014 or the original paper (Newey & West, 1986).

4.2 ARIMA Model

The autoregressive integrated moving average (ARIMA) model is a time series analysis method, which assumes that the current value of a variable can be explained with two factors (Box & Tiao, 1975). The first factor being a combination of lagged values, called the autoregressive (AR) component (Box George et al., 1976). The second factor being a constant term plus a moving average of past error terms, called the moving average (MA) component (Box George et al., 1976). Following common notation, the order of the AR component is denoted by a p and the MA component with a q respectively. Since both the AR and MA components require the weak stationarity condition, differencing is often necessary and thus d specifies the order of differencing applied to the time series (Prabowo & Afandy, 2021). Altogether an ARIMA model gets specified by these three parameters - ARIMA(p,d,q)[28].

The basic idea of building an ARIMA intervention analysis model is to fit an ARIMA model to the pre-change-period as accurately as possible. This is done by identifying the most appropriate ARIMA model on the pre-change-period train set[29] and testing the fit on the test set in the pre-change-period. Optimizing the model fit, ensures that the noise of the time series is modeled as closely as possible and will not distort the estimation of the level change effect. Once the appropriate ARIMA model has been identified, the estimated model is fit over the whole time frame including the post-change-period. Additionally, a step function is included, to indicate the break point in the time series, where the intervention happens and the post-change-period starts. While the ARIMA model gives an estimation of the data generating process, the coefficient of the step function will measure any level change occurring between Pre- and post-change-period (Pickup, 2014).

4.2.1 Box-Jenkins Approach for Interrupted Time Series Analysis

Since the process of building and applying an ARIMA model is lengthy and complex, Box George et al., 1976 invented a systematic process for specifying the model, in order to ensure high accuracy and compliance with the underlying assumptions. Due to the popularity of this approach, the process of fitting an ARIMA model is often called the Box-Jenkins approach (Nelson, 1998). This paper closely

28 For a detailed insight into the mathematics of an ARIMA model, refer to (Pickup, 2014)

29 The train sets in this study each include 67.3% of the pre-change-period observations.

follows the Box-Jenkins approach, which is structured into three stages. First, in the identification stage, the order of the AR(p), I(d) and MA(q) are identified. Second, in the estimation stage, the coefficients are estimated. Third, in the diagnostic stage, the assumptions of the model residuals are tested.

4.2.1.1 Identification

Before fitting an ARIMA model and identifying the AR(p) and MA(q) components, first the assumption of weak stationarity has to be met[30]. Specifically, the time series has to be free from trending, seasonality and structural breaks. The first can be treated by the model itself through the differencing component I(d) in the model specification, which frees most time series of any trends present[31](Hamilton, 2020). Seasonality can be treated very similarly with seasonal differencing. In contrast to the trend differencing, where from an observation t its lag of order d is subtracted, in seasonal differencing each lag corresponds to the respective observation in the last season[32] (Baeriswyl et al., 2021). E.g. for a time series including weekly seasonality with daily observations, a seasonal differencing could be done by subtracting from each daily observation its predecessor from the previous week. Lastly, structural breaks violate the assumption of weak stationarity and have to be addressed (Box & Tiao, 1975). However, in this study the structural breaks posed by the exemption threshold changes are exactly the points of interest. Hence, the included step function is coded exactly to take this structural break into account and thus eliminates this problem entirely (Pickup, 2014).

Once, the data is determined to be weakly stationary, the first step in the Box-Jenkins approach is to identify the appropriate order of the AR(p) and MA(q) components (Box George et al., 1976). Traditionally, this is done with the use of the auto-correlation function ACF and the partial correlation function PACF on the pre-change-period (Box George et al., 1976). By looking at the plot of these functions, one can detect different order of autoregressive or moving average components,

30 Weak stationarity requires the time series to have the same mean at all time points and auto-covariance only depending on the difference but not the location of the time points. E.g. the covariance between to time points t and t-j only depends on j but not on t. (Hamilton, 2020)

31 In economics differencing of order one is normally enough (Pickup, 2014).

32 Seasonality has been tested for and not found in the time series used for this study, hence no seasonal differencing has been applied. For more detailed information about seasonal differencing Pickup, 2014 can be consulted.

that may be included in the time series. However, with the advances in machine learning and ever evolving software libraries, it is also possible to find the appropriate AR and MA components with a brute force grid search algorithm (Kumar et al., 2020). Such an algorithm allows to test all possible combinations and optimizes a selected optimization criterion (e.g. the Bayesian Information Criterion BIC). This new approach simplifies the identification stage and severely reduces the error possibility due to arbitrariness and skill of the researcher (Kumar et al., 2020).

4.2.1.2 Estimation

After an appropriate ARIMA model has been found for the pre-change-period, the coefficients can now be estimated for the whole time frame including the post-change-period [33]. Note, that only now the step function is included in the ARIMA model to measure the possible intervention effect happening. If estimated coefficients are insignificant it often means that the model is over-specified and an ARIMA model of lower order suffices. Thus, the analyst should return to the identification stage once again (Pickup, 2014). This then also illustrates the limits of the machine learning oriented approach in the identification stage. By now the classical approach of manually analysing the ACF and PACF plots is recommended (Kumar et al., 2020).

4.2.1.3 Diagnostics

Finally, when the model has been identified and estimated, the last step is to check if the assumption for the error terms holds. The major assumption is that the error term follows a stationary univariate process. In other words, the error term should be a white noise process[34]. This can either be tested by looking at the ACF and PACF plots, which should show no significant autocorrelation. Alternatively, the Ljung-Box Q test can be used to check for a white noise process. The null hypothesis of the Ljung-Box Q test is that the data is independently distributed, meaning that no group of autocorrelation of the time series is different from zero (Ljung & Box, 1978).

[33] Most commonly this is done using the maximum likelihood estimation, but can also be done with a non-linear least-squares estimation (Pickup, 2014).
[34] A white noise process is equal to a stochastic error with constant variance (Hamilton, 2020)

Chapter 5

Empirical Results

This chapter is structured in two sub-chapters, one for the two exemption threshold ET changes occurred in 2019 and 2020. Both ET-changes get analyzed with a segmented regression and an ARIMA model in the respective time frame to measure the intervention effect of the ET-change on the SARON. Additionally, the segmented regression approach is used to test for trade volume differences in the different periods.

5.1 Exemption Threshold Change 01.11.2019

On the first November 2019, the SNB decided two increase the ET-factor from 20 to 25 and thereby increasing the total amount of sight deposits exempt from the negative interest rate by 25%, while keeping the SNB policy rate constant at -0.75% (SNB, 2019b). This ET-change was the first ever since the introduction of the reserve tiering system in 2015. In the monetary policy assessment on the 19th September 2019, the SNB mentions that it expects the negative interest rate environment to persist for the unforeseeable future and thus it wants to further lower the profitability pressure on the banks by adjusting the calculation method for the exemption threshold from the static to the dynamic model[35](SNB, 2019b). However, note that the SNB did not explicitly inform the public beforehand about the planned raise of the ET-factor on the 1st November 2019 in the monetary policy assessment. Therefore, it is assumed that the banks only knew that the calculation method

[35] Refer to section 2.3.1 for more details on the calculation method change.

for the ET was going to change but could not anticipate the ET-change.

5.1.1 Segmented Regression

Table 5 summarizes the results of the segmented regression for the first time frame. The coefficient of the constant represents the pre-change-period mean of -0.7364% and is highly significant on the 0.1% level. The coefficient of the Measurement Occasion (MO) variable which is simultaneously responsible for measuring the pre-change-period slope and capturing any possible trending in the time series is insignificant on the 5% level. However, by looking at the plotted result in the appendix figure 2 it becomes clear that the insignificance comes most likely from an almost flat pre-change-period slope, which makes it hard to be significant against the null hypothesis of zero slope. This MO coefficient indicates that in the four months preceding the exemption threshold change, there was no significant positive or negative trend. This suggests that the SARON was being stable in the pre-change-period around the -0.7364% level. In the light of the analysis, this would imply that no significant preemptive trading with regard to the exemption threshold occurred before the effective ET-change. This hypothesis about no preemptive trading before the ET-change date will be further tested and discussed in Section 5.1.3. The ETD coefficient captures the level change due to the ET-

SARON	Coefficient	Standard Error	z Statistics	P Value
Constant	-0.7364	(0.001)	-549.581	<0.001
MO	-1.268e-05	(8.19e-06)	-1.549	0.121
ETD	0.0513	(0.007)	7.399	<0.001

Note: Adj. R^2=0.764, T = 387; T = number of time points, MO = Measurement Occasion, ETD = step function coded 0 before and 1 at and after the ET-Change, Newey-West standard errors in parentheses[36]

Table 5 – Segmented Regression Result for ET-Change on the 01.11.2019, from 20 to 25

change with a step function that assumes immediate and persistent change. By looking at 2 and with regard to a R^2 of 0.764, this assumption seems reasonable[37]. The coefficient is highly significant on the 0.1% level, which further supports the suitability of the step function. The coefficient of 0.0513, implies that a 25% increase[38] of the exemption threshold translates to a 5.13 basis points bp increase

[37] Limitations of this assumption and alternatives will be further discussed in chapter 6
[38] The ET-factor increase from 20 to 25 is equivalent to a 25% increase of the exemption threshold

of the SARON. This means that on average an 1% increase of the exemption threshold converts to a 0.2052 bp increase of the SARON. However, figure 2 reveals that the ET-change lead to a a short-term overreaction to this policy change with surge of 10 basis points before it evened out on the new level. Figure 2 also indicates a slight overestimation of the ET-change effect by the segmented regression, which can be seen by the regression line being slightly higher than the plateaued SARON. This effect overestimation illustrates a weakness of the step function, which is the relative inflexibility in taking into accounting such adjustment processes at the beginning of a level change (Pickup, 2014). Nevertheless, the level change is clearly visible and the following ARIMA analysis should give further insights into the exact nature of the change.

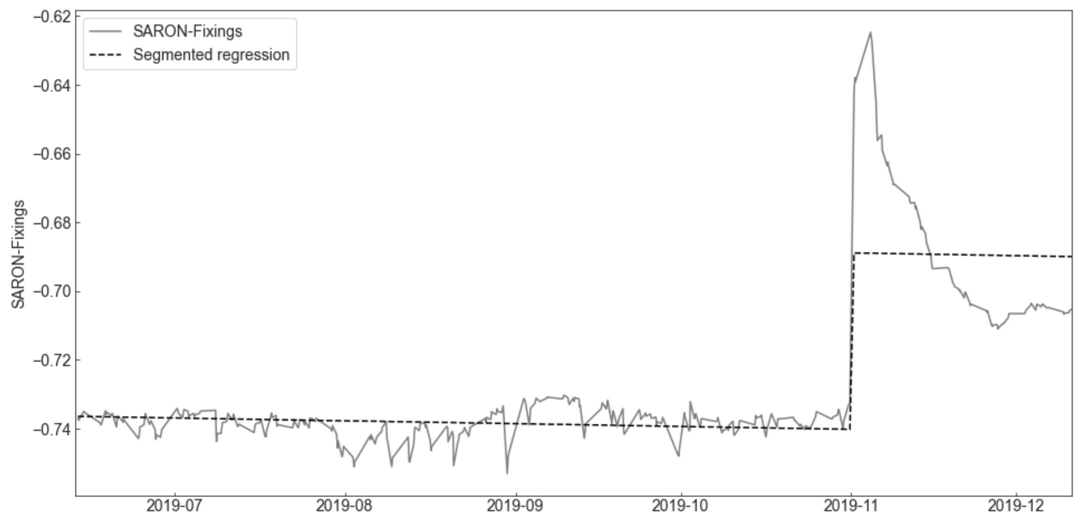

Figure 2 – Effect on the SARON time series from the ET-change on the 01.11.2019, from 20 to 25

5.1.2 ARIMA

Prior to applying the ARIMA model, the time series has to be made weakly stationary. Thus, in order to find the optimal amount of differencing, an Augmented Dickey-Fuller (ADF) test is conducted. The ADF test, on the 5% level, is not able to reject the null hypothesis of non-stationarity for the whole time frame (Pre- and post-change-period combined), with a p value of 0.189. For further robustness a Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, on the 5% level, is conducted, which rejects the null hypothesis of stationarity for the whole time series, with a p value of $> 0.1\%$. Hence, the time series is differenced once in order to make it stationary.

Next seasonality is examined with multiple dummy regressions for each of the three fixings per day [39]. Additionally, daily, weekly and monthly seasonality is tested with and ruled out by a grid search algorithm, that uses the Canova-Hansen test for seasonality as the decision criterion (Canova & Hansen, 1995). Further, a dummy regression tests a pre-weekend fixing effect, due to the fact that the SARON is a forward-looking interest rate and is not calculated for the weekend days [40]. However, the assumed pre-weekend effect appears to be insignificant in this time series. Hence, no seasonality has been found in this time frame and the trending problem has been dealt with thanks to the differencing. Lastly, the structural break at the ET-change, which would be the last possible infringement of the ARIMA-model's weak stationarity assumption can be ruled out thanks to the step function catching the exemption threshold change.

5.1.2.1 Identification

For the identification of the appropriate p and q for the respective AR and MA components, a step wise grid search algorithm on the differenced pre-change-period is conducted. By iterating over all the possible p and q combinations, the fit on the pre-change-period test set is optimized using the BIC criterion[41]. The grid search algorithm suggests that an ARIMA(1,1,1) is the best fit due to the highest BIC. However, a look at figure 3 shows an after lag one gradually towards zero decreasing ACF plot and a PACF plot that spikes at lag one. Thus, analysing the two plots suggests the choice of either an ARIMA(0,1,1) or an ARIMA(1,1,0). Only by applying all of these three models over the whole time frame can tell, which of these models performs best in the end.

[39] Refer to table 9 in the appendix, for a detailed output of the seasonality testing regressions

[40] For more information on the calculation method, refer to section 2.2.1 or even more detailed in the Swiss reference rate manual (SIX, 2022b). For the output of the weekend effect regression, refer to table 9 in the appendix.

[41] The BIC criterion is chosen over the AIC, because it leads to a more parsimonious model, which is desired in this paper (Pickup, 2014).

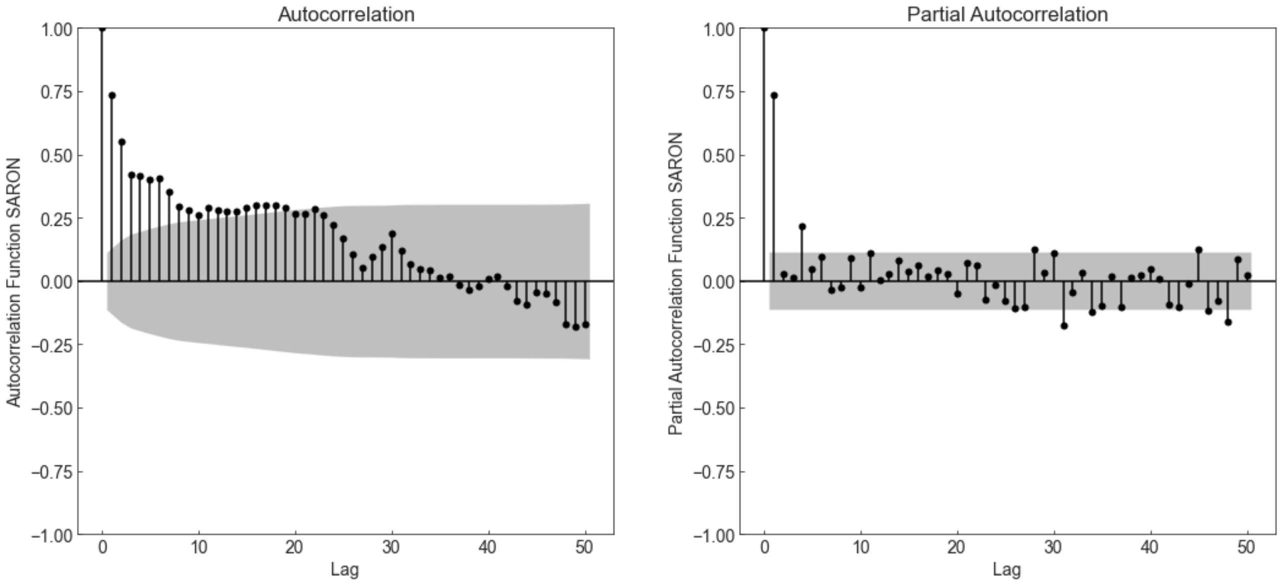

Figure 3 – ACF and PACF plot for the SARON in the pre-change-period for the time frame of the ET-change on the 01.11.2019

5.1.2.2 Estimation

By estimating the identified ARIMA models over the whole time frame, it quickly becomes clear that the ARIMA(1,1,1) model appears to be over-parameterized with both the AR(1) and the MA(1) coefficient being highly insignificant[42]. Next, the ARIMA(1,1,0) gets applied and yields a insignificant AR(1) coefficient on the 5% level and is therefore disregarded as well[43]. Finally, table 6 shows the estimated coefficients of the ARIMA(0,1,1) model applied over the whole time frame including the ETD variable for measuring the ET-change effect. All coefficients are significant on the 5% level. The coefficients other than the ETD variable, measuring the ET-change are not of major interest in this study. However, it is worth mentioning, that with a coefficient of -0.0849 for the MA(1), the time series seems to include a systematic moving average component. The estimated coefficient for the ET-change step function is 0.0906 and highly significant even on the 0.1% level, indicating that the change of the exemption threshold from 20 to 25 lead to an increase of the SARON by 9.06 basis points. This translates to an average increase of 0.3624 bp per 1% increase of the exemption threshold. This measured ET-change effect by the ARIMA model is almost double the effect[44]

[42] For the detailed output refer to table 10 in the appendix
[43] For the detailed output refer to table 11 in the appendix.
[44] The segmented regression estimated an 0.2052 bp increase per 1% increase of the ET

measured by the segmented regression for the same time frame in section 5.1.1. This difference is likely to be attributed to the higher sensitivity of the ARIMA model to the short-term overreaction adjustment process of the SARON until it plateaued on the new level (Pickup, 2014).

SARON	Coefficient	Standard Error	z Statistics	P Value
ETD	0.0906	0.027	3.405	$<$0.001
MA(1)	-0.0849	0.040	-2.112	0.035

Note: BIC = -3369.967, T = 387; T = number of time points, ${\sigma_\varepsilon}^2$ = 9.017e-06; ${\sigma_\varepsilon}^2$ = estimate of the error term variance, ETD = step function coded 0 before and 1 at and after the ET-Change

Table 6 – ARIMA(0,1,1) result for ET-change on the 01.11.2019

5.1.2.3 Diagnostics

The ACF and PACF plots confirm the appropriateness of the ARIMA(0,1,1) level, with lags up to fifty being all insignificant and affirm no autocorrelation in the error terms [45]. For further robustness, a Ljung-Box test is conducted, which yields a test statistic of 0.0549 that produces a p value close to one. Thus, the null hypothesis of independently distributed error terms cannot be rejected and the assumption of the errors being a white noise process holds. Hence, the ARIMA(0,1,1) model including the ET-change step function satisfies all the necessary assumptions.

5.1.3 Trade Volume Analysis

By definition of the step function used in this paper, it is implicitly assumed that no increased preemptive trading before the ET-change dates took place that would significantly affect the SARON. While the segmented regression approach used, can account for a pre-change-period slope other than zero (MO variable), it cannot take into account anything other than a linear trend as for instance a preemptive trading frenzy would produce (Healey, 2004). Thus in this section a segmented regression approach is used, to examine the daily trading volume of the repo market and its level differences.

First, a three-phase segmented regression is applied that captures any possible trading volume level difference in the pre-change-period between the announcement date (19.09.2019) and the effective ET-change date (01.11.2019). The trading volume level in this announcement period is compared

[45] Refer to figure 8 in the appendix for a visual representation.

to the level before the announcement. However, the regression announcement-period dummy ($\mathrm{AN_t}$) turns out to be insignificant with a p value of 0.311, thereby confirming the hypothesis of no significant increase of preemptive trading between the monetary policy assessment press release on the 19.09.2019 and the effective ET-change on the 01.11.2019 [46].

Second, a two-phase segmented regression with only the step function indicating the ET-change on the 01.11.2019 is applied, which points out a drastic increase in trading volume between the pre- and post-change-period. Figure 4 presents this trade volume difference finding, with a clear cut between the pre-change-period trade volume level of CHF 2590 millions and the post-change-period trade volume level of CHF 6512 millions [47]. In other words, the trade volume average of the post-change-period is 151% higher than the pre-change-period trade volume average. This translates to a trade volume level increase of 6.05% per 1% ET-increase.

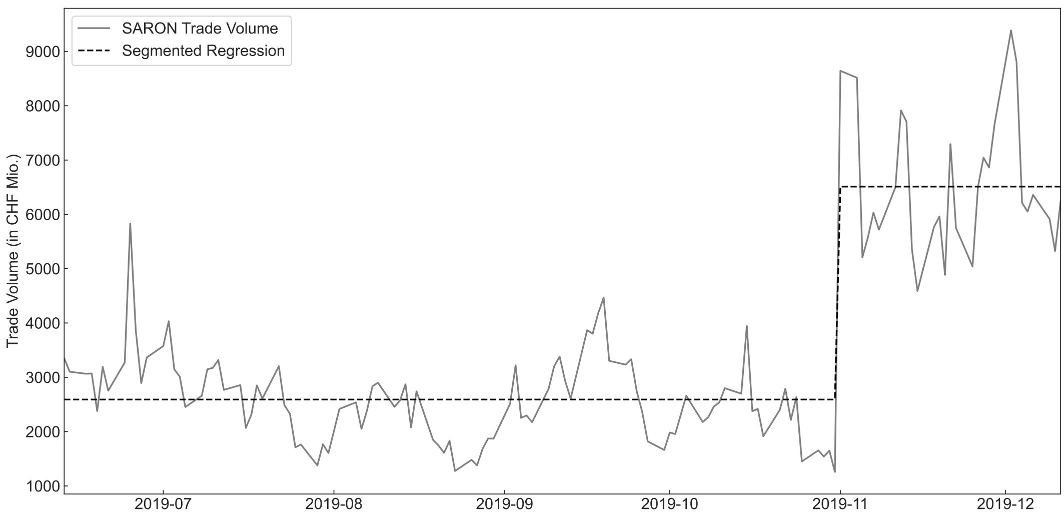

Figure 4 – Two-phase segmented regression of the daily trade volume for the ET-change on the 01.11.2019

46 For the detailed results, please refer to table 12 in the appendix.
47 For the detailed output of the segmented regression, refer to figure 13 in the appendix.

5.1.4 Interpretation

The exemption threshold change on the first November 2019 posed an ideal opportunity to examine the effect of an ET-change on the SARON for several reasons. First, the SNB did not change the SNB policy rate at the same time, hence there was no interest change confound. Second, it was the first time the exemption threshold was changed ever. Last, because the SNB did not explicitly mention a change in the ET-factor in its monetary policy assessment before the effective ET-change date. This lead to no significant preemptive trading, as has been shown by the trade volume analysis in section 5.1.3.

Both empirical methodologies find a significant persistent ET-change effect starting immediately on the ET-change date. The segmented regression analysis estimated a positive ET-change effect on the SARON of 0.2052 bp per 1% increase of the ET, whereas the ARIMA approach estimates the effect at 0.3624 bp per 1% increase. While these findings differ in their magnitude, both models find a significant positive effect of the ET-change on the SARON.

These findings are emphasized by the trading volume analysis which finds a 151% increase in trading volume on the Swiss repo market from the pre- to the post-change-period and no preemptive trading. Thus, the analysis of the ET-change on the first November 2019 provides evidence that an exemption threshold increase leads to an immediate and persistent positive effect on the SARON, for at least one and a half months after the ET-change.

These findings are in line with the statement of the SNB in their annual report of 2019, where they admit that the exemption threshold change did indeed lead to a positive deviation of the SARON from the SNB policy rate (SNB, 2019a). Recapitulating the supply and demand effects on the interbank market detailed in section 2.1.1, the empirically measured increase of the SARON can thus be traced back to an excess liquidity demand on the interbank market. This in turn would mean that in this case the demand effect of banks with sight deposits below the newly set ET outweighed the supply effect of the banks with sight deposits above the newly set ET. The SNB reinforces this conclusion by stating in its annual report that it countered the upwards pressure produced by the liquidity shortage with its own liquidity-providing repo transactions(SNB, 2019a). In essence, the ET-increase effect of the 1st November 2019 lead to a significant positive reaction of the SARON for the following one and a half months, which can be attributed to the rebalancing process on the interbank market, in which the demand effect outweighed the supply effect.

5.2 Exemption Threshold Change 01.04.2020

On the first of April 2020, the SNB raised the exemption threshold for the second time. This time the SNB raised the exemption threshold factor from 25 to 30 which translates to a 20% increase (SNB, 2020c). This second raise within half a year was intended to further lower the profitability pressure on the money market participants in the uncertain times at the start of the COVID-19 pandemic and to inject more liquidity into the economy by increasing the bank's latitude for lending (SNB, 2020c).

This time the SNB informed the public specifically about the planned ET-change in advance with a press release on the 19th March 2020[48], stating that the ET will be raised from 25 to 30 on the first of April 2020. This approach slightly deviates from the one the SNB followed the first time they changed the exemption threshold, where they did not inform the public explicitly about a specific amount in advance. This announcement in advance confounds the ET-change-effect analysis, as can be seen in figure 5. The information leakage effect from the press release is clearly visible in the upwards trend of the SARON at the end of the pre-change-period. Interbank market participants were able to trade on this information with the assurance that the policy change will take effect only thirteen days later.

Another important factor that could have fueled this behavior is the learning-curve of the interbank market participants from the ET-change in 2019. The participants now knew, that last time the SARON spiked shortly after the policy change, so they had an incentive to rearrange their sight deposit structure preemptively[49](Fuhrer et al., 2021).

[48] The Monetary policy assessment press release was sent to all subscribers of the SNB News Alert at exactly 09:30 a.m. and was published on the SNB website at 10:00 a.m. Thus, this paper assumes that interbank market participants have definitely been informed from this point on and were able to act on this new policy change.

[49] This hypothesis will be the major focus point in section 5.2.4.

5.2.1 Segmented Regression

In figure 5 the visual result of the segmented regression looks similar to the result of the first ET-change analysis. However, two things stand out immediately. First, the positive trend in the pre-change-period that suddenly surges beginning on the 19th March 2020 (date of the announcement), thirteen days earlier than the actual policy change. Second, there is no spike that levels off shortly after at the ET-change date, but the SARON appears to be jumping precisely to the new level. The absence of an overreaction suggests that this time the interbank market participants estimated the impact more precisely. Alternatively, it could be an indication for the successful spike capping by the SNB, as they state in their annual report of 2020, that not clearly defined when, they started to try and cap extraordinary positive spikes in the SARON (SNB, 2020a). Disregarding the announcement

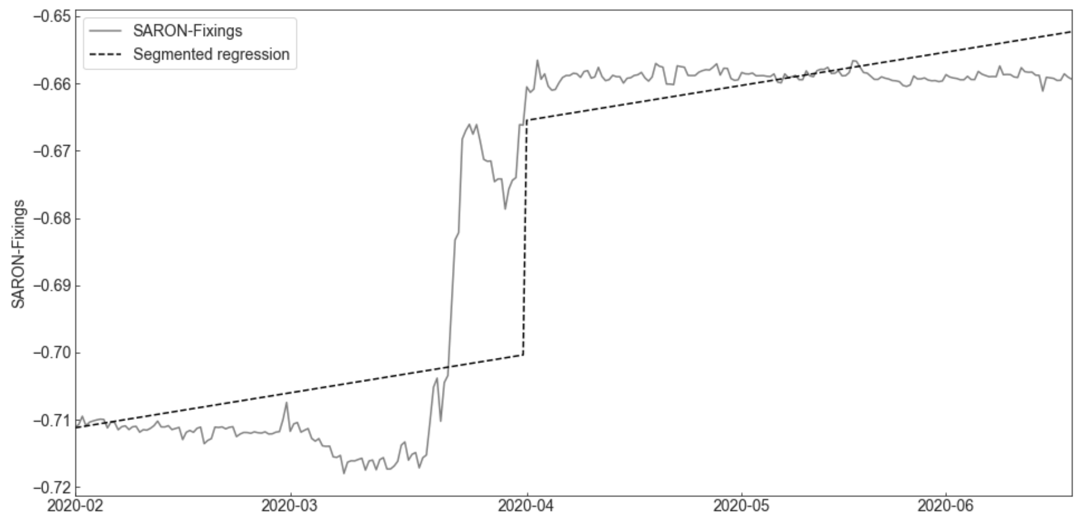

Figure 5 – Effect on the SARON time series from the ET-change on the 01.04.2020, from 25 to 30

confound, the persistent and immediate level shift from the pre-change-period to the post-change-period is clearly visible and the plot in figure 5 suggests that a step function appears to be a reasonable choice for measuring the intervention effect. Table 7 depicts the quantitative result of the ET-change effect. The coefficient of the constant describes the pre-change-period mean of -0.7113% with a high significance on the 0.1% level. The Measurement Occasion (MO) variable indicates the pre-change-period slope and is significant on the 5% level, but due to the announcement confound, which leads to an exploding SARON at the end of the pre-change-period, its interpretability is low. On the other hand, the 0.0348 ETD coefficient is highly significant on the 0.1% level and implies that an ET-increase of 20% results in a raise of the SARON by 3.48 basis points. This in turn translates to an average SARON increase of 0.174 bp per 1% increase of the exemption threshold.

SARON	Coefficient	Standard Error	z Statistics	P Value
Constant	-0.7113	(0.001)	-493.137	<0.001
MO	8.663e-05	(3.81e-05)	2273	0.023
ETD	0.0348	(0.008)	4.421	<0.001

Note: Adj. R^2=0.859, T = 279; T = number of time points, MO = Measurement Occasion, ETD = step function coded 0 before and 1 at and after the ET-Change, Newey-West standard errors in parentheses[50].

Table 7 – Segmented Regression Result for ET-Change on the 01.04.2020, from 25 to 30

Because figure 5 strongly suggests to use the announcement date (19.03.2020) of the ET-change as the break point of the segmented regression. Thus in order to try and achieve a better fitting model, an additional regression is fitted with the announcement date as the break point for the step function. While this model results in a higher Adj.R^2 of 92%, the new ETD* coefficient of 0.0403, which in turn would imply an 0.2015 SARON increase per 1% ET increase and[51] and is very similar to the original approach using the ET-change date. However, this model not only resembles the effective ET-change effect but incorporate a substantial amount of preemptive speculation. Thus, it would not lead to a consistent comparison with the first ET-change event.

5.2.2 ARIMA

First, before applying an ARIMA model, the time series has to be made weakly stationary. Therefore, an ADF test and a KPSS test are conducted, followed by a grid search approach to find the optimal amount of differencing using these tests. The ADF test, on the 0.05 level, is not able to reject the null hypothesis of non-stationarity, with a p value of 0.706. Additionally, the KPSS test, on the 0.05 level, yields a test statistic of 2.155, which translates into a p value < 0.001. Thus the KPSS test clearly rejects its null hypothesis of stationarity. In line with the individual tests, the grid search finds the series non stationary and suggests trend differencing of order 1. Hence, the time series is

[51] For a more detailed output of this model, refer to table 16 and for the visual representation to figure 11.

differenced once before identifying the appropriate ARIMA model.

Second, seasonality of the time series is examined with the help of a multiple dummy regression for the three fixings per day. For further robustness, daily, weekly and monthly seasonality is tested for and ruled out, applying a grid search approach using the Canova-Hansen test for seasonality as the decision criterion (Canova & Hansen, 1995). The regression, testing for level difference in the fixings, finds no seasonality, with both the be beginning of day (BOD) and the middle of the day (MOD) fixing dummies being insignificantly different from the end of day (EOD) dummy serving as the base line[52]. Likewise, the dummy regression for the pre-weekend fixing effect finds the effect to be insignificant[53]. Additionally, the grid search algorithm using the Canova-Hansen test, indicates no daily, weekly or monthly seasonality and suggests no seasonal differencing.

Third, the structural break problematic is accounted for by the ETD variable catching the exemption threshold change. In short, the three assumptions trending, seasonality and no structural breaks have all been accounted for and the SARON time series now fulfills the weak stationarity condition.

5.2.2.1 Identification

The grid search algorithm to find the best fitting ARIMA model uses the train set of the pre-change-period, which equals to 67.3% of the per-change-period observations and validates in on the remaining 23.7% as the test set. By optimizing the BIC criterion, it identifies the ARIMA(0,1,0) as the most appropriate model. However, an ARIMA(0,1,0) model is a special case, which boils down to be just a random walk process (Pickup, 2014). Henceforth, the grid search implies that it could not find an ARIMA model that can better describe this time series than a random walk process. This result is mainly due to the fact, that because of the announcement on the 19.03.2020 and the following SARON surge before the effective ET-change, the test set consists of very dissimilar observations compared to the train set, which poses a problem for the algorithm.

Since, the grid search algorithm does not work on this time frame, the classical approach using the ACF and PACF plots for identification is used. Figure 6 reveals that a an AR(1) or AR(3) process

52 For detailed results about the intraday seasonality regression, refer to table 9 in the appendix.
53 For detailed results about the pre-weekend regression, refer to table 9 in the appendix.

could be present. However, the PACF also reveals an oscillatory explosion in the lags starting at the 40th lag, which indicates a possible white noise process (Pickup, 2014). Nevertheless, an ARIMA(1,1,0) or an ARIMA([3],1,0)[54] are tested before accepting the white noise verdict.

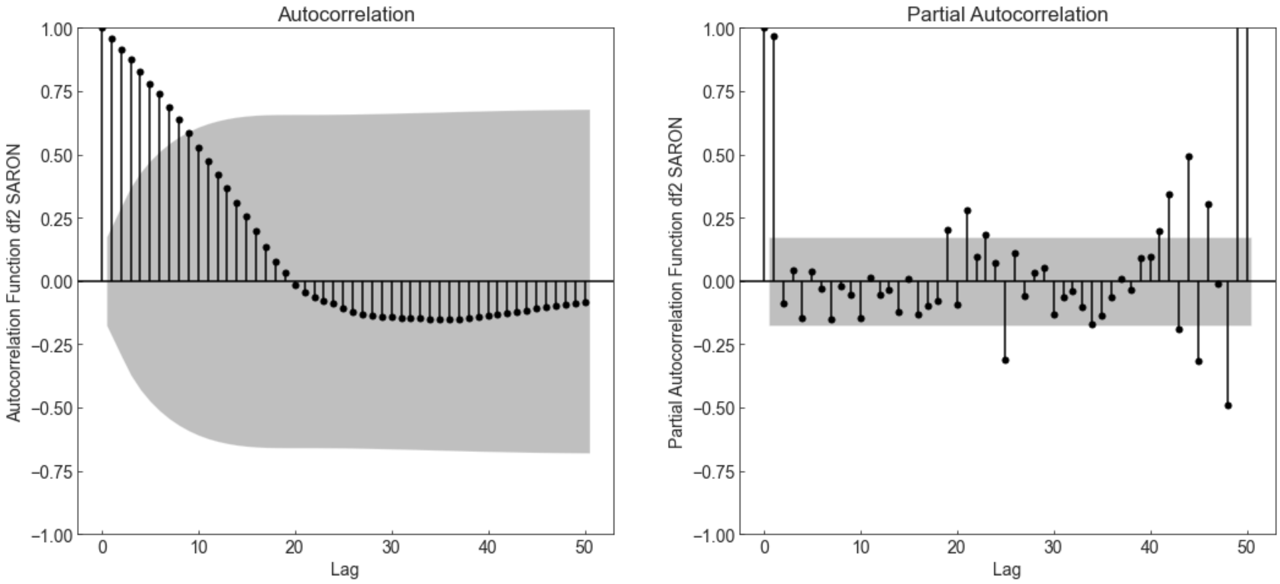

Figure 6 – ACF and PACF plot for the SARON in pre-change-period for the time frame of the ET-change on the 01.04.2020

5.2.2.2 Estimation

While the ARIMA(1,1,0) renders the ETD variable insignificant and is thus discarded[55], table 8 shows the result of the ARIMA([3],1,0) estimated over the whole time frame, including the ETD variable. Both coefficients are highly significant. The coefficient of the AR(3) is positive, which indicates that there is a positive correlation with every third lag. This is interesting, because with three fixings a day, each of the three fixings of the day thus correlates with its respective previous fixing a day earlier. The 0.0057 coefficient of the ETD indicates an 0.57 basis point rise of the SARON when the exemption threshold is raised by 20%. This translates to a 0.0285 bp rise of the SARON for every 1% raise in the exemption threshold. Compared to an average SARON increase of 0.174 bp per 1% ET-increase measured by the segmented regression for the same ET-change, this seems

[54] An ARIMA([3],1,0) includes only an AR(3) term, an ARIMA(3,1,0) on the other hand includes an AR(3), an AR(2) and an AR(1) component (Pickup, 2014).

[55] For the detailed output of the ARIMA(1,1,0) model, refer to table 17 in the appendix.

rather low. This wide difference of the measured effects can be explained by the high sensitivity of the ARIMA model towards noise and confounds like the announcement effect, that lead to a strong distortion of the pre-change-period (Pickup, 2014).

SARON	Coefficient	Standard Error	z Statistics	P Value
ETD	0.0057	0.003	5.920	<0.001
AR(3)	0.2134	0.018	11.889	<0.001

Note: BIC = -2730.976, T = 279; T = number of time points, ${\sigma_\varepsilon}^2$ = 2.973e-06; ${\sigma_\varepsilon}^2$ = estimate of the error term variance, ETD = step function coded 0 before and 1 at and after the ET-Change date (01.04.2020).

Table 8 – ARIMA([3],1,0) output ET-change on the 01.04.2020

For the sake of completeness, the same model is estimated using the announcement date (19.03.2020) as the break point for the measurement of the ET-change effect. The coefficient of the ETD* variable[56] is 0.0072, which in turn translates to a measured ET-change effect of 0.036 bp per 1% increase of the ET. Notably, the measured effect is still close to the original ARIMA([3],1,0) model with the ET-change as the break point and thus with the same line of reasoning as in section 5.2.1 this announcement model is discarded.

5.2.2.3 Diagnostics

The ACF and PACF plots confirm the validity of the assumption of no autocorrelation in the residuals of the ARIMA([3],1,0) model, with lags up to fifty all being insignificant[57]. For further robustness, a Ljung-Box test is conducted, which results in a test statistic of 0.00371. This translates to a p value close to one and thus the null hypothesis of independently distributed errors holds and supports the conclusion of the ACF and PACF plot of no autocorrelated error terms. Hence, the applied ARIMA([3],1,0) model including the ET-change step function satisfies all the necessary assumptions to be unbiased (Box & Tiao, 1975).

[56] The ETD* variable is coded 0 before the announcement and 1 at and after the announcement date (19.03.2020). For the detailed result of this regression, refer to table 18 in the appendix.

[57] For a detailed visualization of the ACF and PACF plots, refer to figure 12 in the appendix.

5.2.3 Trade Volume Analysis

With the same line of reasoning as stated in section 5.1.3 of the first ET-change analysis, the assumption of no preemptive trading is analysed in this section. Thus, the daily trading volume of the repo market in the second time frame is examined, in order to find trading volume level differences between periods.

First, the three-phase segmented regression is applied to capture any trading volume level difference in the pre-change-period between the announcement date (19.03.2020) and the effective ET-change date (01.04.2020), compared to the level before the announcement. Since, there is a sharp rise SARON in exactly this period a higher trading volume is also expected. However, the announcement-period dummy turns out to be insignificantly different from zero with a p value of 0.427[58], thereby providing empirical evidence against the hypothesis of increased trading volume in the period between the announcement date (19.03.2020) and the effective ET-change date (01.04.2020).

Second, a two-phase segmented regression is applied, which only contains a step function indicating the ET-change on the 01.04.2020 and illustrates an increase in the trading volume level between the pre- and post-change-period. Figure 7 reveals the trade volume level difference with a clear cut between the pre-change-period trade volume level of CHF 7828 millions compared to a post-change-period trade volume level of CHF 1.174 billions [59]. In essence the trade volume analysis could not find any level difference amongst the period in-between the announcement date and the effective ET-change date, compared to the period before the announcement. However, an increase in the trading volume level of 43% from the pre- to the post-change-period is found. This translates to a trade volume level increase of 2.14% per 1% ET-increase.

5.2.4 Interpretation

The exemption threshold change on the first April 2020 posed a second exceptional opportunity to examine the ET-change effect without an SNB policy rate change that would have strongly confounded the analysis. However, the antecedent announcement of the planned ET-factor increase from 25 to 30, specifically mentioned in the monetary policy assessment, on the 19th March 2020,

[58] For the detailed results, please refer to table 14 in the appendix.
[59] For the detailed result of the segmented regression output, refer to figure 15 in the appendix.

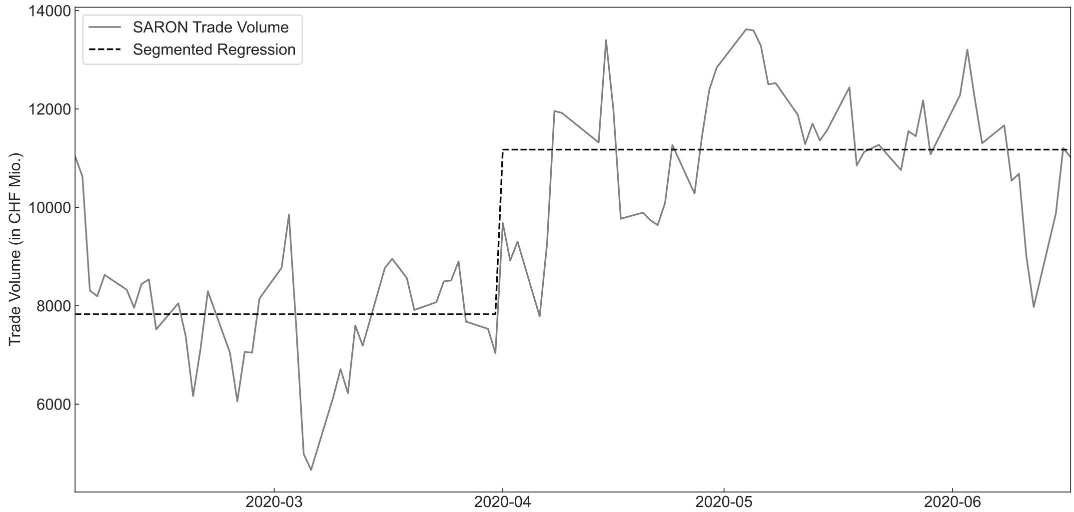

Figure 7 – Two-phase segmented regression of the daily trade volume for the ET-change on the 01.04.2020

turned out to be a difficult confound to deal with (SNB, 2020c).

The announcement was followed by a steep surge in the SARON rate, even before the effective ET-change date. This, lead to problems in identifying an appropriate ARIMA model and most likely played a role in the ET-change effect measured at only 0.036 bp SARON increase per 1% ET-increase. On the other hand, the segmented regression proved to be more robust to the confound and measured an ET-change effect on the SARON of 0.174 bp per 1% ET-increase. Just like for the first ET-change, these result differ in their magnitude. However, again both imply a significant positive correlation between the ET-change and the change in the SARON. Additionally, both models found empirical evidence for an immediate level change in the SARON due to the ET-increase with a persistence of at least two and a half months[60].

Notably, the measured effect in the first ET-change is significantly higher, than in this second ET-change event. Even by disregarding the more extreme ARIMA results, the results of the segmented regression show a smaller effect for the second time frame. This could be an indication for a learning effect of the interbank market participants. While in the first ET-change event, they had no reference

[60] Since, the post-change-period is cut off on the 18.06.2020, the date of the second quarterly monetary policy assessment.

point on how the ET-change would affect the SARON, they were now able to draw more educated guesses on the potential impact of the ET-change. As it has been elaborated in section 5.2.4, this absence of overestimation of the SARON spike could also be attributed to the fact, that in contrast to the first ET-change, the banks were informed about the precise ET-factor change previous to the actual ET-change (SNB, 2020c).

The trade volume analysis, which finds a 51% increase in the average trading volume from the pre- to the post-change-period supports the hypothesis of banks reacting actively to the ET-change and optimizing their reserves at the SNB in the overnight repo market. However, the trade volume analysis can not offer an explanation for the preemptive surge of the SARON following the monetary policy assessment, due to no significant trading volume level difference found, compared to the period before the announcement date.

In light of the supply demand dynamic from section 2.1.1, the analysis of this second ET-change finds evidence for the demand effect to once again outweigh the supply effect and thus leading to an increase in the SARON. On the contrary, the findings of the trading volume level not being significantly higher in the period where the SARON surged opposes the rebalancing process theory. Be that as it may, the SNB states in their annual report 2020, that the upwards pressure developed because some of the larger money market participants wanted to quickly increase their sight deposits (SNB, 2020a), thereby supporting the initial hypothesis of the rebalancing dynamic. In the annual report 2020 the SNB also mentions, that in order to lower the SARON again to the level of the SNB policy rate, its classical approach of short-term repo transaction did not suffice and it had to engage in longer-term repo transactions, starting in July 2020 (SNB, 2020a).

Chapter 6

Discussion and Implications

This study made use of two unique policy events to study the effects of an exemption threshold change on the SARON, in a negative interest rate environment[61]. The magnitude of the measured ET-effect varies depending on the method applied and ET-change event. However, every approach confirms a significant positive correlation between an ET-factor increase and a rise in the SARON. The bandwidth of the measured SARON effect reaches from 0.2052 bp to 0.3624 bp per 1% ET-increase for the ET-change in November 2019 and from 0.0285 bp - 0.1740 bp per 1% ET-increase, for the ET-change in April 2020.

The trade volume analysis yielded similar results, with a trading increase from the pre- to the post-change-period of 151% for the first time frame and 43% for the second time frame. Additionally, in both time frames no empirical evidence was found to indicate preemptive trading, although in the second time frame a preemptive surge in the SARON strongly suggested such a hypothesis[62].

In light of the supply and demand dynamic[63] on the repo market, the empirical evidence supports the following hypothesis. The ET-increase leads to an overpowering demand effect of banks seeking loans to fill up their newly gained interest free space at the SNB. This in turn creates a liquidity shortage on the repo market and thereby a significant rise of the SARON. The trade volume analysis findings underline this line of reasoning with the trade volume level being significantly higher following

61 The two unique policy events refer to the ET-change on the 01.11.2019 and the ET-change on the 01.04.2020.
62 Refer to section 5.2.4 for a more in depth interpretation of the announcement confound and the hypothesis of preemptive trading.
63 Recapitulate the supply and demand effects in section 2.1.1.

an ET-change.

The main purpose of the exemption threshold as a monetary policy instrument is to be able to steer and predominantly lower the profitability pressure on the banks (Jordan, 2009). However, this study provides empirical evidence for the presence of significant side effects attributed to changes of the exemption threshold. First, this paper's findings imply a significant positive correlation between an ET-change and the SARON. Thus, whenever the SNB changes the exemption threshold, it has to take into account the reaction of the SARON, which has established itself as the major short-term reference interest rate in the Swiss financial market (Jordan, 2020).

Second, the increased trading volume due to the rebalancing process provides the SNB with an additional monetary policy instrument to effectively stimulate the trading activity on the repo market. However, as has been discussed in section 5.2.4 this increase in trading activity can also lead to a short-term liquidity shortage, which can be problematic in turbulent market times, as has been the case in the financial crisis 2008 (Cecchetti & Disyatat, 2010).

Third, in a more political view, the increase of the exemption threshold leads to less interest income for the SNB and thus less profit for the SNB (SNB, 2020a). Since, the profit of the SNB is mainly distributed to the Swiss government, an ET-change is directly linked to the revenue of the Swiss government and ultimately to the taxes of the households (Federal Assembly of the Swiss Confederation, 2003). Hence, by increasing the exemption threshold, the SNB redistributes its profits away from the Swiss government (public sector) and towards the the banks participating in the repo market (private sector). Specifically, banks with reserves below the exemption threshold benefit from this redistribution of profits. By assuming that mostly smaller banks are below the ET and act as the cash takers. These smaller banks would fill up their exempt reserves and rake in these profits. Under this assumption, the ET-changes would not only redistribute the profits to the banking sector in general, but specifically boost the profitability of the smaller banks.

Fourth, the effects of an ET-change on the SARON are mostly not passed on to the households, which take out a variable mortgage tied to the SARON. The reason being, that banks issuing the SARON mortgage often have a condition in their contracts stating, that if the SARON is in negative territory a floor of zero percent is used instead[64]. Consequently, with such a contract the ET-change

[64] For the detailed configurations of such contracts with a zero lower interest floor, refer to these SARON mortgage

effect on the SARON is not passed through to the mortgage borrower, because by the nature of things, this ET-effect can only appear while the SARON is in negative territory. This SARON mortgage with a zero interest floor is a prime example of banks not transferring the negative interest rate over to the households as been shown by Basten and Mariathasan, 2018 and Berentsen et al., 2020.

This study contains limitations regarding the chosen methodology and the time frame selection. First, the application of the deterministic-step function implies an immediate change to the new level due to the ET-change. However, it is inflexible in accounting for short-term adaption processes, like a short-term overreaction as in the first time frame or a preemptive build up towards the new post-change-period level as in the second time frame (Pickup, 2014).

Second, the time frame selection was specifically chosen to try and exempt as many confounds as possible, while having the largest possible time frame, believed to be representative for the ET-change effect. Therefore, both time frames ends were cut off due to the respective next monetary policy assessments, which otherwise would have brought completely new dynamics into the repo market [65]. Hence, this study quantifies the magnitude of the ET-change effect on the SARON, but, falls short of determining the exact duration of the explored rebalancing process on the repo market.

fact sheets of Swiss banks UBS, 2021, **cs˙saron˙2020**, AKB, 2020.

[65] Refer to section 3.2, for more details on new confounds introduced after the time frame ending.

Chapter 7

Conclusion and Lookout

By analyzing the effect of exemption threshold changes on the SARON in two separate unique events, this study has provided empirical evidence on the existence of a positive relation between the two. The findings of this study imply that an ET-increase is followed by an immediate increase in the SARON rate, which has been measured between 0.0287 bp and 0.3624 bp per 1% increase of the ET. Additionally, empirical evidence has been found of an increased trading volume level in the period after the ET-change, with a measured effect magnitude between 2.14% and 6.05% per 1% ET-increase.

The findings of this paper imply, that the SNB has to be careful in adjusting the height of the exemption threshold. Besides the official objective of lowering the profitability pressure on the banks, this paper has shown that an ET-change has some significant side effects. These side effects include the positively correlated SARON reaction and the increased trading volume effect on the repo market. Additionally, an ET-increase means redistributing money from the public sector towards the private sector. Lastly, the impact of the ET-change effect on the SARON is not expected to transmit to the SARON mortgage borrowers, because banks tend to not transmit the negative SARON rate to the mortgage borrower.

Further research could tie in with different statistical approaches, such as more sophisticated transfer functions, examining the found announcement effect in the second time frame in more detail. In another direction, a study could investigate the time dimension of the rebalancing process with longer time frames. Last, the ET-change on the 1st July 2022 can be used to validate the findings of this study with the use of an ET-factor change event in negative direction from 30 to 28 (SNB, 2022b).

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Appendix A

Additional Figures and Tables

A.1 Seasonality Testing Regressions

SARON	Time frame 1		Time frame 2	
	Coefficient	Standard Error	Coefficient	Standard Error
Panel A: Regression testing for intraday seasonality				
Constant	-0.7271*	(0.003)	-0.6798*	(0.004)
BOD	-0.0003	(0.001)	-0.0006	(< 0.001)
MOD	-0.0003	(0.001)	-0.0002	(< 0.001)
Observations	387	387	279	279
Panel B: Regression testing for Pre-Weekend Seasonality				
Constant	-0.7273*	(0.003)	-0.6799*	(0.004)
WKND	-0.0004	(0.004)	-0.0035	(0.006)
Observations	387	387	279	279

Note: BOD = beginning of day dummy coded 1 for every 12:00 fixing and zero else, MOD = middle of day dummy coded 1 for every 16:00 fixing and zero else, constant represent the mean of the end of day fixings at 18:00, Newey-West standard errors in parentheses, * = significant on the 5% level.

Table 9 – SARON seasonality regressions for both time frames

A.2 Exemption Threshold Change 01.11.2019

A.2.1 Additional Output and Alternative ARIMA Models

SARON	Coefficient	Standard Error	z Statistics	P Value
ETD	0.0906	1.17e-10	7.74e+08	<0.001
AR(1)	-3.988e-07	0.021	-1.94e-05	>0.99
MA(1)	-3.989e-07	0.021	-1.94e-05	>0.99

Note: BIC = -3361.548, T = 387; T = number of time points, ${\sigma_\varepsilon}^2$ = 9.066e-06; ${\sigma_\varepsilon}^2$ = estimate of the error term variance, ETD = step function coded 0 before and 1 at and after the ET-Change

Table 10 – ARIMA(1,1,1) output for ET-Change on 01.11.2019

SARON	Coefficient	Standard Error	z Statistics	P Value
ETD	0.0906	0.027	3.405	<0.001
AR(1)	-0.0763	0.041	-1.863	<0.1

Note: BIC = -3369.754, T = 387; T = number of time points, ${\sigma_\varepsilon}^2$ = 9.036e-06; ${\sigma_\varepsilon}^2$ = estimate of the error term variance, ETD = step function coded 0 before and 1 at and after the ET-Change

Table 11 – ARIMA(1,1,0) output for ET-Change on 01.11.2019

A.2.2 ACF/PACF plots for the ARIMA Model residuals in time frame 1

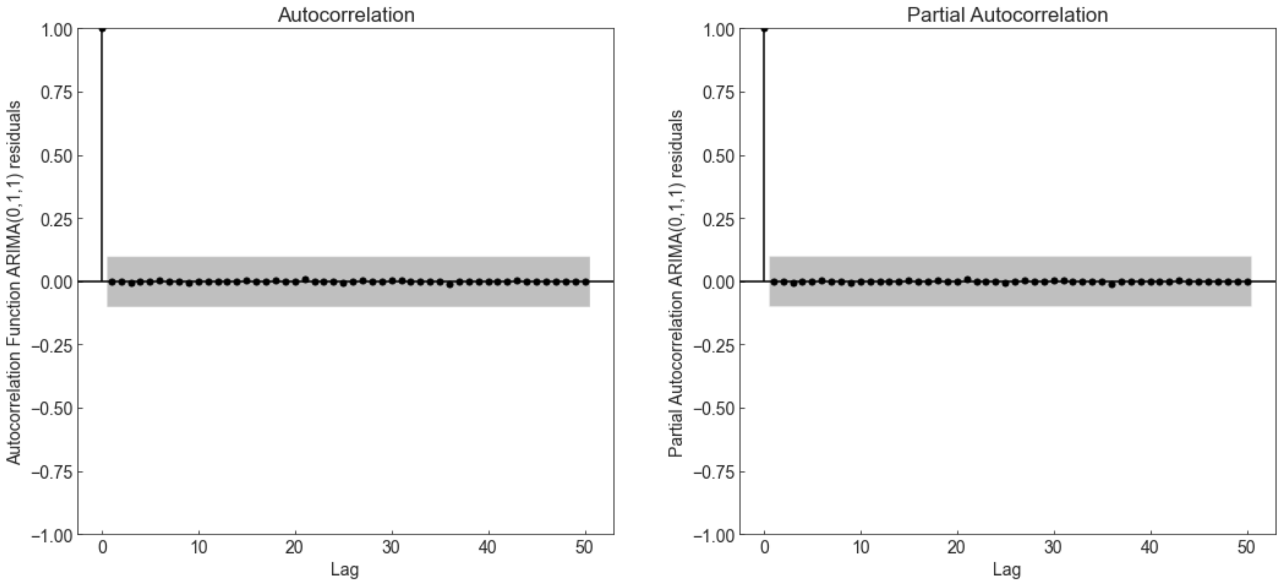
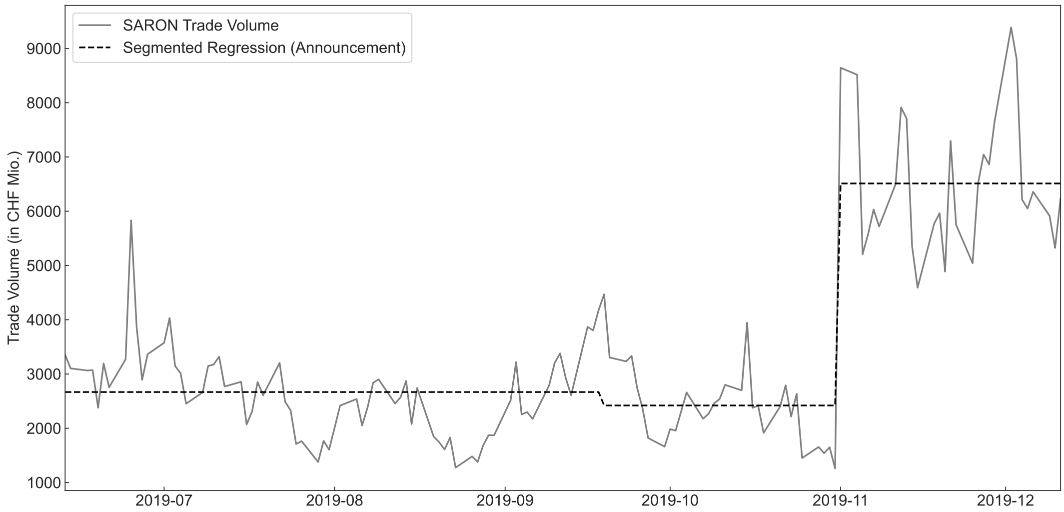


Figure 8 – ACF and PACF plot for the residuals of the ARIMA(0,1,1) model on the time frame 1

A.2.3 Trade Volume Analysis with Announcement Period



Note: The second phase (19.09.2019 - 01.11.2019) of this three-phase segmented regression is insignificant on the 5% level and thus only serves as an illustration of the separate trade volume phases.

Figure 9 – Three-phase segmented regression of the daily trade volume for the ET-change on the 01.11.2019

Trade Volume	Coefficient	Standard Error	z Statistics	P Value
Constant	2667.3768	(166.408)	16.029	<0.001
AN	-247.0865	(243.742)	-1.014	0.311
ETD	3844.2784	(330.394)	11.635	<0.001

Note: Adj. R^2=0.768, T = 129; T = number of time points, AN = dummy variable coded 1 between and at announcement date of the ET-change (19.09.2019) and excluding effective ET-change date (01.11.2019), ETD = step function coded 0 before and 1 at and after the ET-Change, Newey-West standard errors in parentheses.

Table 12 – Three-phase segmented regression output of the daily trade volume for ET-Change on the 01.11.2019

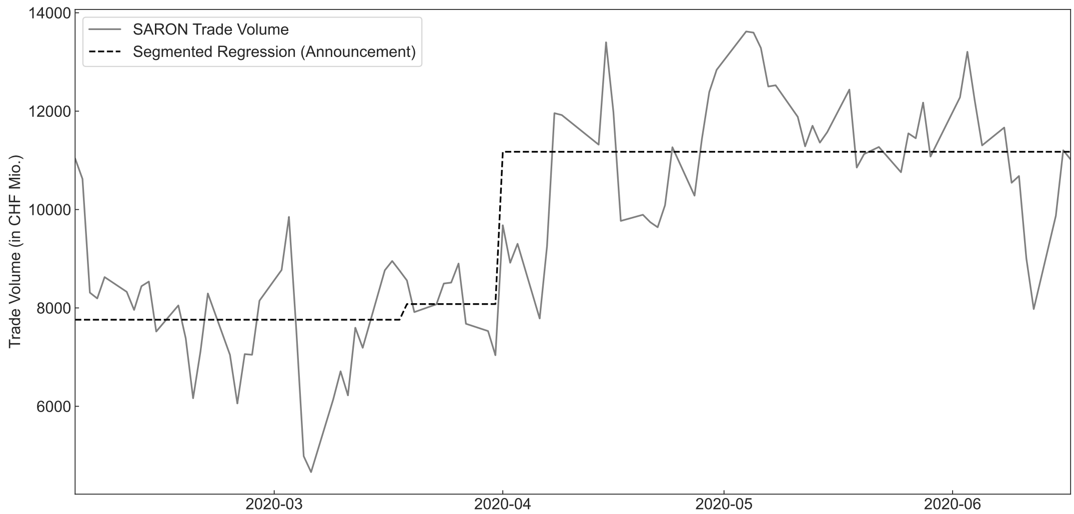
Trade Volume	Coefficient	Standard Error	z Statistics	P Value
Constant	2590.78	(137.113)	18.895	<0.001
ETD	3920.8752	(323.503)	12.120	<0.001

Note: Adj. R^2=0.767, T = 129; T = number of time points, ETD = step function coded 0 before and 1 at and after the ET-Change date (01.11.2019), Newey-West standard errors in parentheses.

Table 13 – Two-phase segmented regression output of the daily trade volume for ET-Change on the 01.11.2019

A.3 Exemption Threshold Change 01.04.2020

A.3.1 Trade Volume Analysis with Announcement Period



Note: The second phase (19.03.2020 - 01.04.2020) of this three-phase segmented regression is insignificant on the 5% level and thus only serves as an illustration of the separate trade volume phases.

Figure 10 – Three-phase segmented regression of the daily trade volume for the ET-change on the 01.04.2020

Trade Volume	Coefficient	Standard Error	z Statistics	P Value
Constant	7760.2121	(354.551)	21.887	<0.001
AN	318.3434	(400.952)	0.794	0.427
ETD	3414.1408	(481.495)	7.091	<0.001

Note: Adj. R^2=0.609, T = 93; T = number of time points, AN = dummy variable coded 1 between and at announcement date of the ET-change (19.03.2020) and excluding effective ET-change date (01.04.2020), ETD = step function coded 0 before and 1 at and after the ET-Change, Newey-West standard errors in parentheses.

Table 14 – Three-phase segmented regression output of the daily trade volume for ET-Change on the 01.04.2020

Trade Volume	Coefficient	Standard Error	z Statistics	P Value
Constant	7828.4286	(290.927)	26.909	<0.001
ETD	3345.9244	(432.878)	7.729	<0.001

Note: Adj. R^2=0.611, T = 93; T = number of time points, ETD = step function coded 0 before and 1 at and after the ET-Change, Newey-West standard errors in parentheses.

Table 15 – Two-phase segmented regression output of the daily trade volume for ET-Change on the 01.04.2020

A.3.2 Segmented Regression with Announcement Date

SARON	Coefficient	Standard Error	z Statistics	P Value
Constant	-0.7164	(0.002)	-340.652	$<$0.001
MO	7.367e-05	(3.54e-05)	2.079	0.038
ETD*	0.0403	(0.006)	6.388	$<$0.001

Note: Adj. R^2=0.92, T = 279; T = number of time points, MO = Measurement Occasion, ETD* = step function coded 0 before and 1 at and after the ET-Change announcement date (19.03.2020), Newey-West standard errors in parentheses.

Table 16 – Two-phase segmented regression output for ET-Change on the 01.04.2020, announcement date as break point

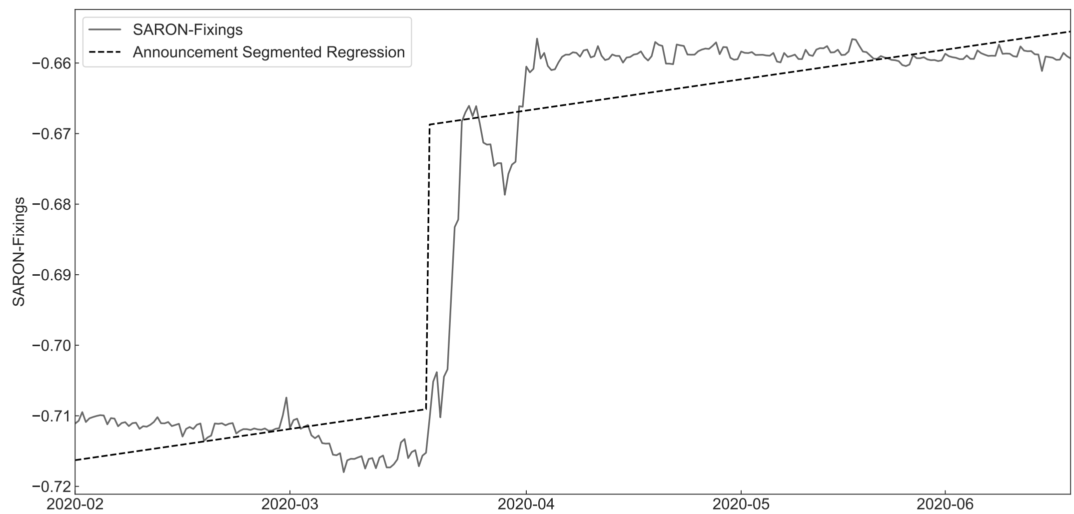


Figure 11 – Two-phase segmented regression plot for ET-Change on the 01.04.2020, announcement date as break point

A.3.3 Additional Output and Alternative ARIMA Models

SARON	Coefficient	Standard Error	z Statistics	P Value
ETD	0.0057	0.038	0.149	0.882
AR(1)	0.0983	0.030	3.242	0.001

Note: BIC = -2720.809, T = 279; T = number of time points, ${\sigma_\varepsilon}^2$ = 3.094e-06; ${\sigma_\varepsilon}^2$ = estimate of the error term variance, ETD = step function coded 0 before and 1 at and after the ET-Change date (01.04.2020).

Table 17 – ARIMA(1,1,0) output for the ET-Change on 01.04.2020

SARON	Coefficient	Standard Error	z Statistics	P Value
ETD*	0.0072	0.001	5.920	<0.001
AR(3)	0.2903	0.017	17.109	<0.001

Note: BIC = -2741.739, T = 279; T = number of time points, ${\sigma_\varepsilon}^2$ = 2.851e-06; ${\sigma_\varepsilon}^2$ = estimate of the error term variance, ETD* = step function coded 0 before and 1 at and after the announcement date (19.03.2020).

Table 18 – ARIMA([3],1,0) output for ET-Change on 01.04.2020, announcement date as break point

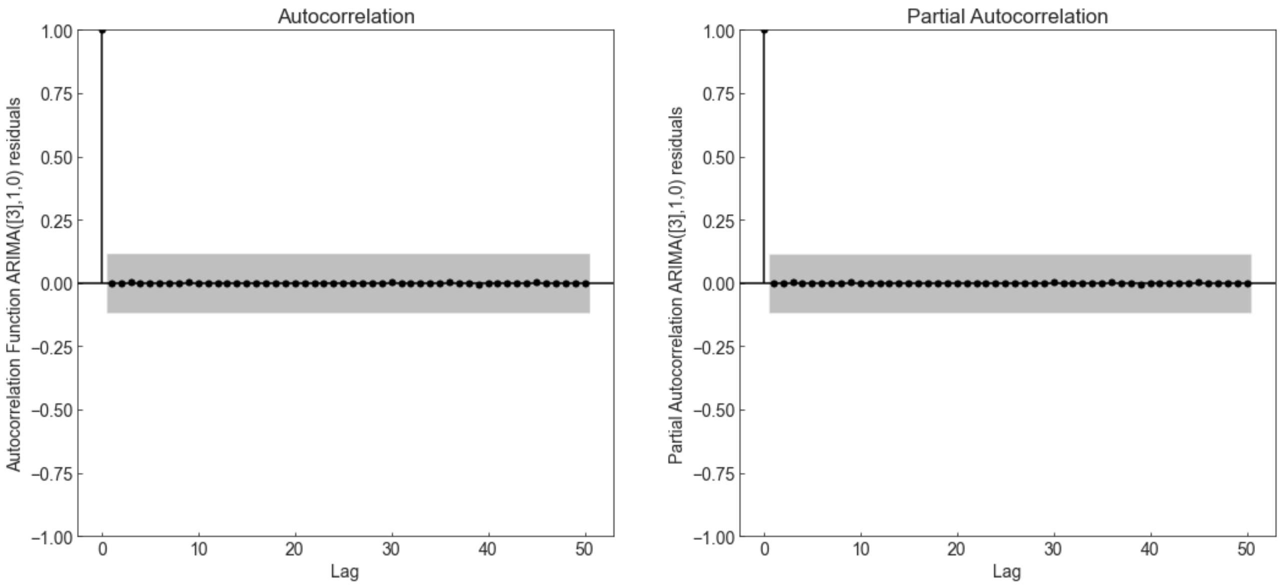


Figure 12 – ACF and PACF plot for the residuals of the ARIMA([3],1,0) model on time frame 2