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Investment Flows Between ETFs and Stocks During Covid-19

Bachelor Thesis in Business and Finance

Nicolas Künzli

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Abstract

In this study, I investigate the relationship between Exchange Traded Funds (ETFs) and stock market shares during the Covid-19 pandemic within the Swiss Equity market, using trading turnover as a proxy for market shares. Additionally, I use signed order flows to represent initiated buying and selling pressure during this time. Previous research assesses asset flows for ETFs and individual stocks in isolation while neglecting the investigations of its relationship. I expand the literature on market shares in the Swiss market, using time series data from January 2019 to December 2022. Furthermore, I apply an ordinary least square (OLS) regression as the main model. I find that ETF market shares increase as stock market shares decrease and vice versa. However, when considering signed order flows, there is no indication that the market shares of ETFs increase (decrease) at the expense (in favor) of individual stock market shares. Additionally, I investigate what happens to market shares when interest rates increase. To analyze this, I use the interest rate spike, represented by the SARON, of September/October 2021 in an OLS regression. The findings suggest that market shares for both ETFs and stocks decrease when interest rates increase. However, the results are more suggestive rather than conclusive.

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1 Introduction

Exchange traded funds (ETFs) are a key investment vehicle in the financial markets. ETFs are considered to be a recent innovation that has gained popularity over the last decades. They allow investors to diversify their portfolios and eliminate firm-specific risks. First offered in 1972 and originally introduced on the marketplace in 1993, ETFs have become a popular alternative investment instrument compared to conventional index mutual funds (Agapova, 2011). Some even argue that ETFs potentially became the largest segment in the mutual fund marketplace by 2020 (Ferri, 2009). Due to the interest of investors, ETFs have become the focus of many researchers, exploring the advantages compared to other investment opportunities. An ETF is a construct to represent a basket of underlying assets that combined equals a portfolio with the aim to diversify firm-specific risks. Diversifying firm-specific risk is essential to increase the expected return for a given level of risk of an investment portfolio (Markowitz, 1952). Markowitz's perspective represents the rational investor. However, the question arises, whether investors really do diversify their portfolio optimally.

Therefore, this study investigates the behavior of investors measured in market shares of ETFs and individual stocks on the Swiss financial market. Ma et al. (2022), whose approach I adapt and replicate in this thesis, find that there has been a positive fund flow for ETFs during the Covid-19 pandemic, while showing that mutual funds exhibited a fund outflow. This raises the question of how the newly released liquidity is allocated. I explore the relationship between ETFs and stocks asking, whether there is a connection of fund in- and outflows. Due to data limitations, I use daily trading turnover as a proxy for in- and outflows. Moreover, I use the concept of signed order flows to represent buying and selling pressure, initiated by investors. While Ma et al. (2022) used time series data from the US, I utilized Swiss data extracted from the SIX. I use a sample size covering the timeframe of January 3rd, 2019, until December 31st, 2022.

With the purpose of investigating the interplay between ETF and stock market shares, I apply an ordinary least square (OLS) regression to explore the effect of stock market shares on ETF market shares. Additionally, I implement volatility and a Covid-Dummy as the independent variables. The adjusted R^2 of 0.54 represents a good fit of the model to predict ETF turnover. Furthermore, I test to what extent alterations in interest rates can influence market shares. I use the interest rate increase, represented by the SARON, of September/October 2021 as the appropriate event. For the analysis, I apply an OLS regression with ETF trading turnover as the dependent variable while stock turnover, volatility, and interest rates to be the independent variables.

I find that ETF market shares do in fact increase as stock market shares decrease and vice versa. I support this finding with the average correlation of ETF and stock turnover to be negative. However, when combined with signed order flows, I find that ETF market shares do not increase (decrease) at the expense (in favor) of stock market shares. In addition, buying pressure increases for ETFs during Covid-19, indicating risk-reduction through diversification of investors during the pandemic. This is in line with the findings of Ma et al. (2022) and Blackrock (2020), showing that ETFs exhibit positive fund flows and thus are looked at as a "source of stability". On average measurable buying pressure exists for ETFs and stocks, indicating their popularity as an investment. I assume the stocks not to be underlying assets of the ETFs investigated. This might lead to biases in the results, since the possibility of stocks being underlying assets of the ETFs is considered to be likely. Further, I find that both ETF and stock market shares react negatively to an increase in interest rate. Therefore, the government and the national banks can have an influence on market shares. However, there is almost no connection between trading turnover and the expected returns for an investor.

1.1 Purpose

The purpose of this study is to investigate *whether ETF market shares increase (decrease) at the expense (in favor) of individual stock market shares for Swiss listed companies and ETFs.* Market shares are crucial to understand how firms finance themselves. However, most of the research has been focused on the US market. Therefore, expanding the previous findings for countries such as Switzerland is highly relevant. Not only because Switzerland counts itself to the most influential financial markets worldwide (Dimson et al., 2017), but also since the relationship between market shares of ETFs and stocks in Switzerland has been scarcely investigated. To further explore the applicability of the model, I also investigate the effect of interest rates on market shares using the interest rate spike in September/October 2021 as the event. Thereby, asking *how market shares of ETFs and stocks reacted to the increase in interest rates in September/October 2021.* Thus, I cover the economic point of view using interest rates as a crucial influence on market shares.

1.2 Contribution

This study contributes to the previous research in three ways. Firstly, I extend the investigation of ETFs and stocks during the Covid-19 pandemic on Swiss data. Secondly, I contribute to the previous literature using trading turnover as a proxy for market shares while exploring the relationship between ETF and stock market shares. The research done on the named relationship so far, has been scarce. Thirdly, I use signed order flows to represent buying and selling pressure as a contributor to the accuracy of the analysis conducted.

1.3 Scope

I follow the approach of Ma et al. (2022) using a slightly different model on Swiss data. Ma et al. (2022) used a sample of 6'356 unique share classes and 1'942 funds. Due to limitations in the data collection, monthly fluctuations and inconsistencies in the sample size are inevitable. I use a time series reaching from January 2019 to December 2022 and break it down into an ex-ante, Covid-19, ex-post window. Furthermore, I evaluate market shares of ETFs and individual stocks using daily trading turnover as an approximation for market shares. I also conduct signed order flows as an indicator of buying and selling pressure, since using trading turnover alone does not provide insights on asset in- or outflows.

1.4 Disposition

This study is structured in 8 sections. Section 2 consists of a literature review and a description of previous research in the area of asset flows generally, and of ETFs specifically. Section 3 describes the data used throughout the study and presents descriptive statistics for the entire sample period as well as for the Covid-19 period. Section 4 provides the necessary knowledge to develop the hypotheses while section 5 presents the methodology. Section 6 contains the presentation and analysis of the results while section 7 provides further discussion and interpretation. In addition, section 7 provides real world implications and suggestions for future research. I present the conclusion in section 8. After section 8, references and an appendix can be found.

2 Literature review

This study aims to investigate the disparity in investment flows between ETFs and individual stocks during the Covid-19 pandemic, which has received limited attention in the extant literature. I utilize Swiss daily turnover data as a proxy for investment flows and compute the aggregate turnover for both ETFs and stocks, relative to the aggregate turnover of all assets traded on the Swiss stock exchange. I divide the sample period into three distinct market behavior phases: pre-Covid, Covid, and post-Covid. Therefore, the research contributes to the understanding of investor behavior in times of market distress, mainly when high volatility, risk, and uncertainty dominate financial markets. Not only do I pursue the understanding of investors' behavior in a crisis, but I also want to investigate whether this behavior offers arbitrage opportunities in ETFs. For this reason, the present analysis builds upon the research methodology established in a recent study by Ma et al. (2022).

Following the emergence of the Covid-19 pandemic, a substantial number of research papers have been published, analyzing the impact of the pandemic in general and, specifically, on financial markets. Although the literature on ETFs had already gained considerable attention before the outbreak (Liebi, 2020), it increased even more afterwards, with most articles focusing on assets traded solely in isolation. However, there is a shortage of research investigating the relationship between ETFs and individual stocks.

This literature review acts as an overview of references used throughout the study. First, I clarify the definition of ETFs. Second, I provide general knowledge about what creates asset and ETF flows regarding buying and selling assets. Lastly, I elaborate on how assets and, thus, ETFs react during market disruptions. Information about further elaborations on the methodology and data employed in the study can be found in the section Data and Methodology.

2.1 Exchange Traded Funds

This section defines Exchange Traded Funds as per Lettau and Madhavan (2018) and Staer (2017). Unlike mutual funds, an ETF, as the name suggests it, is a financial investment vehicle traded on the stock exchange. It comprises a basket of securities that aims to replicate the performance of a particular index, such as the S&P500. Typically, ETFs are categorized as physical or synthetic, where the former holds underlying securities, such as stocks or bonds, while the latter employs derivatives to replicate index returns (Lettau & Madhavan, 2018). Due to data collection limitations, this study does not differentiate between physical and synthetic ETFs.

Unlike stocks, where the market price is determined by demand and supply, ETFs should always reflect the value of the underlying securities (Meier & Maier, 2022). Moreover, buying ETFs offers advantages over individual stocks or mutual funds, including lower expense ratios and fewer broker commissions (Chen et al., 2020).

Additionally, it is essential to differentiate between ETFs and mutual funds to comprehend this study. Unlike mutual funds, ETFs are created and distributed by the fund itself, such as Vanguard or iShares, to authorized participants (APs), typically prominent institutional investors and market makers such as JPMorgan Chase, Morgan Stanley, or UBS. This issuance process takes place on the primary market, with the APs subsequently engaging in purchasing and selling ETF shares with investors on the secondary market (Staer, 2017). Thus, the fund interacts with APs rather than with investors.

2.2 Driver of asset flows

The research conducted by Grinblatt and Keloharju (2001) sheds light on the fundamental inquiry of what makes investors trade. The comprehension of this question is crucial to understand the motivation and analysis undertaken in this study. Grinblatt and Keloharju (2001) employ a Logit regression to identify the determinants of buy and sell orders placed by individual and institutional investors. Their analysis reveals that historical price patterns significantly influence investor trading trends, indicating that the efficient market hypothesis is not supported (Fama, 1970). Additionally, the authors provide evidence indicating that life-cycle trading patterns also shape the buy and sell order dynamics. Kaniel et al. (2008) offer robust support for these findings, suggesting that individuals tend to exhibit contrarian behavior, purchasing stocks following a decline in the previous month and selling assets after an increase in prices. Moreover, the authors explain that contrarian behavior allows individuals to provide liquidity to institutions in urgent situations.

Furthermore, Fischer and Merton (1984) establish the interconnection between finance and macroeconomics, contending that risk and uncertainty increase trade, and thus trade volume, in both domains. Without any uncertainty, every asset, particularly in finance, becomes a perfect substitute. Consequently, the demand and supply of an asset determine its asset flows.

2.3 Driver of ETF flows

Much of what drives ETF flows derives from the recent findings of Clifford et al. (2014). They argue that an increase in ETF flows results from a change in fund sizes, expenses, and turnover. In addition, the authors show that an increase in ETF flows cause high trading volume, small spreads, and high price/net asset value ratios. Furthermore, little evidence is provided of superior market timing in ETF flows, suggesting that return chasing in ETFs is most likely the result of a naïve extrapolation bias (Clifford et al., 2014).

Using Swiss data, the investigation conducted by Rompotis (2012) provides insight into the performances and characteristics of Swiss ETFs. Notably, the study revealed that the trading volume of ETFs is influenced by intraday return volatility, trades executed, and trading frequency.

Moreover, Staer (2017, p. 280) explains the structure of ETF flows as follows: *"In the ETF case, daily creation and redemption are transacted with underlying stocks grouped into so-called "creation units" instead of cash. These "in-kind" transactions occur in the primary market between the fund and Authorized Participants (APs), who are usually large institutional investors and market makers who have signed a special agreement with the fund. APs then operate in the stock market to buy or sell the transacted stocks underlying the ETF shares. Essentially, flow-related trading activity in ETFs is shifted towards APs and not the fund itself as in the case of mutual funds."*.

Staer (2017) also claims arbitrage opportunities to be another driver of ETF flows. He states that an excess demand (supply) of ETF shares increases the premium (discount) and thus leads to arbitrage opportunities for APs. Given low transaction cost trading for APS, they can buy and sell the underlying assets quickly and thus cheaply create or redeem the ETF shares.

The elucidation of the factors that drive ETF flows was investigated by Clifford et al. (2014) and Staer (2017), while Rompotis (2012) expounded on the characteristics and delineated ETFs traded on the Swiss stock exchange. Their academic contributions served as the fundamental groundwork for the examination and consequent interpretation of findings in the present inquiry.

2.4 Trading activity during market distresses

Regarding market disruptions, Chiah and Zhong (2020) have examined the impact of Covid-19 on trading volume, documenting a significant spike in trading intensity among 37 international equity markets. Their findings suggest that investors from a wealthy institutional environment, such as Switzerland (*Swiss National Bank (SNB)*, 2023), tend to be more risk-taking and that increased trade intensity is considered a substitute for gambling. Furthermore, Cahill et al. (2021) have investigated the relationship between mobility restrictions due to Covid-19 and the attention of retail investors in equity markets. By observing daily average company Wikipedia page views, they found a positive association between lockdown duration and retail investor awareness, resulting in higher market trading activity.

Moreover, Coval and Stafford (2007) discuss the phenomenon of fire sales in equity markets, which results in immediate selling pressure and high liquidity premia. This leads to increased transaction costs, and thereby causes prices to fall below their intrinsic value. In addition, the impact of market disruptions on different asset classes have been explored by several studies, including Fleming and Ruela (2020) for Treasuries, J. Chen et al. (2020) for mortgage-backed securities, and Haddad et al. (2021) for corporate bonds. Fleming and Ruela (2020) assess market liquidity of US Treasuries, explicitly examining the extraordinary actions of the Federal Reserve System in March 2020 relative to the previous 15 years. However, Haddad et al. (2021) focus on corporate bonds and their movements in response to the Fed's increased purchase of these bonds, which is believed to have resulted from the selling pressure of bond investors attempting to acquire liquidity.

2.5 Trading activity of funds during market distresses

Ma et al. (2022) have identified fixed-income mutual funds as a particular contributor to the inflated selling pressure of liquid assets during the Covid-19 crisis. Using a three-step approach, the authors investigate the impact of mutual fund liquidity transformation on the likelihood of experiencing a "reverse flight-to-liquidity" during a market-wide liquidity shock. Their findings indicate that higher liquidity transformation is more likely to experience a reverse flight-to-liquidity during a liquidity shock and that funds, held mainly by retail investors, are also more likely to experience a reverse flight-to-liquidity. While the authors used data from CRSP Mutual Fund Database to create a sample of US open-end fixed-income mutual funds, the paper has certain limitations, such as being limited to US data. Employing the methodology on other markets would shed more light on the results and thus provide general implications.

Additionally, Blackrock (2020), a leading asset manager worldwide, investigated the behavior of ETFs in 2020 using US data. Blackrock (2020) finds that ETFs were a "source of stability" during the pandemic. Despite the unprecedented market volatility, the authors show that liquidity in the underlying market deteriorated during the selloff. ETFs, however, continued to trade efficiently during the market disruptions, giving insights of transparency into the values at which investors were willing to exchange risk. Furthermore, the paper concludes that ETFs were resilient during the crisis, resulting in an elevated trading volume compared to the equity market. These findings are strongly corroborated by Kiryluk (2020), who found that investors tend to invest in ETFs during market disruptions, such as Covid-19. The dynamics of short-term ETF flows and returns support this. In contrast, Pan and Zeng (2017) analyzed ETFs during market disruptions caused by the Flash Crash in 2010. They found that despite usually being highly liquid and low-cost options, ETFs became significantly illiquid during the Flash Crash due to a decline in trading volume of "Authorized Participants" caused by increased market volatility.

Furthermore, Ben-David et al. (2018) show that ETFs are a potential catalyst for short-term liquidity traders due to low transaction costs. Hence, low transaction costs and liquidity attract high-frequency traders, whose trading behavior increases the systematic risk of ETFs and, thus, their underlying securities, especially for short-horizon investors. The attraction of high-frequency traders increases trading volume and thus indirectly increases turnover (Biais et al., 2012). Rakowski and Wang (2009) explore the difference between fund investors and investors that buy the underlying securities directly, finding that investors have contrarian behavioral tendencies at a daily level.

Meanwhile, Meier and Maier (2022) provide a qualitative analysis where they found that retail investors migrate from investing in stocks to ETFs due to pull and push factors. Unlike stocks, ETFs reveal two pull factors: perceived investment opportunities and perceived risk reduction, which retail investors found appealing. However, the study contains limitations, such as a small data set of only 21 retail investors, and thus, potentially indicating biases and noise within the data. The authors also do not provide insights into why retail investors might migrate to ETFs, which questions the validity and reliability of the study conducted.

Given that Meier and Maier's (2022) study only utilizes qualitative analysis, this research aims to supplement their findings using quantitative analysis, thereby enhancing the potential to generalize the outcomes.

3 Descriptive statistics

This section contains the principal empirical analysis. First, I describe the dataset used throughout the study and name some limitations. Thereafter, I present a descriptive summary statistic. A second summary statistics will be offered for the Covid-19 period to mention the discrepancy of the overall sample.

3.1 Data

The study uses daily data from the Swiss Stock Exchange to create the sample. Although Switzerland is considered to be one of the biggest and most important financial markets worldwide, literature on it is rather scarce (Gugler, 2005). Therefore, Switzerland provides a database that is deemed appropriate for research purposes. The data is publicly available and can be found in the section "statistics" on the website of SIX[1]. The adjusted dataset contains 2'820'578 observations and 11 variables. For each asset, I observe daily returns, daily trading volume, and daily turnover. I use time series data from January 3rd, 2019, to December 31st, 2022. This enables me to investigate an ex-ante, Covid-19, and ex-post window. According to Llorente et al. (2002), trading volume and, thus, turnover is related to short-horizon returns which therefore justifies the time series used throughout this paper. Moreover, I use an adjusted definition of the Covid-19 window of Chia and Zhong (2020) and define the period between the 1st of February 2020 and the 1st of June 2020 as the Covid-19 period.

[1] Find the data on https://www.six-group.com/en/products-services/the-swiss-stock-exchange/market-data/statistics/monthly-reports/archive.html#tfl_XRzX2xpc3Q=/year/2019

In addition, it is worth noting, that the total number of observations utilized in the analysis may not entirely capture the full range of available assets throughout the sample period. This limitation is attributed, in part, to the fact that certain assets were not traded on specific days, resulting in fewer observations in certain months and more observations in others. Consequently, the findings may be influenced by potential biases, such as outliers, introduced by this irregularity in the available data. It is also important to mention that the Swiss Stock Exchange exhibits inconsistency in presenting annual data. This, in turn, results in instances where specific observations were unavailable, necessitating their elimination from the dataset. Ultimately, this inconsistency in data presentation resulted in eradicating 1.28% of the data, which equals 36’636 observations.

The sample incorporates the following traded assets on the Swiss Stock Exchange: Blue Chip Shares, Mid and Small Cap Shares, Exchange Traded Funds (ETFs), Exchange Traded Products (ETPs), CHF Bonds, Global Depository Receipts, Investment Funds, Rights and Options, Secondary Listed and Misc. Shares, Sparks Shares, Sponsored Foreign Shares, Sponsored Funds, Structured Products, and Warrants. These assets represent the total Swiss equity market during the sample period. In my analysis, I integrate Blue Chip Shares as well as Mid and Small Cap Shares and classify them as individual stocks. My approach involves utilizing ETFs as a collective asset class without distinguishing between various sub-categories of ETFs. This is due to a limitation in the dataset used, which does not differentiate between physical and synthetic ETFs. Additionally, the study employs eleven variables including “Six Product Segment Description”, “Issuer”, “Valor Number”, “Trading Currency”, “Trade Date”, “Closing Price”, “Turnover”, “Trading Volume”. Furthermore, to augment the analysis, I calculate the fluctuations in daily returns, turnover, and trading volume, incorporating three additional variables.

For further investigations, concerning the interest rate spike in September / October 2021, I utilize data extracted from SIX. Therefore, I use data of the Swiss Average Rate Overnight (SARON) that represents the monetary reference rate for repo-businesses of banks (Jordan, 2009).

3.2 Summary statistics sample period

By presenting summary statistics in Table 1, this study offers a comprehensive display of the sample, reaching from January 3rd, 2019, to December 31st, 2022. The statistics reveal that all assets' joint average daily return is -0.028%, and the average daily turnover and trading volume are -0.024% and 0.004%, respectively. Additionally, the standard deviation of daily return for assets is 0.25%, whereas, for both turnover and trading volume, it stands at 1.9%.

Furthermore, ETFs display the lowest daily standard deviation of 0.023% compared to all assets (0.25%), as well as individual stocks (0.035%). In addition, the analysis reveals that turnover fluctuations exhibit negative trends across all asset classes, including ETFs and stocks. Similarly, the trend is consistent for trading volume across ETFs and stocks but inconsistent for all assets joint.

Table I ***Summary Statistics of the data representing the whole sample period***

	Mean	**Median**	**Std. Dev.**	**Min**	**Max**	**25th pctl.**	**75th pctl.**
Return (%)							
Total equity	-0.028	0	0.25	-11	8.9	-0.012	0.011
ETF	0.000078	0.00048	0.023	-3.7	3	-0.0064	0.0076
Stocks	-0.00023	0	0.035	-2.1	1.6	-0.0095	0.0095
Turnover (%)							
Total equity	-0.024	0	1.9	-18	17	-0.91	0.87
ETF	-0.0025	-0.0007	2.4	-15	15	-1.3	1.3
Stocks	-0.0013	-0.0044	1.3	-12	12	-0.44	0.42
Volume (%)							
Total Equity	0.004	0	1.9	-18	16	-0.88	0.89
ETF	-0.0026	0	2.4	-15	15	-1.3	1.3
Stocks	-0.001	0	1.3	-12	12	-0.44	0.43
Daily Turnover							
Total Equity	1.94 Mio	26’012	22.29 Mio	0.001	4295.8 Mio	5’118	0.18 Mio
ETF	0.63 Mio	59’889	13.41 Mio	0.08	4295.8 Mio	10’633	0.25 Mio
Stocks	19.36 Mio	0.85 Mio	72.98 Mio	0.01	2804.6 Mio	91’765	6.98 Mio
Daily Volume							
Total Equity	0.25 Mio	10’000	2.02 Mio	1	439.74 Mio	1’500	55’000
ETF	18’806	1’564	0.32 Mio	1	85.68 Mio	250	7’560
Stocks	0.53 Mio	12’289	3.63 Mio	1	408.25 Mio	1’639	97’270

Table I. Summary statistics of the sample period reaching from January 2019 until December 2022. Column 1 shows daily returns, daily turnover and daily trading volume of the market, ETFs, and stocks. Further Column 2 shows the mean measurements. Column 3 represents the median while Column 4 represents standard deviations. Columns 5 and 6 illustrate minimum and maximum sample values while Columns 7 and 8 describe the 25th and 75th percentile. Source: own illustration.

3.3 Summary statistics Covid-19 period

In section 3.2, I provide a broad overview of the total sample analyzed throughout the study. Nevertheless, comparing the entire sample period with the period where the pandemic deteriorated the markets would give more insights. Thus, this section provides additional descriptive statistics in Table 2 of the Covid-19 period from the 1st of February 2020 to the 31st of July 2020. This sample period includes 279'773 observations and 13 variables. For ETFs, there were 55'799 observations of 13 variables and 16'850 observations of 13 variables for individual stocks. It is essential to note that the number of observations for all assets combined deviates sufficiently from the previous descriptive statistics, which might lead to insufficient data.

Table II ***Summary Statistics of the data representing the Covid-19 period***

	Mean	Median	Std. Dev.	Min	Max	25th pctl.	75th pctl.
Return (%)							
Total equity	-0.027	0	0.31	-7.5	4.6	-0.041	0.023
ETF	-0.0029	0.0009	0.043	-0.94	0.95	-0.014	0.014
Stocks	-0.002	0	0.055	-1.7	1.4	-0.016	0.014
Turnover (%)							
Total equity	-0.018	0	1.9	-15	14	-0.92	0.88
ETF	-0.0014	-0.0049	2.5	-15	14	-1.3	1.3
Stocks	0.0025	-0.0099	1.2	-11	10	-0.42	0.41
Volume (%)							
Total Equity	0.0095	0	1.9	-15	14	-0.88	0.9
ETF	0.0015	0	2.5	-15	13	-1.3	1.3
Stocks	0.0045	-0.0059	1.2	-11	10	-0.42	0.42
Daily Turnover							
Total Equity	2.5 Mio	20'709	35.3 Mio	0.01	4295.8 Mio	4'275	0.14 Mio
ETF	0.907 Mio	77'493	24.2 Mio	0.08	4295.8 Mio	13'134	0.33 Mio
Stocks	33.6 Mio	1.2 Mio	132.2 Mio	0.01	2804.6 Mio	101'206	11.2 Mio
Daily Volume							
Total Equity	0.28 Mio	11'000	2.8 Mio	1	408.2 Mio	2'000	60'000
ETF	0.027 Mio	2'200	0.47 Mio	1	85.7 Mio	341	10'932
Stocks	0.97 Mio	20'384	6.6 Mio	1	408.3 Mio	2'500	0.17 Mio

Table II. Summary statistics of the Covid-19 period reaching from February 2020 until June 2020. Column 1 shows daily returns, daily turnover and daily trading volume of the market, ETFs, and stocks. Further Column 2 shows the mean measurements. Column 3 represents the median while Column 4 represents standard deviations. Columns 5 and 6 illustrate minimum and maximum sample values while Column 7 and 8 describes the 25th and 75th percentile. Source: own illustration.

The average daily return for all assets combined demonstrates a negative return of -0.027%. The average daily return of ETFs is -0.0029%. In contrast, individual stocks display an average daily return of -0.002%. Furthermore, the equity market displays a daily standard deviation of 0.31%, while ETFs and individual stocks exhibit a lower standard deviation of 0.043% and

0.055%, respectively. Comparing these results to the previous table shows that the standard deviations increase for all assets during the pandemic. More remarkable is the change in daily turnover during market disruptions. The total equity market increased its average daily turnover during Covid-19 by 0.6 million, whereas the daily turnover of ETFs increased by 0.3 million. The most prominent increase in daily turnover is displayed by individual stocks, almost doubling its average daily turnover from 19.36 to 33.6 million. The data also reveals a similar trend in trading volume, attributed to the direct convergence of trading volume and turnover. Additionally, the standard deviations for both trading volume and turnover manifest a significant disparity from the overall sample period during the pandemic. Notably, all categories reflect almost a twofold increase during this period.

4 Hypotheses development

This section represents the identification of the empirical problem, which has already been elaborated on in the literature review section. First, I identify the pattern of daily trading volume, and thus, trading turnover in the data. Moreover, I provide justifications on why the use of turnover is an appropriate proxy for market shares. Second, I explain selling/buying pressure during the Covid-19 pandemic using the concept of signed order flows. Thereafter, the research question and its hypotheses are specified based on the pattern in daily trading turnover and signed order flows. Additionally, I pose a sub-question with the according hypotheses to further emphasize the economic side. Finally, I introduce an appropriate approach to test the hypotheses. Therefore, I present the methodology used throughout the analysis while further discussing the independent and dependent variables.

4.1 Daily trading volume and turnover

In recent years, there has been an observed upsurge in the trading volume of ETFs during periods of market distress, as reported by Blackrock (2020). This trend has been observed during the Covid-19 pandemic, one of the most turbulent market conditions in over a decade. Blackrock (2020) further notes that on days of high market volatility in Europe, the trading volume of ETFs on the secondary market increased by 34%. Consistent with these findings, this study finds an increase in trading volume across all assets as well as in the ETF secondary market in Switzerland.

Figure 1 shows the daily trading volume of the total equity market (blue), more specifically for ETFs (green) and individual stocks (red) over the whole time series. During the market disruptions in March 2020, the daily trading volume for both individual stocks and ETFs increased relative to the overall sample period by 82.5% for individual stocks and 45% for ETFs. Generally, stocks exhibited a greater trading volume than ETFs. Interestingly, individual stocks exhibit a greater trading volume in general after the outbreak of the Covid-19 pandemic, as visible in Figure 1. While Figure 1 presents the trading volume over the whole sample period for all assets in comparison, Figure 2 represents the trading volume of ETFs in isolation[2] within the Covid-19 window. The reason for the isolated display of trading volume lies in the increase of the averaged trading volume of ETFs from CHF 11’962’933 for the total sample period to CHF 18’835’136 in the pandemic. Figure 2 reveals a significant spike at the beginning of the Covid-19 period, coinciding with the WHO's official announcement of more than 20 Covid cases in Europe (WHO, 2023). By the 25th of February, the average trading volume increased significantly for all assets in response to the first registered case in Switzerland (WHO, 2023). This reasoning can also be applied to individual stocks and the total equity market to explain the extreme spike at the beginning of the Covid-19 pandemic.

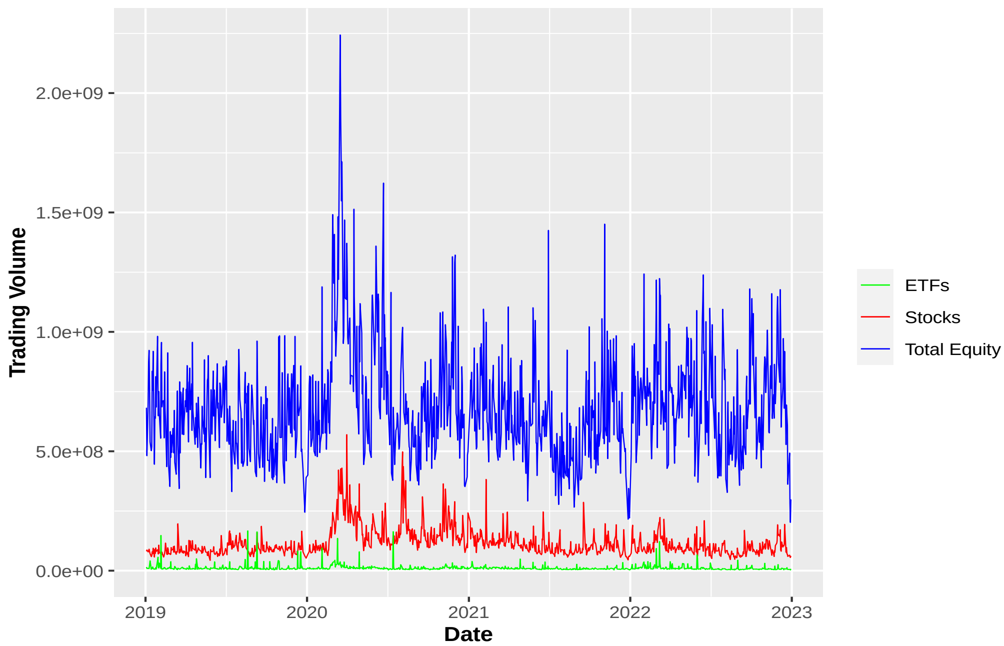

Figure 1. Trading Volume (y-axis) over the whole sample period (x-axis) regarding all asset categories used throughout the analysis. Source: own creation.

[2] The use of ETFs in isolation enables to present the pattern of ETFs more clearly, due to the relative difference in trading volume exhibited of ETFs and individual stocks as well as the total equity market.

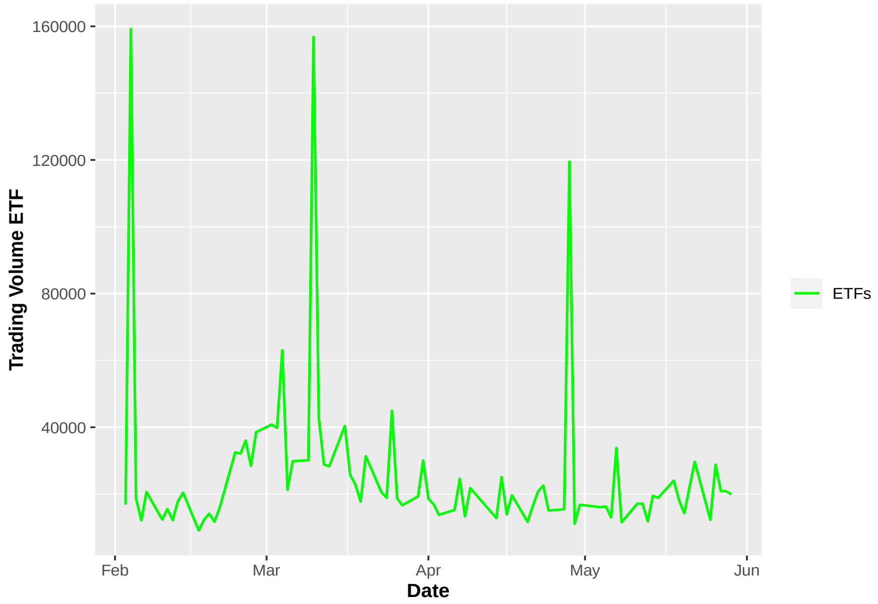

Figure 2. Trading Volume (y-axis) over the Covid-19 sample period (x-axis) regarding only ETFs to show the striking increase in trading volume. Source: own creation.

Figures 1 and 2 display the daily trading volume for all asset classes examined in the study. However, it is noteworthy to mention that trading volume might not provide an accurate proxy for market shares of equity shares, as it does not account for differences in share prices. Specifically, lower-priced assets may exhibit higher trading volume than higher-priced assets. This is due to a higher traded quantity for low-priced shares. Consequently, turnover, which represents the total value of shares traded on the exchange, serves as a better proxy for equity shares in the market than trading volume.

$$turnover_{t,i} = trading\ volume_{t,i} \times asset\ price_{t,i}$$

Equation 1: Trading turnover on day t for asset class i as the product of trading volume on day t for i and the price of an asset on day t for i

Thus, using daily trading turnover allows a more accurate comparison of market shares across different asset classes, regardless of their price. Hu (1997), for example, uses trading turnover as a proxy for liquidity to examine the relationship between trading activity and expected return. The results indicate that assets with a higher turnover tend to have lower expected returns. This finding validates the application of turnover as a suitable proxy for trading activity and, thus, market shares of the whole equity market.

Figure 3 depicts the daily trading turnover for all assets throughout the sample period. Not surprisingly, individual stocks account for a significant share of the equity market turnover, given that the highest closing price of an individual stock of the sample is 123’800 CHF. In contrast, the maximum closing price for ETFs in the sample is only 5’799.64 CHF.

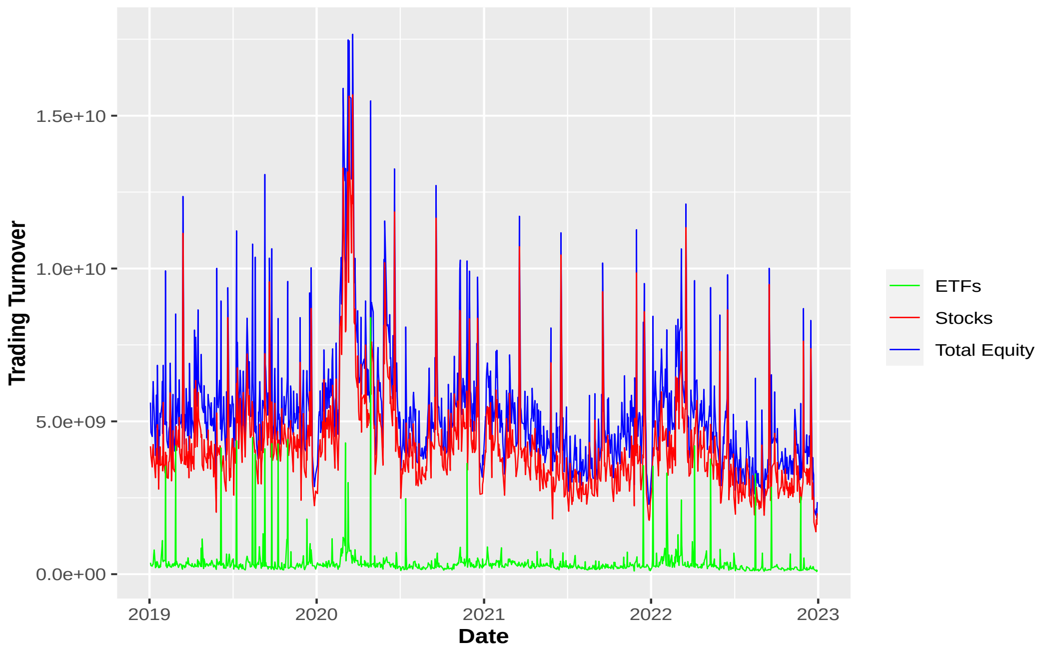

Figure 3. Trading Turnover (y-axis) over the whole sample period (y-axis) regarding all asset categories used throughout the analysis. Source: own creation.

4.2 Signed order flows

While using daily trading turnover as a proxy for equity share in the market is a commonly accepted approach, it fails to provide insight into the direction of investor trades, for example, whether there occurs to be a buying or selling pressure for an asset. To address this issue, an additional source of trading activity and investment flows must be examined. In this study, the concept of signed order flow is utilized as a supplement. Specifically, I compute the signed order flow as the product of trading turnover and the overall market direction [3], represented by the market return for each asset class on a given day.

$$signed\ order\ flow_{t,i} = turnover_{t,i} \times market\ direction_{t,i}$$

Equation 2: Signed Order flow on day t for asset class i equals the product of trading turnover on day t for i and the market direction on day t for i

This approach enables the identification of buying or selling pressure within the asset classes.

[3] Market direction in this sense means whether the market closes with a positive or negative daily return.

Figure 4 displays the signed order flow for each asset on a given day. Strikingly, a negative spike is observed for all assets at the beginning of 2020, followed by a subsequent upward spike. This pattern indicates that there had been selling pressure at the beginning of the Covid-19 pandemic, which was promptly followed by a surge in buying pressure across all asset classes. This trend explains the rapid plunge of the financial markets at the beginning of the pandemic, followed by an immense recovery of the markets. Overall, there seems to be no clear trend of buying and selling assets over time, although the fear of Covid-19 was still felt in the markets. This observation aligns with the random walk theory, claiming that returns on a given day t are independent of returns on the previous day t-1 (Fama, 1965). As such, the computed signed order flow, which employs market returns as an indicator of market direction, is also consistent with the principles of the random walk theory.

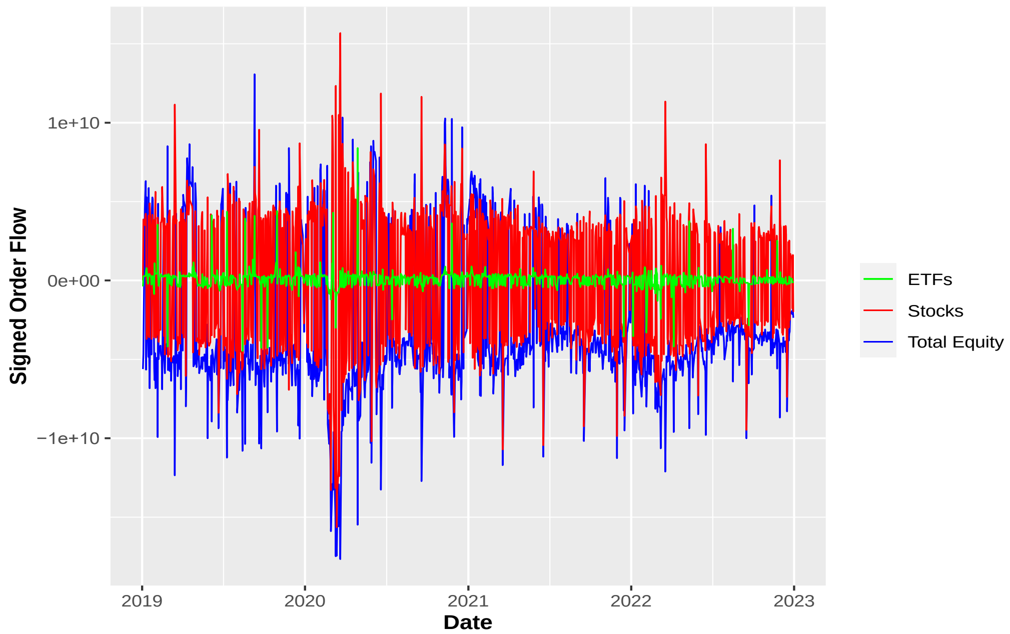

Figure 4. Signed Order Flow (y-axis) for each asset class over time (x-axis). Signed Order Flow as an indicator of buying and selling pressure over the sample period. Source: own creation

4.3 Research question and hypotheses

Given the assumption of daily trading turnover being an appropriate proxy and signed order flow to reflect buying and selling pressure, it is of interest where I further assume that investors seek stability and less risk, by diversifying their portfolios through ETFs, during Covid-19. Thus, I test whether a "flight-to-diversification" occurs, which directly incorporates stability in a crisis such as the Covid-19 pandemic. For this reason, I pose the following research question and, accordingly, the hypotheses that need to be tested:

Does the share of investments in ETFs increase while the share of individual stocks decreases within the total Swiss equity market during the Covid-19 pandemic?

$H0_1$*: Trading turnover of ETFs does not increase at the cost of trading turnover of individual stocks during the Covid-19 pandemic.*
$H1_1$*: Trading turnover of ETFs does increase at the cost of trading turnover of individual stocks during the Covid-19 pandemic.*

Furthermore, I want to test to what extent interest rates can influence the research question stated. During the period of September / October 2021, significant volatility could be observed in the SARON, with interest rates ranging from -0.72% to -0.67%, leading to massive adjustments in the financial markets. Since migration from individual stocks to ETFs and vice versa is a subject of sentiment, incorporating interest rates is of great importance (Chen et al., 2021). Chen et al. (2021) support this additional approach by finding that the stock market is not only subject to investor sentiment but also stating that sentiment serves as a connection between the financial markets and the macroeconomy. They further find that the macroeconomy influences the stock market through sentiment and thus impacts the derived fundamental value. Therefore, I add a sub-question to the research question to cover the mentioned issue concerning the interconnection between interest rates and financial markets:

Did the ETF investment flow decrease when interest rates increased in September/October 2021? How did stocks react to the same interest rate hike compared to ETFs? What happened to the ratio of ETFs and Stocks in the Swiss equity market in September/October 2021?

To answer the sub-question, I test the following H0 hypothesis:

H0₂: *The interest rate spike in September/October 2021 had no impact on trading turnover of ETFs and individual stocks, leading to no change in market shares in the equity market.*
H1₂: *The interest rate spike in September/October 2021 impacted trading turnover of ETFs and individual stocks, leading to a change in market shares in the equity market.*
H2₂: *The interest rate spike in September/October 2021 impacted trading turnover of ETFs and individual stocks, while there was no obvious change in market shares in the equity market.*

These hypotheses set the foundation for the analysis. The further section introduces the methodology to test the stated hypotheses.

5 Methodology

This section serves as the core of the analysis. First, I introduce an OLS-regression as the primary model to analyze the stated research question and its hypotheses. Second, I describe the independent and dependent variables in the OLS regression used. Third, I introduce the regression for the sub-question. After that, I investigate the signed order flows in more detail. Finally, I undertake and elaborate further steps that need to be done to receive valid results.

5.1 Estimation of ETF flows

To estimate whether there is a change in market shares for ETFs at the cost of individual stocks and thus an increase in trading turnover of ETFs, I use an OLS regression as the main model in the analysis. By doing so, I follow the approach of Ma et al. (2022). The OLS regression helps to examine one variable's specific effect on another (Burton, 2021). Therefore, the main regression looks as follows:

$$ETFs = \alpha + \beta_1 Stocks + \beta_2 Volatility + \beta_3 Covid + \varepsilon$$

Equation 3: OLS regression to compute the variation in ETF turnover as a result of changing the stock turnover, volatility and Covid-Dummy variables.

Equation 3 is crucial to answer the main research inquiry. However, to address the sub-question, regarding the interest spike, a second regression needs to be conducted. Consequently, I introduce an additional independent variable called "Interest" while excluding the Covid-dummy variable, as it becomes redundant given the focus on factors outside the realm of Covid.

$$ETFs = \alpha + \beta_1 Stocks + \beta_2 Volatility + \beta_3 Interest + \varepsilon$$

Equation 4: OLS regression for computing the influence of the interest rate spike in September/October 2021 on daily trading turnover of ETFs.

5.2 Dependent and independent variables

Equation 3 incorporates ETFs as the dependent variable, which necessitates an explanation based on several independent variables. The dependent variable represents the ETF daily turnover relative to the overall turnover of the equity market. Therefore, the dependent variable "ETFs" portrays the portion of ETFs within the whole equity market. The use of relative numbers as a metric for quantifying shares within the equity market provides distinct advantages in terms of comparability and interpretability (Citrome, 2010). By employing these measures, I can engage in meaningful comparisons, thus, resulting in the feasibility of the exploration and analysis of relationships among variables.

Moreover, "Stocks" as the first independent variable, is the main predictor of the ETF turnover share. Like the dependent variable ETFs, the dependent variable "Stocks" does represent the share of individual stocks of the overall equity market. The second independent variable "Volatility" stands for market volatility. I computed market volatility as the standard deviation of each return for each asset on every given day. Although the VIX could also be used as a potential indicator of volatility, I find it more appropriate to use the standard deviation of the dataset as an indicator, since the VIX portrays the volatility of the S&P500 rather than specific volatility measured in the equity market of Switzerland. Market volatility changes over time and heavily influences expected returns and hence, the attractiveness of an asset (Schwert, 1989). Additionally, it impacts risk-aversion of investors resulting in a change of market activity, directly represented by trading volume and thus trading turnover. By incorporating market volatility, I control for uncertainty and risk within the sample period. Therefore, volatility as an explanatory variable for ETF flows is crucial and enables more accurate statements about the relationship between the shares of stocks and ETFs.

The third independent variable is the Covid-19-dummy, simply indicating whether Covid-19 is present (1)[4] or Covid-19 is not present (0)[5].

In Equation 4, however, the Covid-19 dummy is omitted while a novel independent variable, denoted as "Interest", is introduced. The variable "Interest" represents the fluctuations of the SARON during the time of September/October 2021. Given the restricted time frame, the Covid-Dummy, which refers to an earlier time-period, is dropped. Incorporating interest as an independent variable allows controlling for macroeconomic shocks. Notably, interest rates do have a large impact on the financial market (Chen et al., 2021).

However, this might not be the optimal incorporation of other variables, as there are many other factors that should be taken into account. For instance, the inclusion of ETF sizes and expenses as independent variables could also be noteworthy approaches, as suggested by Clifford et al. (2014). Additionally, following the advice of Staer (2017) would involve incorporating excess demand and supply as another explanatory variable in the regression. Nevertheless, due to the scope of this study and limitations in data collection, I only implemented interest rates, as an indirect indicator of demand and supply, while neglecting other factors. This simplifies the analysis but reduces its accuracy. To evaluate the extent to which the chosen independent variable predicts the dependent variable, I present the adjusted R^2 in the result section. This provides insight into the overall accuracy of the model fit.

5.3 Estimation of signed order flows

The relationship between ETF turnover and various independent variables, including stock turnover, a Covid-Dummy variable, and volatility, does not yield conclusive findings. Consequently, I conduct an additional regression analysis to investigate the signed order flow of ETFs. This section examines whether changes in the signed order flow for individual stocks influence the signed order flow for ETFs. To explore this relationship, the dependent variable in this regression is the signed order flow for ETFs, while the independent variables include the signed order flow for individual stocks, market volatility, and a Covid-Dummy variable. This approach aims to reveal whether buying pressure occurs for ETFs when selling pressure is present for individual stocks, and vice versa. The regression model used in this analysis is

[4] Covid-19 window, which is introduced in the data section.
[5] Time period that is not part of the Covid-19 window.

presented as follows:

$$SOF\ ETFs = \alpha + \beta_1 SOF\ Stocks + \beta_2 Volatility + \beta_3 Covid + \varepsilon$$

Equation 5: Ordinary Least Square regression for computing the signed order flow of ETFs explained by the signed order flow of stocks, market volatility and a Covid-Dummy variable.

5.4 Robustness and validity of regressions

To receive robust results, I run various statistical tests. Creating a regression alone would not be adequate. Firstly, I adjust standard errors from non-robust standard errors to robust standard errors. This makes the regression estimator reliable even though outliers are present (Croux et al., 2004). Secondly, I test the residuals for stationarity. I find that the residuals of all regressors are stationary. Thirdly, I check whether there occurs to be seasonality or trends within the residuals. I can conclude that there is no seasonality or trend visible when plotting the residuals. Fourthly, I use the Box-Pierce and Breusch-Pagan test to check for first-order autocorrelation (lag 1) and heteroscedasticity. I find both to be significant, resulting in autocorrelation and heteroscedasticity. Thus, the appearance of autocorrelation and heteroscedasticity necessitates the use of robust standard errors (Croux et al., 2004).

Doing the exact same as above mentioned for the computations of the interest rates spike, I find that there occurs to be heteroscedasticity and autocorrelation. This, once again, does necessitate the use of robust standard errors. Further, I find that the residuals are stationary.

Lastly, I do the same analysis to validate the OLS regression for the computed signed order flow. I find autocorrelation and heteroscedasticity in the residuals, necessitating the use of robust standard errors once again (Croux et al., 2004). Furthermore, stationarity is found in the pattern while no seasonality or trends are apparent.

The following section serves as the presentation of the results. I first present the outcome of the main regression model including t-statistics and adjusted R^2. Secondly, I do the same for the sub-question. Thirdly, I shed light on the buying and selling pressure by presenting the regression for the signed order flow. Thus, answering the research inquiry becomes possible.

6 Results

This section builds upon the presentation of the main empirical findings. Including tables becomes imperative, as they serve as effective visual aids to elucidate the conducted analyses. The ensuing tables present a concise summary of the results obtained. However, it is important to mention that this section only presents the results neglecting its deeper interpretation and implication. The subsequent chapter Discussion provides a precise interpretation of the results, therefore discusses its potential implications.

Firstly, Table 3 provides an elucidation of the outcomes pertaining to the principal research question, which seeks to ascertain whether alterations in ETF turnover shares are attributable to variations in stock turnover. Secondly, Table 5 presents the regression findings concerning the signed order flow, which strengthens the interpretation later on. Finally, Table 4 addresses the subsidiary research question, asking whether the increase of interest rates in September/October 2021 by the SNB had an effect on the market shares of ETFs and stocks.

6.1 ETF flows

Table III presents the findings of the primary research inquiry that aims to examine the influence of fluctuations in individual stock market shares on ETF market shares, utilizing trading turnover as a proxy. Thus, this section considers Equation 3. Column 1 delineates the effect of stock turnover, acting as the independent variable, on ETF turnover, the dependent variable. Notably, a unit increase in individual stock turnover leads to a substantial -0.58% decline in ETF turnover, thereby the t-statistics of -11.20 indicate high significance. In Column 2, market volatility is introduced as an additional independent variable. The results show that a unit increase in volatility corresponds to a 0.09% increase in ETF turnover, supported by a t-statistic of 5.13, which indicates high significance. Column 3 incorporates the influence of a Covid-Dummy on ETF turnover. Notably, the analysis reveals that the Covid-19 pandemic had a positive effect on ETF turnover, leading to an increase of 0.01%. This effect is statistically significant with a t-statistic of 2.65.

In total, the dataset comprises 1’009 observations, with each observation representing a daily occurrence. It is noteworthy that the adjusted R^2 value increases from column 1 to column 2, indicating a moderate role of the inclusion of volatility as an explanatory variable. However, the addition of the Covid-Dummy variable fails to alter the adjusted R^2 value, suggesting redundancy in its inclusion. Further analysis shows that regressing ETF turnover on volatility does necessitate in an adjusted R^2 of 0.00, which contradicts the inclusion of volatility as an explanatory variable.

Table III	***OLS Estimates of the Effect of Stock Turnover on ETF Turnover*** Dependent Variable: ETF Turnover as a proxy for market shares		
	(1)	(2)	(3)
Stock turnover (t-test)	**-0.58 ***** (-11.20)	**-0.60 ***** (-11.46)	**-0.61 ***** (-11.52)
(SE)	(0.05)	(0.05)	(0.05)
Volatility (t-test)		**0.09 ***** (5.13)	**0.09 ***** (4.88)
(SE)		(0.02)	(0.02)
Covid-Dummy (t-test)			**0.01 **** (2.65)
(SE)			(0.00)
No. of Obs.	1’009	1’009	1’009
Adj. R^2	0.53	0.54	0.54

*Table III. T-statistics are in parentheses. The trading turnover data for individual stocks are taken from the SIX database and defined as market share of the equity market. Volatility is defined as the standard deviation of the returns for the market on given day. The Covid-Dummy variable represents the Covid-19 pandemic, indicating 1 when the day is in the Covid-19 window [6], 0 elsewise. *** p<0.01, ** p<0.05, * p<0.1.*

Generally, Table III shows that over the sample period individual stock turnover is negatively correlates with ETF turnover. Furthermore, it is important to mention that an increase in both ETF and stock turnover lead to an increase in market returns, 0.008% for ETFs and 0.014% for stocks (see Table VI in the appendix). However, this result is not of statistical significance based on the p-value of 0.55 for ETFs and 0.19 for stocks. Moreover, the correlation between ETF and stock turnover in general is -0.72, indicating highly negative correlation. Strikingly, this negative correlation becomes even more dramatic when observing the Covid-19 period, exhibiting a negative correlation of -0.85.

In conclusion, Table III gives us a partial answer to the main research inquiry. In general, ETF turnover increases when stock turnover decreases. This can be seen in row 1 by observing the correlation itself. However, during the Covid-19 pandemic, both ETF and stock turnover increased simultaneously. This allows us to accept $H0_1$, thus I fail to reject the null hypothesis.

[6] The Covid-19 window is defined as follows: The 1st of February 2020 until the 1st of June 2020.

Nevertheless, this is only partially the case since we cannot state whether the ETF turnover increases in favor of or at cost of stock turnover. Consequently, we need to consider the concept of signed order flow.

6.2 Signed Order Flow

This section investigates buying and selling pressure of ETFs at the cost of stocks using signed order flows as the appropriate indicator. Therefore, Table IV presents the results of the OLS regression in Equation 4 that inquires the signed order flow of ETF as a dependent variable, while using signed order flow of stocks, volatility, and a Covid-Dummy as an independent variable. As stated above, testing Equation 4 allows to fully fail to reject $H0_1$ and thus, completely answering the research question.

<u>Table IV</u>	***OLS Estimates of the Effect of SOF of Stocks on SOF on ETFs*** Dependent Variable: ETF Signed Order Flow		
	(1)	(2)	(3)
Signed Order Flow Stocks (t-test)	**0.04 ***** (16.09)	**0.04 ***** (15.74)	**0.04 ***** (15.78)
(SE)	(0.00)	(0.00)	(0.00)
Volatility (t-test)		**-0.09 **** (-3.07)	**-0.10 **** (-3.31)
(SE)		(0.03)	(0.03)
Covid-Dummy (t-test)			**0.01** (1.26)
(SE)			(0.01)
No. of Obs.	1’009	1’009	1’009
Adj. R^2	0.14	0.15	0.15

*Table IV. T-statistics are in the parentheses next to the predictor. Robust standard errors are in the parentheses below the predictors. The signed order flow for individual stocks represents the product of trading turnover and market direction for each asset class. The data is gathered from the SIX database[7]. Volatility is defined as the standard deviation of the returns for the market on a given day. The Covid-Dummy variable represents the Covid-19 pandemic, indicating 1 when the day is in the Covid-19 window, 0 elsewise. *** p<0.01, ** p<0.05, * p<0.1.*

Table IV supports answering the main research inquiry by stating whether there has been buying or selling pressure in the pandemic, while also providing general results. As clearly visible in Column 1, the signed order flow of ETFs increases by 0.04 when the signed order flow of stocks increases by one unit. This comes with a t-statistics of 12.87, indicating high significance on the 1%-confidence level. This means that ETFs and stocks provided a buying pressure at the same time. However, the adjusted R^2 with 0.14 is generally low and thus

[7] See https://www.six-group.com/en/products-services/the-swiss-stock-exchange/market-data/statistics/monthly-reports/archive.html#tfl_XRzX2xpc3Q=/year/2019

describes the model as a poor fit to predict the dependent variable (Saunders et al., 2012). Column 2 incorporates volatility, being -0.09, as an additional explanatory variable. The regressor "Volatility" decreases in Column 3, where the Covid-Dummy is added in the regression. The added Covid-Dummy, with a coefficient of 0.01, however, is not significant based on the t-value of 1.26.

The data contains again 1'009 observations, with each observation representing a daily occurrence. The adjusted R^2 does improve little from Column 1 to Column 2. However, according to Saunders et al. (2012), this value indicates an inappropriate model fit to predict the signed order flow of ETFs.

Keeping this in mind, I conclude the main research inquiry as to be answered with failing to reject $H0_1$. Although the share of investments in ETFs increases when the share of investments in stocks decreases, it does not necessarily mean that there exists a "flight-to-diversification" of investors.

6.3 ETF flows during the Interest rate spike in September/October 2021

Table V represents the investigation of the effect of the interest rates spike in September / October 2021 on ETF turnover. Regarding interest rates enables to cover the monetary policy action of the SNB, thereby causing investments to change (Conrad, 2022). As observed in column 1, I only considered the effect of stock turnover on ETF turnover. This must be the same as column 1 from Table III. Column 2 incorporates the independent variable "Interest". It shows that an increase in interest rates of one unit leads to a strongly significant decrease in ETF turnover by -0.02. The independent variable "Volatility" significantly increases ETF turnover by 0.01 on the 0.001%-significance level. Moreover, the adjusted R^2 is 0.53 for Column 2, representing a good fit for the model. However, adding volatility to the model makes it fit even better with an adjusted R^2 of 0.55.

Table V shows us what happens with ETF turnover and thus stock turnover when interest rates increase. This allows me to answer the sub-question of this thesis, that asks how ETFs reacted to the increase in interest rates in September / October 2021. I answer this question by concluding that an increase in interest rates decreases ETF turnover.

Table V	***OLS Estimates of the effect of the interest rates spike on ETF turnover*** Dependent Variable: ETF Turnover		
	(1)	(2)	(3)
Stock Turnover (t-test)	**-0.58 ***** (-11.20)	**-0.59 ***** (-11.37)	**-0.61 ***** (-11.67)
(SE)	(0.05)	(0.05)	(0.05)
Interest (t-test)		**-0.02 **** (-4.41)	**-0.02 ***** (-4.47)
(SE)		(0.00)	(0.00)
Volatility (t-test)			**0.10 ***** (5.25)
(SE)			(0.02)
No. of Obs.	1’009	1’009	1’009
Adj. R^2	0.53	0.53	0.55

*Table V. T-statistics are in the parentheses next to the predictor. Robust standard errors are in the parentheses below the predictors. The independent variable “Interest” represents the interest rate spike in September / October 2021. The data is gathered from the SIX database[8]. Volatility is defined as the standard deviation of the returns for the market on a given day. *** p<0.01, ** p<0.05, * p<0.1.*

Moreover, the turnover of individual stocks reacted even more, indicating a decrease of 0.03% for every unit increase in interest rates. However, due to data limitations, it is not possible to draw any conclusion whether there has been a change in market shares of ETFs or individual stock flows. This is also because both ETF and stock turnover decrease when interest rates increase.

The data once again comprises 1’009 observations. The adjusted R^2 reaches from 0.53 in Column 1 to 0.55 in Column 5. According to Saunders et al. (2012), there no set criteria exists, that universally represents a “good” fit. However, when comparing two models with each other, we can draw a conclusion in terms of a model’s fit. Thus, compared to the model of signed order flow in Table IV, we can conclude that the fit of this model is generally better.

The conclusion of this section incorporates the rejection of HO_2 in favor of $H1_2$, which states that an increase in interest rates in September / October 2021 is negatively associated with turnover of ETFs and individual stocks. However, as mentioned above, we cannot definitely say whether there was an adjustment in market shares within the equity market of Switzerland.

[8] See https://www.six-group.com/en/products-services/the-swiss-stock-exchange/market-data/statistics/monthly-reports/archive.html#tfl_XRzX2xpc3Q=/year/2019.

7 Discussion

This section provides a deeper understanding of the main results. For the sake of the interpretation, I consider references that are named in the section Literature Review while also adding new references that are not described in the Literature Review. I start off by interpreting the negative interplay between ETF and stock turnover, while also referring to signed order flows. Next, I draw a conclusion of how a change in interest rates is associated with a change market shares with regards to the economic perspective. Finally, I provide real world investment implications, limitations of the research conducted and other alternative approaches that can be looked at in future research. Once again, it is crucial to assume that trading turnover is used as a proxy for market shares for the sake of the discussion section.

7.1 Interpretation of the main findings

Firstly, the primary finding of this thesis establishes a negative correlation between ETF turnover and stock turnover within the sample period spanning from the 3rd of January 2019 to the 31st of December 2022. This finding implies that the increase in market share of ETFs comes at the expense of stock market shares, and vice versa. However, when considering the signed order flows of both ETFs and stocks, this conclusion is not valid. This discrepancy arises from the analysis presented in Table IV, which demonstrates a simultaneous increase in signed order flows of ETFs and stocks. As previously mentioned, the signed order flow represents either buying pressure (when SOF > 0) or selling pressure (when SOF < 0). Consequently, Table IV exhibits a positive signed order flow for both ETFs and stocks concurrently, indicating buying pressure for both categories simultaneously. However, this is only applicable when the stocks in question are not underlying stocks of the ETFs being examined. In contrast, assuming a dependency between ETFs and stocks precludes drawing a definitive conclusion, as the trading activity of ETFs directly influences the trading activity of stocks (Staer, 2017). Consequently, it can be concluded that ETFs are not acquired at the expense of stocks to mitigate risk, nor are they purchased solely based on perceived investment opportunities, as suggested by Meier and Maier (2022). This inconsistency with the findings of Meier and Maier (2022) may be attributed to limitations in the available data, as it was not possible to ascertain the level of independence between stocks and ETFs.

Secondly, I observe an increase in trading turnover of ETFs during the Covid-19 pandemic, corresponding to a one-unit increase of stock turnover. Furthermore, I find the signed order flow of ETF to increase during Covid-19 indicating buying pressure. This finding is consistent with the findings of Blackrock (2020) who emphasized that ETFs served as a "source of stability" during the pandemic. Moreover, my findings are consistent with those of Ma et al. (2022), who also find positive fund inflows for ETFs during the pandemic. Additionally, Chiah and Zhong (2020) support my findings, as they discovered that individuals exhibited a greater propensity for risk-taking during the pandemic, resulting in increased turnover for both ETFs and stocks. Furthermore, not only did people display higher risk-seeking behavior, but they also demonstrated heightened awareness of the equity market. Thus, my findings align with those of Cahill et al. (2021), who also reported heightened trading activity during the Covid-19 pandemic. Furthermore, Ben-David et al. (2018) assert that ETFs have the potential to attract short-term liquidity traders. At the onset of the pandemic, many assets, including the SMI, experienced declines below their intrinsic values, creating an arbitrage opportunity. Consequently, short-term traders were drawn in, leading to an increase in trading turnover and signed order flows (Biais et al., 2012). Therefore, the increased trading turnover observed for both ETFs and stocks is in line with the findings of Ben-David et al. (2018). However, it is noteworthy that the signed order flow for both ETFs and stocks remained positive during the pandemic, as depicted in Table IV. This is mainly due to the fast recovery of the market after the dramatic plunge at the beginning of the pandemic.

In conclusion, a negative relationship exists between ETF turnover and stock turnover. With regards to the signed order flows of both ETF and stocks, however, I draw the conclusion that ETF market shares do not increase at the expense of stock market shares and vice versa. Moreover, during the Covid-19 pandemic ETF turnover increased along with stock turnover. One must note that the signed order flows of ETFs and stocks are positively correlated. Although, there is no significance with regards to the independent variable "Covid-Dummy" in Table IV, I can answer the research inquiry as: Yes, ETF market shares do increase when stock market shares decrease, but not at the expense of stock market shares according to signed order flows. Thus, we fail to reject $H0_1$. Moreover, I can state that there has been buying pressure for both ETFs and stocks during the pandemic. There is no final statement whether there has been a "flight-to-diversification" since buying pressure also occurred for stocks.

7.2 Main findings from an economic point of view

A potential reason for both assets to increase in the turnover while also indicating buying pressure can be the reduction in consumption level during Covid-19 (H. Chen et al., 2021). The consumption level decreased across almost every country since there had been several restrictions, such as mobility restrictions or population movement restrictions (Han et al., 2020). These restrictions impacted the monetary behavior of the people which resulted in less consumption; thus, increased the possibility of people investing their additional savings in the equity market (Cahill et al., 2021). This is consistent with the findings of Fischer and Merton (1984).

While the consumption level at the outbreak of Covid-19 could barely be influenced by the government or the Swiss National Banks, the second factor, interest rates, can directly be altered by the Swiss National Bank through their monetary policy (Friedman, 2000). Table V represents what happens to trading turnover when interest rates adjust over time. An increase in interest rates per capita decreased trading turnover for both ETFs and stocks. This is inconsistent with the findings of Pazner and Razin (1974), who state that interest rates that reflect uncertainty increase the investment level, thereby increasing market shares. In my case, this does not align. Therefore, I can suggest a solution to the sub-question asked: Yes, increasing interest rates had an effect on the market shares of ETF and stocks. However, I cannot conclude whether the market shares interplayed with each other. Thus, I reject $H0_2$ and $H1_2$ in favor of $H2_2$.

7.3 Implications for investors and policymakers

An investor usually wants a high expected return while taking on low risk (Statman, 2004). According to the results presented in Table VI, neither ETF nor stock turnover has a significant impact on daily returns. However, when including uncertainty in the computations there exists a strong significance in the negative relationship between daily returns and volatility. Therefore, an investor need not be concerned about the trading turnover of an asset. The investor should rather observe the daily individual volatility to realize the highest possible return.

As presented above, policymakers have a significant influence on market shares within the financial markets. They can do so by altering the consumption level or the interest rates. Therefore, interest rates maintain an instrument to change the market shares within the equity market. Also with regards to the fact that interest rates influence the pricing of bonds (Baaquie, 2009).

7.4 Future research suggestions

Conducting this study has provided two primary insights on how future research could be expanded. One is related to the approximation of market shares as well as the application of the model within different markets and the other to how limitations in the dataset can be handled.

Firstly, an area for future research that could be of interest for further analysis is to extend the applied model in independent variables. Furthermore, the model could be applied to other markets, other assets or even differ between stock categories, such as Blue Chip, Mid- and Small cap shares. Additionally, the model could be applied across countries in which the economy as well as the political system differs from Switzerland. The worldwide importance of Switzerland's financial market enabled me to explore a mature financial market. However, providing insights into emerging markets could also shed light on interesting outcomes. Furthermore, using trading turnover might not be the best approximation for market shares. Thus, using precise indicators such as asset in- and outflows would increase the accuracy of the analysis conducted and therefore increase the validity and reliability of the results. In addition, comparing the results from the Covid-19 pandemic with other financial crisis in Switzerland could give more insights on how market shares alter during crisis times.

Secondly, the SIX database I used for this study is missing data for all assets. Since SIX only records assets that are traded during a day, fluctuations in the number of ETFs and stocks occur. Thus, potential biases could impact the outcome of the study. Further, inconsistency in the display of the data led to deleting 1.28% of the sample size. For this reason, using several databases could potentially increase the comprehension of the analysis. Additionally, extending the sample period would decrease biases and inherently increase its accuracy.

8 Conclusion

This study investigates how market shares of ETFs and individual stocks fluctuate during the Covid-19 pandemic, asking whether the market share of ETFs increases (decreases) at the expense (in favor) of stock market shares. I follow the approach of Ma et al. (2022) using an OLS regression on Swiss data. For the data to be examined, I use daily trading turnover as a proxy for market shares. I further assume that the stocks examined are not underlying stocks of the ETFs. I find that ETF market shares increase as stock market shares decrease and vice versa. However, with regards to signed order flows, representing buying and selling pressure of an asset, I find that both ETF and stocks exhibit a positive signed order flow over the sample period. Therefore, indicating buying pressure for both ETFs and stocks. I further find the signed order flow of ETF to even more increase during the Covid-19 pandemic. This indicates that on average ETFs and stocks are bought rather than sold, while for both buying pressure increases during a crisis. These findings are in line with most previous research, but they are also inconsistent with some extant findings. However, due to the limited number of observations as well as the use of trading turnover as an approximation of market shares, the comparability, validity, and reliability of the results are somewhat problematic.

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Appendix

This section serves as the extension of the thesis. Anything that is mentioned in the text, but not necessarily the core of the thesis is presented in this section. I purposely neglect further explanation on figures or tables that are mentioned in this section, since the rationale behind including these is mentioned in the main body of the thesis. However, I provide a short caption as a type of explanatory to every figure, table, or graph.

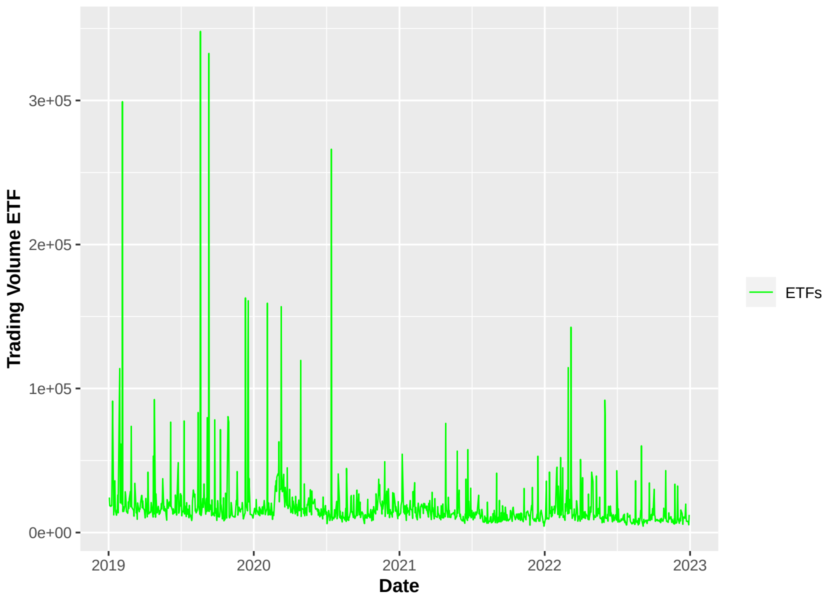

Figure 5: Trading Volume of ETFs (y-axis) over the whole sample period (x-axis). This figure serves as an extension of Figure 2, which only displays the trading volume of ETFs over the Covid-19 period. Source: own creation.

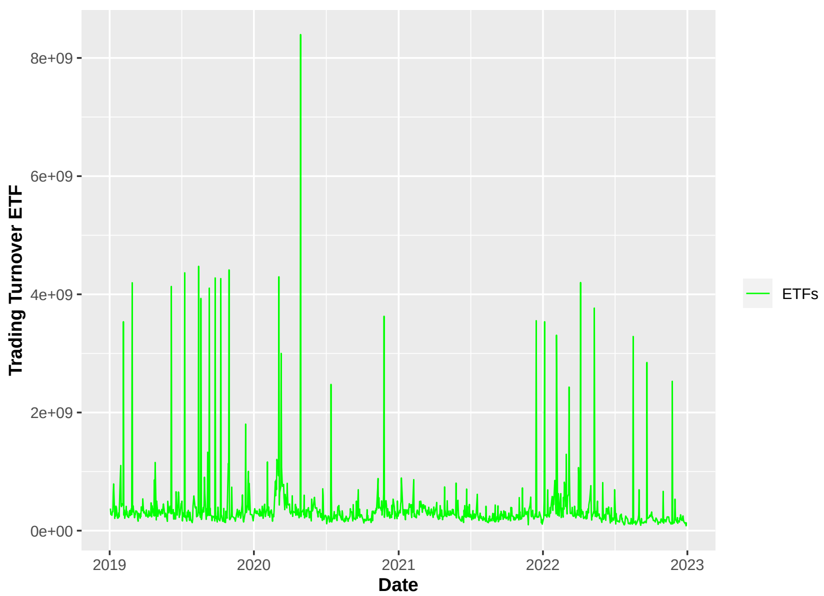

Figure 6: Trading Turnover of ETFs (y-axis) over the whole sample period (x-axis). This figure serves as an extension of Figure 5. Source: Own creation.

Table VI	***OLS Estimates of the effect of market shares on daily returns*** Dependent Variable: Daily returns		
	(1)	(2)	(3)
Stock Turnover (t-test)	**-0.07 ***** (-5.11)	**0.02** (1.57)	**0.01** (1.31)
(SE)	(0.01)	(0.01)	(0.01)
ETF Turnover (t-test)	**-0.05 ***** (-3.09)	**0.01** (0.79)	**0.01 (0.61)**
(SE)	(0.02)	(0.01)	(0.01)
Volatility (t-test)		**-0.20 ***** (-29.29)	**-0.21 ***** (-29.28)
(SE)		(0.01)	(0.01)
Covid-Dummy (t-test)			**0.00 *** (2.27)
(SE)			(0.00)
No. of Obs.	1'009	1'009	1'009
Adj. R^2	0.02	0.47	0.47

*Table VI. T-statistics are in the parentheses next to the predictor. Robust standard errors are in the parentheses below the predictors. This figure illustrates the dependency of daily returns on the different market shares. Stock Turnover and ETF turnover stand for its market shares. Volatility is defined as the standard deviation of the returns for the market on a given day. *** p<0.01, ** p<0.05, * p<0.1.*

Table VII	***OLS Estimates of the effect of market shares on daily returns without bonds*** Dependent Variable: Daily returns without bond returns		
	(1)	(2)	(3)
Stock Turnover (t-test)	**-0.08 ***** (-4.68)	**0.03 *** (2.13)	**0.02 *** (1.97)
(SE)	(0.02)	(0.01)	(0.01)
ETF Turnover (t-test)	**-0.06 **** (-2.79)	**0.02** (0.79)	**0.01 (1.01)**
(SE)	(0.02)	(0.02)	**(0.01)**
Volatility (t-test)		**-0.24 ***** (-29.22)	**-0.25 ***** (-16.89)
(SE)		(0.01)	(0.01)
Interest (t-test)			**0.00** (0.64)
(SE)			(0.00)
No. of Obs.	1'009	1'009	1'009
Adj. R^2	0.02	0.47	0.47

*Table VII. T-statistics are in the parentheses next to the predictor. Robust standard errors are in the parentheses below the predictors. This figure illustrates the dependency of daily returns excluding bonds on the different market shares. Excluding bond returns increases the accuracy of the result, since bond return is strongly correlated with interest rates. Therefore, I avoid the influence of interest rates on returns. Stock Turnover and ETF turnover stand for its market shares. Volatility is defined as the standard deviation of the returns for the market on a given day. *** p<0.01, ** p<0.05, * p<0.1.*

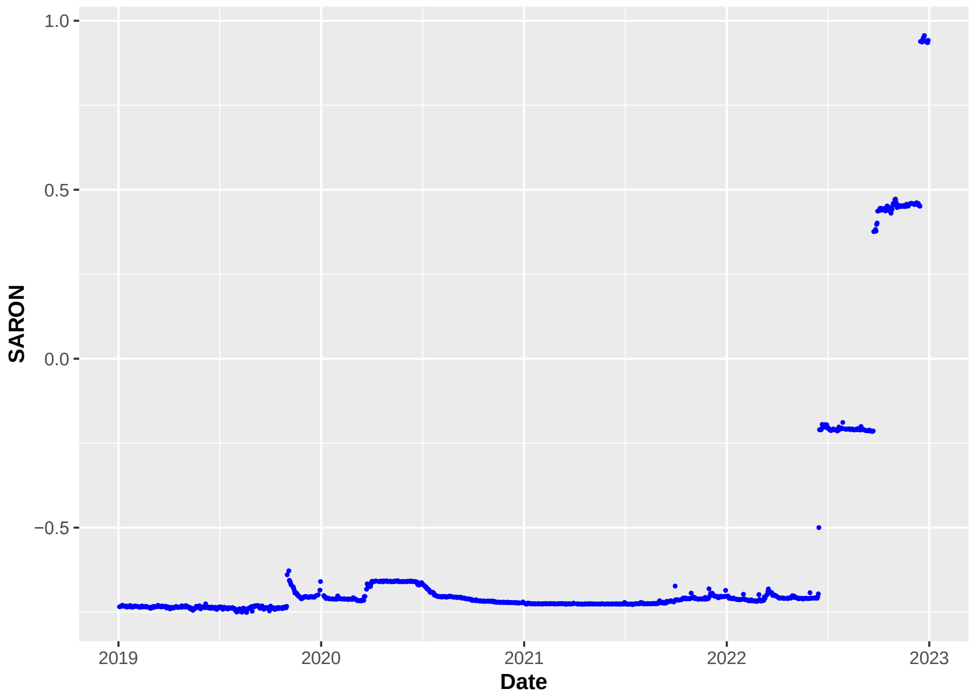

Figure 7. Illustration of the SARON (y-axis) over the restricted timeframe (x-axis). Source: own creation.

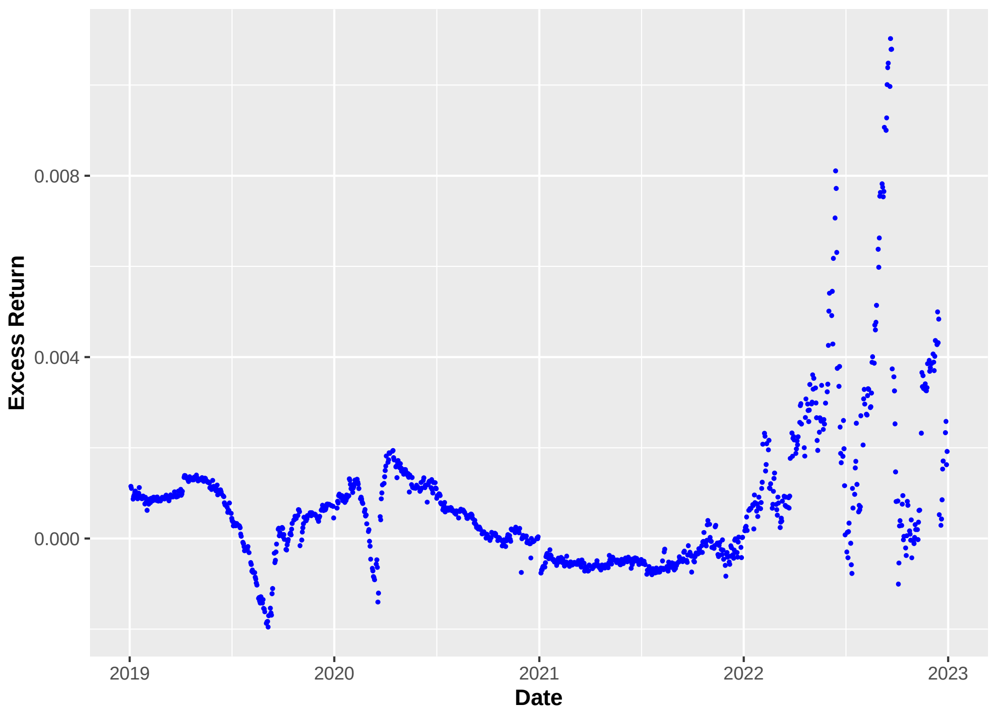

Figure 8: This figure represents the difference between the SARON and a 1-year maturity bond over the chosen timeframe. Thus, the excess return is computed as SARON minus the return of a 1-year maturity bond. Source: own creation.