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Master Thesis

GRA 19703

# The impact of fundamental shocks on bond ETF premiums

by

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*Master of Science in Finance*

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# Abstract

This thesis explores how fundamental shocks in form of surprising changes in the federal funds rate can impact bond exchange-traded fund (ETF) premiums. We utilize a linear model with interaction terms, and ETF fixed effects on a representative sample of U.S. bond ETFs between 2012-2022. We find that the fundamental shocks do not impact bond ETF premiums during ordinary times, as they impact the underlying bonds and the ETF equally. However, post Covid as well as on days of monetary policy announcements, surprises are negatively related to changes in premiums. It suggests that under certain circumstances fundamental shocks can impact ETF premiums due to the illiquidity of the underlying assets.

# Acknowledgements

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# Chapter 1

# Introduction

## 1.1 Introduction

Bond exchange-traded funds (ETFs) are an asset class that has experienced increasing popularity over the last two decades. Between 2011-2021 alone, the bond ETF market has increased from $220 billion to $1.2 trillion (Shim & Todorov, 2022). Bond ETFs provide institutional and retail investors easy and cheap access to the bond market, a market not accessible to most investors and characterized by its low liquidity.

However, connecting the illiquid bond market with the liquid stock market through ETFs is not straightforward. Researchers have found that the liquidity mismatch in the two markets impacts the mechanisms keeping the ETF's price close to the Net Asset Value (NAV), i.e., the value of the underlying securities. (e.g., Madhavan and Sobczyk, 2016; Pan and Zeng, 2017; Shim and Todorov, 2022). Bond ETF prices, therefore, deviate more severely from their NAV than the more liquid ETFs, such as equity ETFs. Consequently, bond ETFs are often found to trade above the NAV at a *premium* or below the NAV at a *discount*.[1]

The literature discusses two different theories with respect to the root and consequences of these premiums in ETFs. The first is that ETFs are prone to transitory liquidity shocks, where the ETF prices temporarily depart from the fundamental value only to move back to their intrinsic value over time (Ben-David, 2018). In that case, the dislocations of ETF price from the NAV carry a cost to the uninformed investor who is ignorant to the source of the premium and will pay too much for the ETF or receive too little when selling the ETF (Petajisto, 2017).

[1] For convenience, we will use the term *premium* for both cases. We will use the terms *positive premiums*, and *discounts* when explicitly discussing one of the two cases.

The second theory is that ETF prices incorporate shocks to the fundamental value quicker than the underlying assets, which causes premiums to occur. This is especially true for bond ETFs, where the underlying securities are staler than the ETFs that trade on the stock market as shares. Hence, bond ETFs can be seen to promote price discovery (Madhavan & Sobczyk, 2016). Provided that the ETF price reflects the true value of the underlying, the ETF can offer investors a liquid, transparent, and cost-effective investment vehicle into the bond market.

Observing the conflicting theories, we want to further investigate the idea of bond ETFs as a tool for price discovery in the bond market. To do so, we utilize surprising changes in the federal funds, estimated from Federal Funds Future Contracts, as shocks to the fundamental value. First introduced by Kuttner (2001), this method has often been used in the context of Federal Open Market Committee (FOMC) announcements to study the efficiency and impact of monetary policy decisions. Kuttner finds that these surprises explain much of the 1-day changes in interest rates after FOMC announcements. We believe that due to the inverse relationship between interest rates and bonds, these *Kuttner-surprises* can also function as shocks to the fundamental value in bond ETFs, thereby offering an approach to explore the potentially diverse impacts the shocks have on NAV and ETF price. Consequently, we propose the following research question: "How do fundamental shocks in the form of surprising federal fund rate changes impact ETF premiums?" By answering this research question we hope to reveal the appropriateness of bond ETFs as price discovery tools, and thereby contribute to the general understanding of bond ETFs.

To answer the research question, this thesis discusses how surprising rate changes might impact ETF premiums in general and how different factors might impact the relationship between the two. The factors include (1) the general bond market illiquidity, (2) the size of the ETF, (3) FOMC announcement days, and (4) the period after the initial COVID-19 (Covid) shock.

To empirically assess how the Kuttner-surprises and the factors mentioned determine changes in ETF premiums, we use a panel data set consisting of 65 of the largest U.S. bond ETFs over the period 2012-2022. The different factors are tested using interaction terms between proxies of these and the surprise measure. Next to observing the impact of surprises on the premiums, we also look at their impact on the price and NAV of the ETFs individually. We do so to identify whether the observed shock is due to prices reacting more quickly to the surprises than the NAV.

Pooled ordinary least squares (POLS), fixed effects (FE), and random effects (RE) estimators are tested on which is the most appropriate estimator to use for the analysis by using a set of statistical tests. Based on the tests, we conclude that the fixed effect estimator is the most appropriate method to use, and the empirical analysis is conducted using this method.

The findings of the empirical analysis suggest that in normal times, the Kuttner-surprises impact ETF prices and the NAV. However, the impact on the two variables is equally strong, making the impact on ETF premiums insignificant. Still, we find that on FOMC announcement days and during the period after Covid, prices are impacted significantly more by the surprises than the NAV, which causes premiums to change. Therefore, we conclude that small fundamental shocks do not impact ETF premiums during standard times and that the NAV can incorporate the news as quickly as the ETF. Conversely, during more volatile and uncertain times, such as the post-Covid period and the FOMC announcement days, the NAV is staler than the price, and the ETF can enhance price discovery.

The paper adds to the existing literature in various aspects: First, we add to the emerging but still small literature on bond ETFs. Second, we contribute to the understanding and knowledge of bond ETF premiums by examining how these changes are due to small but fundamental shocks. Third, we introduce the application of surprising federal funds rate changes as regular fundamental shocks to the bond ETF market. Prior application of Kuttner-surprises has exclusively been to study the impact of monetary policy on the market on FOMC announcement days. We show that surprising federal funds rate changes can also impact the market in regular periods.

The remainder of the paper is structured as follows: In section 2, we present the institutional details on (bond) ETFs, discuss the literature on how ETFs enhance price discovery, and present the factors that have been associated with the size and persistence of ETF premiums in the literature. In section 3, we introduce the method of using Kuttner-surprises as fundamental shocks to the ETF and develop hypotheses on how these surprises alone and in interaction with before mentioned factors can impact ETF premiums. Section 4 presents the methodology used to test the hypotheses empirically. In Section 5, we present and examine our data before presenting and discussing the results of the empirical analysis in Section 6. In section 7, we conclude.

# Chapter 2

# Literature Review and Background

## 2.1 Institutional Details

Exchange-traded funds are investment funds similar to mutual funds, but unlike mutual funds, ETFs are traded as stocks on the stock market. Much like index funds, ETFs usually aim to replicate the performance of a specific index. From the first ETF tracking the S&P 500, there are now ETFs for several asset classes, including equity, bonds, commodities, and currencies. There is also a broad spectrum of ETFs with more specific investment scopes, such as geography, maturity, ESG, or investment style. Due to its relatively low cost, access to liquidity, and diversification benefits, it has become a popular investment vehicle among investors. Since first introduced in 1993, the ETF market has grown substantially, and as of 2020, the total ETF market had about $7 trillion in assets under management globally (Todorov, 2021).

To understand the cost-effectiveness of ETFs, one must understand the unique mechanisms behind the asset class. ETFs generally rely on authorized participants (APs) to conduct trades that arbitrage the differences between an ETF and the value of its underlying securities. APs are usually large market-makers or broker-dealers that have an agreement with the ETF sponsor/trustee to participate in an in-kind transaction where the APs create or redeem ETF shares in exchange for a basket of the underlying whenever the ETF price is above or below the NAV.

To better understand the arbitrage process, we can look at creation and redemption scenarios separately. First, let us say an ETF experiences a surge in popularity, and its price moves above the NAV, then the ETF trades at a premium. In that case, APs are incentivized to step in and reconcile the difference between the price and NAV in a process known as the creation process. In a creation process, APs will go to the secondary market and purchase a creation basket, a basket of the underlying securities in the necessary weights, and exchange it with the ETF sponsor for a set of ETF shares. The APs can then sell the received ETF shares in the secondary market. In doing so, they put downward pressure on the ETF price and upward pressure on the NAV, which closes the gap between ETF price and NAV.

The opposite is the case when the ETF price moves below the NAV. The ETF then trades at a discount, and a redemption process is initiated. In this scenario, APs are incentivized to step in and purchase ETF shares in the secondary market. The APs will then exchange these ETFs with the ETF sponsor for a redemption basket of securities. The APs can take the redemption basket and sell it in the market. By doing so, they put upward pressure on the ETF price and downward pressure on the NAV, closing the gap between the ETF price and NAV. After accounting for transaction costs, the APs gain either the initial premium or discount as an arbitrage profit in both the creation and the redemption scenarios.

The ETF mechanisms described reduce the costs of ETFs compared to mutual funds and passive index funds. Since most ETFs passively track an index, the costs of setting up and managing them are relatively low compared to actively managed mutual funds. Still, when comparing the costs of ETFs with the costs of passive funds, ETF costs are lower. There are primarily two factors that reduce the costs of ETFs in comparison to other funds: (1) Operational cost transfer: Since APs are doing all the buying and selling, the hidden costs of operating a fund, such as transaction fees, distribution fees, and transfer agent fees, are moved to the APs. (2) Tax benefits: Take a redemption situation when the ETF trades at a premium. In this case, the fund would have to pay tax on the capital gains it makes when selling the redemption basket. Through the in-kind system, the APs can avoid the tax cost by controlling when the capital gain occurs by trading the ETF shares instead.

Bond ETFs incorporate unique features that make the asset class interesting to explore. Bond ETF shares trade on the liquid stock market, and the underlying securities trade on the relatively illiquid bond market. The implications of tying together two markets with contrasting properties and the liquidity mismatch this generates are worth understanding better. There are three primary factors for why bonds are more illiquid than equity: First, bonds trade in the over-the-counter market, a market that is not accessible to most investors, which means that there are fewer sellers and buyers. Second, minimum trade amounts are usually high, meaning fewer possible trades are made. Third, bonds do not trade as frequently as other assets, sometimes there are days between each transaction.

Additionally, bonds introduce a dimension that equity ETFs do not have, namely maturities. Usually, bond ETFs set a benchmark index and maturity that it seeks to track. Consequently, bonds must regularly be replaced to match target maturity. To optimally match the target benchmark index and maturity, ETF sponsors need to be flexible when deciding what securities to include in the ETF. The same flexibility is required by APs when they compose their baskets to match the key characteristics of the fund.

Bond ETFs have many of the same features as bonds and pay coupons to their investors regularly. The asset class is, therefore, a relatively cheap and convenient tool for investors looking to invest in the traditionally inaccessible bond market. It is, therefore, crucial that the market is as efficient as possible. This thesis seeks to measure and analyze the interplay between ETF price and underlying NAV to assess the efficiency of the asset class.

## 2.2 Bond ETFs as a Tool for Price Discovery

With characteristics such as providing diversification and liquidity at relatively low cost, ETFs have become an attractive asset class for an ever more diversified group of investors. The surge in popularity has made it an interesting topic for researchers. Hence, in the last few years, we have seen a growing body of research on how ETFs impact financial markets and the underlying securities.

Liebi (2020) provides a detailed literature review on some of the most important aspects of ETFs impacting the financial markets. These aspects include liquidity, price discovery, volatility, and the co-movement of the underlying securities. Regarding liquidity, Liebi (2020) finds that papers agree that ETFs usually improve the underlying liquidity, except during extreme market turbulence, when liquidity provision of ETFs can deteriorate, which can transmit to the underlying securities. With volatility, Liebi (2020) finds that when a security is included in an index, as in an ETF, its correlation with other stocks increases, resulting in a co-movement of securities included in the same ETF. We will focus on the aspect of price discovery, as this is the relevant factor we want to investigate in this thesis.

Following Ben-David et al. (2018), there are two opposing hypotheses related to the interplay between ETF and NAV and the fundamental value of the underlying securities. The first is what the authors call the "liquidity trading hypothesis." According to this hypothesis, ETF price movements are predominantly due to liquidity trading or nonfundamental liquidity shocks. When these liquidity shocks happen, the NAV will soon follow when APs arbitrage the gap between price and NAV. Once the shock's effect vanishes, the value of the ETF will revert to its fundamental value. A consequence of this liquidity trading is greater volatility in the underlying assets.

The second hypothesis, which Ben-David et al. (2018) label "the price discovery hypothesis," is, in essence, that fundamental shocks permanently change the value of the underlying securities, to which the ETF price responds quicker than the NAV. The NAV experiences staleness and only moves after the ETF price with a delay. As a consequence, premiums appear.

Utilizing a sample of equity ETFs, Ben-David et al. (2018) test the validity of the two hypotheses by examining whether ETF prices are associated with a large degree of mean reversion, suggesting temporary liquidity shocks. However, using ETF flows, they find that after an initial shock to the ETF price, the underlying securities first follow the movement of the ETF but revert to the original level during the next 40 days. The evidence shows a complete reversal of the price impact, which strongly supports the liquidity trading hypothesis.

However, literature has also found evidence that partially supports the price discovery hypothesis. Madhavan and Sobczyk (2016) developed a model based on the ETF arbitrage mechanisms, that captures the ETF price dynamics. In their model, they divide the premium into two parts: one measures the distance of the ETF price from the fundamental value of the underlying assets, and the other measures the NAV's distance from the fundamental value. The first part reflects transitory liquidity shocks, while the second reflects staleness in the NAV. Calibrating their model, they find that bond ETFs experience a larger degree of staleness than equity ETFs. This is also reflected in the time it takes to reduce the pricing error by half, which is 0.43 days for domestic equity ETFs and 2.02 days for domestic bond ETFs. Regarding the price discovery component, they find that it accounts for about 46% of the size in premiums across asset classes, implying that the NAV is, to a large extent lagging behind the ETF price.

While Ben-David et al. (2018) solely examine equity ETFs, Madhavan and Sobczyk (2016) compare ETFs with different asset classes as the underlying securities. The kind of ETFs the two papers focus on seems to lead to diversified findings on the importance of price discovery. Equity ETFs naturally have similar liquidity as ETF shares and, therefore, do not experience much staleness. Provided that staleness is the primary driver behind the price discovery aspect of premiums, it explains why Ben-David et al. (2018) only find evidence for the liquidity trading hypothesis. While for fixed-income ETFs, price discovery is a more plausible explanation, as the underlying security experience greater staleness, as

Madhavan and Sobczyk (2016) found.

Notably, ETFs can also amplify negative fundamental shocks in times of market turmoil. In a recent study, Dannhauser and Hoseinzade (2022) found that during the Taper Tantrum period, the bonds that were part of ETF holdings experienced greater increases in the yield spread relative to bonds that were not part of an ETF holding. However, with time the yield spreads of the ETF that included bonds revert to the level of the non-ETF bonds. Hence, especially during times of market turmoil not all movements in bond ETFs following a shock are due to price discovery.

The disagreement about whether ETFs can function as tools for price discovery and whether that price discovery is the source of premiums, makes it an interesting topic to investigate further. Madhavan and Sobczyk (2016) findings primarily focus on how the illiquidity of the underlying securities in bond ETFs impacts the size of premiums and the time it takes for the premiums to decrease in size. We aim to add to these results by examining how fundamental shocks initially impact premiums of bond ETFs. To do so, we will explore several factors associated with ETF premiums, and then we will discuss how surprising interest rate changes can function as fundamental shocks that impact the ETF price and NAV.

## 2.3 Factors of Bond ETF Premiums

As mentioned before, the liquidity of the underlying securities is a major factor behind ETF premiums and is one of the most common explanations for why bond ETFs exhibit more significant premiums than, for instance, equity ETFs. The explanation for the relatively bigger premiums in bond ETFs is, according to Madhavan and Sobczyk (2016), related to slower tracking error correction and slower arbitrage. In ETFs with bonds as the underlying securities, APs must weigh the costs of trading illiquid bonds with the benefit of arbitraging. Balancing this trade-off leads to slower arbitraging, slower error correction, and, ultimately, higher premiums. Shim and Todorov (2022) make similar observations in their paper analyzing the different explanations for premiums in bond ETFs. They find that within the ETFs holding exclusively bonds, the ETFs that hold less liquid bonds experience a greater persistence in their premiums. Thus, liquidity plays a crucial role in explaining premiums when comparing the different kinds of ETFs and within the different ETFs holding exclusively bonds.

Further, Shim and Todorov (2022) find that liquidity plays a significant role in explaining the magnitude of positive premiums and a smaller role in explaining the size of negative premiums (discounts). Similarly, Pan and Zeng (2017), who develop a model to predict the efficiency of ETF arbitrage, find that greater bond illiquidity limits arbitrage, which leads to persistent mispricing. They argue that with increased bond illiquidity, the additional costs from trading in the bond market outweigh the profits from arbitraging away the premiums.

Additionally, Pan and Zeng (2017) test whether balance sheet constraints may limit arbitrage. For instance, if an ETF is trading at a substantial discount, the AP would like to initiate a redemption process. However, Pan and Zeng (2017) find that APs sometimes face balance sheet constraints due to already holding large positions in certain bonds. In those cases, the AP's ETF-desks can be reluctant to redeem ETF shares and hinder the arbitraging, and in some cases, even go the opposite direction and *create* ETFs to reduce their bond holdings. Pan and Zeng (2017) find that this activity disconnects the creations/redemptions from initial mispricing, which distorts ETF arbitrage and leads to larger premiums.

Connected to the above point, Shim and Todorov (2022) also examine how the AP's inventory may impact premiums. By analyzing the extreme discounts observed at the outbreak of the Covid-19 pandemic, the authors hypothesize that APs have incentives to restrain from arbitrage under certain situations to protect the bonds in their inventory from fire sales. The idea is that when ETFs are trading at substantial discounts, the APs should ideally redeem ETFs which would lead to a decrease in the price of the underlying bonds, bonds that the APs, to some degree, also hold in their inventory. The market impact costs of redeeming the bonds might be substantial during periods of significant market stress as there is a significant risk of creating fire sales. Hence, in extreme market situations, such as the Covid-19 outbreak, APs weigh the benefits of arbitraging with the costs of creating potential fire sales. This can lead to larger discounts. According to Shim and Todorov (2022), this effect was evident in the period surrounding the outbreak of Covid-19 and the market turmoil that ensued.

The ETF size is another factor that has, in some aspects, been observed to be related to the size of premiums. Madhavan and Sobczyk (2016) find that large ETFs experience greater staleness than smaller ETFs. They suggest that the larger ETFs track larger indexes which are more difficult to mark to market. In contrast, Dannhauser and Hoseinzade (2022), who studied ETFs during the Taper Tantrum period, found that the largest ETFs in terms of AUM maintained ETF prices the closest to the NAV, while smaller ETFs experienced more persistent premiums than the larger ones. These findings are interesting since the largest ETFs in their sample are the ETFs with the highest liquidity, contradicting to a degree what Madhavan and Sobczyk (2016) suggests, that the larger ETFs, tracking larger indexes, experience more staleness than smaller ones. It is, therefore, worthwhile to investigate this further.

To sum up, the literature associates the size and the persistence of premiums to a large degree with the illiquidity of bonds. The result of illiquidity makes arbitraging more costly for the APs, who, in turn, weigh the cost of trading the underlying. The APs further consider how arbitraging affects their balance sheet and may reduce arbitraging if its impact on the balance sheet is too large. Another reason observed to be related to the premiums is the size of the ETFs.

# Chapter 3

# Theory and Hypotheses

## 3.1 Theory and Main Hypothesis

We are interested to see how fundamental shocks in the form of surprising interest rate changes may impact ETF premiums, assuming that ETFs function as tools for price discovery where the price reacts stronger to the shocks than the NAV does. In the following section, we will introduce the idea of using surprising federal funds rate changes as fundamental shocks to ETF and NAV and develop hypotheses on how the premiums react to these shocks under normal and specific circumstances.

As fundamental shocks, we will use surprising effective federal funds rate changes by exploiting a method introduced by Kuttner (2001) that takes advantage of the Fed funds future contracts. Kuttner (2001) developed this method to measure the impact of the Fed's fund rate target changes on interest rates. The idea is that the Fed's policy actions are usually composed of two parts: the anticipated component (i.e., the expected change in the target rate) and the surprise component. As market participants have certain expectations about the Fed's actions and anticipate a certain action with some probability, the anticipated component will likely already be priced in the market. Consequently, when the fund rate target is changed, the market should not react much to the anticipated component. However, the market does not know with certainty the policy action and is partially surprised by the action explained be the surprise component. Kuttner (2001) finds that the response in the interest rates to the surprise component is strong and significant, while the anticipated component's impact is minimal.

Since expectations about the Fed policy actions cannot be directly observed in the market, Kuttner (2001) uses the prices of Fed funds futures contracts[1] as a natural, market-based proxy for the expectations about the target rate changes. These futures are priced based on the expected average effective federal funds rate during a specific month. Krueger and Kuttner (1996) find that they efficiently forecast changes in the federal funds rate by incorporating almost all publicly available quantitative information. Additionally, investors can trade in the "spot month," which is the future contract for the effective federal fund rate of the current month.

The author uses the spot-month contract to extract the surprising target rate changes, described in the following: At any day t during the spot months, the rate used to price the future contract is as follows:

$$f^0_{s,t} = \frac{t}{m}\bar{r}_{i\leq t} + \frac{m-t}{m}E_t\bar{r}_{i>t} \tag{3.1}$$

Where $m$ is the number of days during that specific month, $\bar{r}_{i\leq t}$ is the realized average rate for all days prior to and including day $t$, and $E_t\bar{r}_{i>t}$ is the expected average rate for the remaining days during the month $s$. Consequently, $f^0_{s,t}$ is a weighted average of the already realized average effective federal funds rate and its expected average rate during the remaining month. As the measure includes expectations about the effective federal funds rate for the remaining month, only unexpected changes or changes in these expectations can alter the contract price. A change in the price from *t-1* to $t$ can then be interpreted as follows:

$$(f^0_{s,t} - f^0_{s,t-1}) \ = \frac{m-t}{m}\Delta\tilde{r}^u_t \tag{3.2}$$

In the equation above, $\Delta\tilde{r}^u_t$ is the unexpected change in the average federal funds rate or a change in the expectations about future changes during the current month. $\Delta\tilde{r}^u_t$ is scaled by $\frac{m-t}{m}$ on RHS since a surprise that happens early in the month will have a greater impact on the average expected rate than a surprise happening late in the month. If $f^0_{s,t} - f^0_{s,t-1} = 0$, no surprise has been recorded on day t. To find the surprise rate change we can rewrite the equation as follows:

$$\Delta\tilde{r}^u_t = \frac{m}{m-t}(f^0_{s,t} - f^0_{s,t-1}) \tag{3.3}$$

With a few exceptions, the above equation holds for any day of the month. As for the month's first day, Kuttner uses the previous month's "one-month" future

[1]Initially established at the Chicago Board of Trade, Fed Funds Futures contracts now trade at the Chicago Mercantile Exchange (CME) and trade for all months up to 5 years into the future.

contract rate, as observed on the last day of the month instead of $f^0_{s,t-1}$. The "one-month" future rate $f^1_{s-1,m}$ is used since the "one-month" contract turns into the spot contract on the first day of the month $s$. For the last 3 days of the month, it is suggested to use the unscaled change in the "one-month" contract in order to minimise the effect of possible month-end noise in the effective funds rate (Bernanke & Kuttner, 2005).

Since first introduced, Kuttner's method has been used extensively in academic research to measure the impact and effectiveness of monetary policy and how surprises impact the market (e.g., Bernanke and Kuttner (2005); Faust et al. (2007)). For instance, Bernanke and Kuttner (2005) study how surprising target rate changes impact changes in equity prices on FOMC announcement days and find that they lead to an increase in broad stock indexes. Faust et al. (2007) look at intraday changes in the Federal funds futures contracts to measure the high-frequency response of exchange rates and interest rates to monetary policy announcements.

After observing the advantage of using Kuttner's method for measuring specific impacts of target rate changes on FOMC announcement days, we believe the method can also be used in a more general setting, even when the aim is not to measure the impact of some specific event. Unlike the papers mentioned earlier, we are not interested in measuring the impact of events per se, at least not as our primary objective. Instead, we are interested in analyzing whether ETF prices and NAVs react differently to fundamental shocks and whether the ETFs can function as price discovery tools. The effective federal funds rate, and expectations about its rate, change consistently as new information hits the market, and we argue that the surprising changes can be used as fundamental shocks that we can measure and use for further analysis.

Kuttner (2001) finds that surprising rate changes, as predicted by the Fed funds futures, impact interest rates. More specifically, he finds that surprises impact interest rates of all maturities from 3 months up to 30 years. However, the impact is the strongest for the rates with shorter maturities. According to standard finance theory, interest rates have an inverse relationship with bond prices. Consequently, surprising interest rate changes should impact the price of bonds and the price of any security that has bonds as underlying, such as ETFs. Therefore, we argue that surprises can be applied as fundamental shocks to ETF prices and NAVs. Considering the liquidity mismatch, we can take advantage of the relationship between ETF price and NAV to investigate whether they react differently to fundamental shocks. Specifically, since the interest rate shocks are fundamental in nature, a situation in which the ETF reacts stronger to the surprise than the NAV would suggest that the NAV experiences staleness and the ETF function as a price discovery tool. Consequently, the interplay between ETF price and NAV would result in a change in the ETF premium.

Following this idea, we can predict how an interest rate surprise impacts ETF premiums. A surprising hike (cut) in the effective federal funds rate should lead to a decrease (increase) in ETF price and NAV. However, as the ETF price reacts more strongly, the price decreases (increases) more, and as a consequence, the premium changes negatively (positively). Therefore, our main hypothesis is as follows:

*Hypothesis 1: Surprising federal funds rate changes are negatively correlated with changes in bond ETF premiums.*

## 3.2 Hypothesis 2

Other than the ETF-specific mechanisms discussed earlier, we assume that different economic factors also impact the relationship between surprises and ETF premiums. In the following, we will discuss a few of these factors, building upon the discussion of the different factors related to ETF premiums. The factors we are looking at include (1) bond market illiquidity, (2) riskiness of the underlying bonds, (3) ETF size, (4) FOMC meetings, and (5) the post-Covid period.

Recalling the findings of Pan and Zeng (2017), general bond market illiquidity significantly impacts the AP's arbitrage activity. In particular, as bond market illiquidity increases, the APs arbitrage less for a given size of the ETF premium, which can be associated with the APs weighing the benefits of arbitraging with the additional transaction costs from managing their bond positions. Consequently, the NAV should experience more staleness with greater bond market illiquidity. Assuming that the ETFs price discovery component is unchanged by bond market illiquidity, the effect of an interest rate surprise should be amplified during times of increased bond market illiquidity. In other words:

*Hypothesis 2: With increased bond market illiquidity, the impact of surprising federal funds rate changes on changes in bond ETF premiums is increased.*

## 3.3 Hypothesis 3

Bond ETFs vary in size regarding asset under management (AUM). We have seen before that ETF size seems to impact premiums, even if that impact is ambiguous. Madhavan and Sobczyk (2016) find that large ETFs experience the greatest staleness, which in the context of this thesis, would imply the amplified impact of the surprise on premiums due to AUM size. On the contrary, Dannhauser and Hoseinzade (2022) find that during the Taper Tantrum period, premiums were the smallest for large ETFs, and smaller ETFs usually had more significant and more persistent premiums. If staleness is connected to premium size, those findings contradict each other. Therefore, finding that size significantly affects the impact of surprises on premiums in any direction would shed some extra light on how ETF size might impact premiums. Therefore, we introduce the following non-directional hypothesis:

*Hypothesis 3: ETF size alters the impact of surprising federal funds rate changes on changes in bond ETF premiums.*

## 3.4 Hypothesis 4

Having discussed how liquidity and specific ETF characteristics impact the relationship between surprise and premiums, we now focus on the impact of specific events. One such specific event is the scheduled announcement of changes in monetary policy by the Federal Open Market Committee (FOMC). Eight times a year, the FOMC holds pre-scheduled meetings to review economic and financial conditions and assess the risks to its long-run goals of price stability and maximum employment. Based on these assessments, the FOMC decides on the appropriate stance of monetary policy (Feliz et al., 2021). Towards the end of the two-day meetings, the Chair announces the decisions in a press conference. Statements containing information about the FOMC views on the economy and possible changes to the monetary policy are released with it.

The FOMC announcements are particularly interesting as they are the most direct way the Fed impacts the economy. The Fed's primary tool for conducting monetary policy is lowering or increasing the target interest rate and, by doing so, directly impacting the short-term interest rate. Since the financial crisis, the Fed has also applied more alternative tools for conducting monetary policy, such as large-scale asset purchase programs or quantitative easing (QE), where the Fed will purchase assets in the open market to boost the economy.

Due to its economic implications, the impact of the FOMC meetings has been studied widely, partially using the Kuttner (2001) approach. However, the literature finds that the Fed impacts the market via various additional channels on the days they announce monetary policy changes beyond the impact of surprising target rate changes. One of the alternative channels is the statements that the Fed publishes alongside the decisions about the changes in the target rate. Gürkaynak et al. (2005) find that the information released in the statements accounts for more than three fourth of the explainable variation in the movements of five and ten-year treasury yields on FOMC dates. In comparison, the surprising changes in the target rate only account for about a fourth of the variation of these long-term yields. The authors believe this is due to the statements influencing financial market expectations of future policy actions.

Similarly, Hillenbrand (2021) finds that long-run Fed guidance further impacts long-term bond yields due to the dot plot. This dot plot, published on FOMC announcement days, shows the FOMC members' forecasts for the federal funds rate over the upcoming three years and their forecasts for the federal funds rate over the longer run. The author finds that decreases in the long-run forecasts lead to long-term yield decline. He suggests that this is due to the Fed's guidance about the long-term interest rates causing the market to update its beliefs about the future path of short rates.

Research has also found that the FOMC announcing policy changes can cause the market to update its beliefs about the future path of the economy. Smolyansky and Suarez (2021) examines whether surprising monetary policy changes impact the yield spreads of corporate bonds via a 'Fed information effect.' This effect captures the idea that the Fed's surprising monetary policy tightening (easing) signals a healthier (weaker) economy than previously believed. Using the price reaction of corporate bonds to changes in the 2-year nominal Treasury yield on FOMC announcement dates, they find that riskier corporate bonds outperform safer ones following a target rate hike and underperform following a target rate cut. Hence, surprises in FOMC announcements appear to impact credit spreads by updating the markets' view of the economy.

The literature concludes that the financial markets are impacted in various aspects beyond the unexpected changes in the federal funds rate on FOMC announcement days. Consequently, the impact may also alter the reaction between the Kuttner-surprises and the bond ETF premiums on those dates. For instance, by FOMC announcements affecting long-term yields, the surprises may impact premiums differently than on normal days. The same applies to the affected credit spreads, which can change the relationship between the surprise and the ETF premium. A further factor not discussed yet is that both realized volatility and trading volume jump after the announcement as the market incorporates new information into the market (Lucca & Moench, 2015). All these different factors lead us to specify the following non-directional hypothesis:

*Hypothesis 4: On FOMC announcement days, the impact of surprising federal funds rate changes on changes in bond ETF premiums is altered.*

## 3.5 Hypothesis 5

It is interesting to examine the development of the relationship between the Kuttner-surprises and the bond ETF premiums over time. The last few years are especially interesting to investigate. The 2010s is a period characterized by a long expansion of the U.S. economy, a period that was quickly abrupted by substantial market turmoil and rising interest rates caused by the outbreak of the Covid-19 pandemic.

In early 2020, it became evident that Covid-19 was a global pandemic. To mitigate the impact of the pandemic, governments globally enforced lockdowns, social distancing, and limitations to commercial activity. These lockdown measures led to a substantial hit to the global economy. The market turmoil was characterized by a significant increase in market volatility, plummeting equity prices, a rapid increase in unemployment, and a significant drop in the inflation rate. To battle the economic impact of the lockdowns, the Fed responded with unprecedented measures such as setting the target rate to zero lower bound, substantial open market operations, and large-asset asset purchase programs. (Clarida et al., 2021). The result was that the Covid-19 recession was the shortest recession in U.S. history, only lasting for two months, as the economy started to expand again in May 2020 (NBER, 2021).

No part of the economy was spared, and the bond market experienced soaring yield spreads and an almost standstill in liquidity. To stimulate the bond market, the Fed introduced two programs that directly impacted the bond market and the bond ETF market. The Primary Market Corporate Credit Facility (PMCCF) involved purchasing investment-grade bonds, while the Secondary Market Corporate Credit Facility (SMCCF) was aimed at investment-grade bond ETFs (Clarida et al., 2021). Later on, the SMCCF also expanded to include high-yield bond ETFs (Todorov, 2021)

The initial Covid months corresponding to the economic recession during March and April 2020 were interesting since bond ETFs as premiums increased enormously during this period (Todorov, 2021). However, examining bond ETF premiums during the subsequent expansion is equally interesting. The post-Covid period is characterized by some distinct differences compared to the pre-Covid expansion. Although the economy has been in a boom period since the initial turmoil of the pandemic outbreak, it has shown distinct differences compared to the boom period before the Covid shock. The post-Covid period includes comparable higher levels of inflation and an increased probability of a recession due to the Fed's mitigating actions to battle the persistent inflation.

Initially, the increasing U.S. inflation rates were seen by many, including the Fed, as transitory (Federal Open Market Committee, 2021)). As the unemployment rate fell to only pre-pandemic levels following the initial Covid shock, the persistence of inflation was underestimated (Ball et al., 2022). Finding very high values for the ratio between job vacancies and unemployment during 2021 and 2022, (Ball et al., 2022) suggest that labor markets were actually much tighter during that period, causing core inflation to rise. Further, they suggest that the observers who considered the inflation to be transitory overlooked the concurrent impact of the Covid-related inflation shocks on core inflation. In that regard, Ball et al. (2022) find that shocks such as the shock to energy prices and problems in supply chains make up for 4.6 percentage points of the 6.9 percentage point rise in inflation between late 2020 and September 2022.

The high and persistent inflation levels have motivated the Fed to tighten monetary policy substantially. From a target rate at the zero lower bound, the Fed has increased the target rate to above 4.25 percentage points through several consecutive target rate hikes of up to 75 bps in size until the end of 2022. Increased interest rates have far-reaching economic implications. Higher borrowing costs lead to reduced investments, reduced consumption, cooled economic growth, and a potential recession. If there is a general fear of recession in the market, it could also exaggerate its response to surprising changes in the federal funds rate.

We suspect that the ramifications of the persistent inflation also impact the bond (ETF) market. We suspect that bond ETFs react stronger to surprises compared to the more stable period during the period before Covid. Further, due to the liquidity mismatch, this will exaggerate the impact on the bond ETF premiums:

*Hypothesis 5: During the post-COVID period, the impact of surprising federal funds rate changes on changes in bond ETF premiums is increased.*

# Chapter 4

# Methodology

The following section presents the methodology used to test our hypotheses empirically. We use a linear model, which we extend by adding interaction terms between the Kuttner-surprises[1] and proxies of the factors we believe alter the surprises' impact on the ETFs. The model is run on the change in premiums and the change in ETF price and NAV, respectively, to investigate whether the impact on premiums is due to price discovery in the ETFs. Since the data sample contains observations across both the ETF- and time dimension, we discuss the appropriateness of different panel methods. Lastly, we elaborate on the limitations of our methodology.

## 4.1 The Model

To investigate our hypotheses, we set up a linear model. The change in premium (from now on referred to $\Delta$Premium) is modeled as a function of the Kuttner-surprises, a vector X consisting of the factors we believe alter the relationship between Surprise and $\Delta$Premium and interaction terms between vector X and Surprise. Further, a one-day lag of the premium is included:

$$\Delta\text{Premium}_{i,t} = \beta_0 + \beta_1\text{Surprise}_t + \beta_2 X_{i,t} + \beta_3\text{Surprise}_t \cdot X_{i,t} + \beta_4\text{Premium}_{t-1} + \varepsilon_{i,t} \tag{4.1}$$

Where $i$ is the specific ETF and t the day of the observation.

We choose to use interaction terms as it allows us to test the before-established hypotheses within the framework of a linear model. By keeping the model linear

[1] We define the Kuttner-surprises as the variable *Surprise*

in parameters, we can still estimate the model's coefficients using linear regression techniques like ordinary least squares (OLS). By having interaction terms, we can observe whether the impact of Surprise on ΔPremium is stronger or weaker, e.g., on days of more illiquid bond markets or on days with FOMC announcements.

The one-day lag of the premium is included to proxy and control for general arbitrage pressure on the premiums by the APs. Since APs have strong incentives for closing any existing gap between the ETF price and NAV, yesterday's premium should explain, to some degree, ΔPremium. For instance, if a positive premium is observed at *t-1*, the APs will try to arbitrage the premium away, leading to a negative ΔPremium. Vice versa, if at *t-1* a discount is observed, arbitraging away the premium should lead to ΔPremium being positive.

Apart from analyzing the impact of the surprises on ETF premiums, we are also interested in whether the change in ETF premiums is due to the ETF responding faster to the shock than the NAV. Measuring the impact on ΔPremiums will only tell us that there is a difference in the response of the two, but not to what degree it impacts the ETF price and the NAV individually. To test this, we run the same model separately on the change in price and NAV (see equations 4.2 and 4.3 below). By doing so, we will be able to observe the general reaction of the ETF and the underlying assets to the shock, and more importantly, we can see whether the ETF price responds quicker to the shock than the NAV does.

$$\Delta\text{Price}_{i,t} = \beta_0 + \beta_1 \text{Surprise}_t + \beta_2 X_{i,t} + \beta_3 \text{Surprise}_t \cdot X_{i,t} + \beta_4 \text{Premium}_{t-1} + \varepsilon_{i,t} \quad (4.2)$$

$$\Delta\text{NAV}_{i,t} = \beta_0 + \beta_1 \text{Surprise}_t + \beta_2 X_{i,t} + \beta_3 \text{Surprise}_t \cdot X_{i,t} + \beta_4 \text{Premium}_{t-1} + \varepsilon_{i,t} \quad (4.3)$$

## 4.2 Panel Data Methods

To estimate the coefficients of the model parameters, we will use a panel dataset including several ETFs observed over eleven years. The most straightforward and efficient approach to run the model is to pool the data and use OLS, a method also known as pooled OLS (POLS). In doing so, we ignore the dataset's panel structure and disregard each observations' time and cross-section. However, the panel structure can be useful as it allows us to control for some of the unobserved factors in our model, reducing the chance of omitted variable bias. Those factors for bond ETFs include, e.g., the maturity or rating of the underlying bonds, as well as the investment focus of the ETF.

These unobserved ETF-specific factors can potentially be related to our independent variable $\Delta$Premium and the ETF-specific explanatory variables (i.e., variables regarding the ETF size or the premium in the previous period). If that is the case, using POLS will result in obtaining biased coefficients. However, assuming that these factors are constant over time, advanced panel methods such as the entity fixed effects (FE) or random effects (RE) estimator can be used to control for the unobserved factors. This assumption is likely to hold as, e.g., an ETF that offers exposure to high-yield long-term corporate bonds at the beginning of the sample period will also do so at the end.

Using the FE estimator, the original model is transformed by time-demeaning the data for each ETF. This approach subtracts the ETF-specific time-mean from each variable and thereby controls for unobserved ETF fixed characteristics. This is effectively the same as adding a dummy for each ETF to the model, known as the least squares dummy variable (LSDV) approach. The LSDV approach can also be used to test the appropriateness of the more efficient POLS estimator over the FE estimator. The test uses an F-test for the joint significance of the ETF dummies. If the test result is insignificant, it implies that the ETF dummies in the FE estimator do not improve the estimation, warranting the use of POLS for the regression.

The RE estimator is similar to the entity FE estimator, but it differs in that it assumes that the unobserved variables are uncorrelated with the regressors included in the model. Under that assumption, the estimator subtracts fractions of the average variable values from the original specification, reducing the loss in degrees of freedom compared to FE. Hence, the RE is more efficient than FE, with the RE estimates being between the FE and POLS estimates. To test whether the RE estimator is optimal, we apply the Hausman test. The Hausman test checks whether using FE and RE will give similar estimates. We refrain from using the RE estimator if the Hausman test indicates that the RE estimates differ significantly from the FE estimates.

In our thesis, we initiate the analysis by simultaneously running the complete model 4.1 with POLS, ETF fixed effects (FE), and random effects (RE) estimator. Based on the obtained estimates, we will run the F-test for the joint significance of the dummies and the Hausman test to decide on the most appropriate estimator. We will apply the optimal estimator for the remaining analysis.

## 4.3 Limitation of Methodology

Before exploring the data, it is essential to address a limitation of our methodology. The Kuttner-surprises have initially been used in event studies, which use the controlled release of economic news as a pseudo-natural experiment. This methodology assumes that the jump in an asset price during a small window around the announcement of some news reflects the causal impact of the particular news and likely little else (Gürkaynak & Wright, 2013). As we are not interested in the effect of some specific news that caused a surprise on a specific day, except for FOMC announcement days, this is not necessarily important in our approach.

However, it can be an issue that we do not precisely know when the surprise happens on a specific day. By measuring all variables on a daily end-of-day basis, our approach assumes that all surprises happen shortly before closing time. However, since the surprise can happen anytime during the day, part of the shock may not be observed in our analysis since the NAV may already have caught up with the ETF by the time we measure it. Therefore, since we can miss the initial shock in our analysis, it can lead to measurement errors in our model.[2]

Nevertheless, considering the persistence of premiums, we believe the approach can still be justified in the case of bond ETF premiums. Madhavan and Sobczyk (2016) define the half-life concept, which measures the period over which a given deviation of the ETF price from the NAV is halved. They find that the half-time of domestic bond ETFs equals 2.02 days. This finding implies that it takes, on average, about two days until a bond ETF premium of 2% is reduced to 1%. For comparison, the half-time of domestic equity ETFs is much shorter (0.43 days). Given this evidence, we believe using end-of-day measurements is sufficient for measuring the impact of the surprise on bond ETF premiums since it takes several days to close bond ETF premiums. While high-frequency data provides a superior temporal localization of the surprise shock, we postulate that the described half-time allows us to observe most of the impact of the surprise at the end of the day. Also, any impact we find at the end of the day can be assumed to be even more significant close to the actual occurrence of the surprise.

[2]The exception is the surprises that occur on FOMC announcement days. These announcements are usually made late in the trading day, lately at 2:00 pm. Hence, we have a more accurate measure of the surprise impact on FOMC days.

# Chapter 5

# Data

In this section, we will describe the data used in our analysis to investigate the impact of the fundamental shocks in the form of surprises on bond ETF premiums. Our sample consists of data collected from 65 U.S. bond ETFs from January 2012 until December 2022. We chose this period to obtain a sufficiently large sample of ETFs, allowing us to observe the whole period and acquire a balanced panel. Even though the first bond ETFs have existed since 2002, many current large ETFs were only created afterward. By applying a sample starting in 2012 and ending in 2022, we cover a large part of the expansion period of the U.S. economy during the 2010s and the post-Covid period. In total, we have data from 2786 trading days.

According to etf.com (2023), one of the leading information providers on ETFs, there are, as of June 2023, 592 ETFs traded on the U.S. market, with $1,388 billion in total assets under management (AUM). While most of these ETFs include bond ETFs focusing exclusively on the U.S. market, a fraction includes global bonds, focusing, e.g., on emerging markets or developing countries. We exclude the international ETFs as U.S. interest rate changes might impact underlying international bonds differently than U.S. bonds. Further, we exclude any inverse and leveraged fixed-income ETFs. The remaining 425 U.S.-bond ETFs make up $1,235 billion in AUM. The 65 bond ETFs in our sample are among the 150 largest bond ETFs in terms of AUM today and correspond to $871 billion in AUM. [1] Therefore, our sample accounts for 70.5% of the corresponding U.S. bond ETF market today. An overview of the raw data, which we either use directly or manipulate to obtain the variables of interest, can be found in Table 5.1 below.

[1] For a closer look at the sample, please refer to Table A.1 and Table A.2

Table 5.1: Data Sources

| Data | Description | Source |
|---|---|---|
| ETF-Prices | End-of-day ETF prices | Bloomberg |
| NAV of ETFs | End-of-day net asset value of the ETFs' underlying assets | Bloomberg |
| 30 day Fed Funds Futures | End-of-day prices of 30-Day Federal Fund Futures | Bloomberg |
| VIX | End-of-day prices CBOE Volatility Index | Yahoo |
| AUM | End-of-day ETF asset under management size | Bloomberg |
| FOMC Statistics | Dates of FOMC announcements | Bloomberg |

## 5.1 Dependent Variable

To obtain a measurement of the ETF premiums required to compute changes in the premiums, we collect data on the daily ETF closing prices and closing NAVs from Bloomberg. Bloomberg collects data on an ETF's NAV directly from the ETF sponsor, who uses proprietary models to estimate the NAV (Pan & Zeng, 2017). Further, Bloomberg adjusts the data on the NAV for differences in the closing times of the equity and bond market, aligning the ETF price and the NAV to the closing time of the equity market (Pan & Zeng, 2017). This process ensures that ETF price and NAV are measured at the same time.

The premium measured for a specific ETF on day t is then simply the relative difference between its price and NAV on that day:

$$\text{Premium}_{\text{ETF},t} = \frac{\text{Price}_{\text{ETF},t} - \text{NAV}_{\text{ETF},t}}{\text{NAV}_{\text{ETF},t}} \tag{5.1}$$

Since we are not interested in the level of the price discrepancies but in how they get affected by the surprises, we are computing the change in the premiums (ΔPremium) by taking the differences between the premiums on the date of the observed surprise and the day before. Further, we multiply the change by 10,000 in order to analyze the results in basis points (bps):

$$\Delta\text{Premium}_{\text{ETF},t} = (\text{Premium}_{\text{ETF},t} - \text{Premium}_{\text{ETF},t-1}) \times 10,000 \tag{5.2}$$

Hence, $\Delta\text{Premium}_t = 1$ is a change in the price discrepancies of one bps.

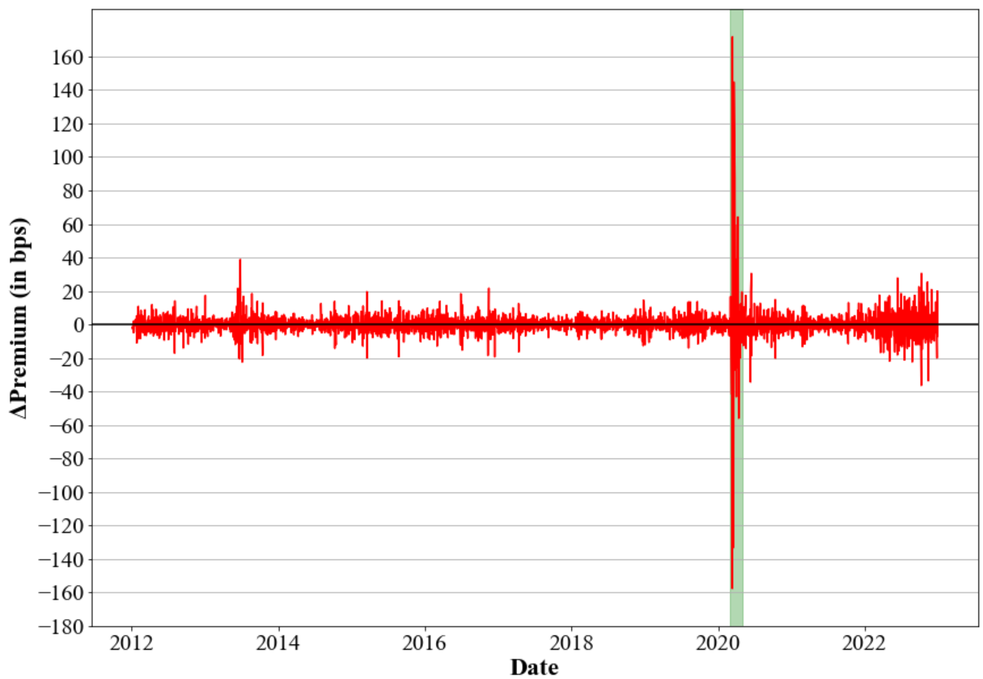
Figure 5.1 below shows the average ΔPremium of the 65 ETFs in our sample from 2012 to 2022. A few things can be observed. First, the average ΔPremium for the ETFs in our sample is for most days within a range of ±20 bps from zero, or at least between ±40 bps. The exception is some very large observations during the initial period of Covid-19 in March-April 2020, highlighted in green in the figure. During that time, the changes in average $\Delta$Premium extend from +160 bps to -160 bps. These extreme outliers suggest that the two months should be excluded from the analysis, as they can potentially alter any estimate significantly.

As described in the methodology, we also look at the change in the ETF price and NAV, respectively. We do that to gain more insight into how both react to the surprises and discuss the applicability of ETFs as a price discovery tool. The relative day-to-day changes in the ETF price and the NAV itself, which reflect the returns of both variables, are again multiplied by 10,000 to be measured in bps (see equations 5.3 and 5.4).

$$\Delta \text{Price}_{\text{ETF},t} = \left( \frac{\text{Price}_{\text{ETF},t} - \text{Price}_{\text{ETF},t-1}}{\text{Price}_{\text{ETF},t-1}} - 1 \right) \times 10,000 \tag{5.3}$$

$$\Delta \text{NAV}_{\text{ETF},t} = \left( \frac{\text{NAV}_{\text{ETF},t} - \text{NAV}_{\text{ETF},t-1}}{\text{NAV}_{\text{ETF},t-1}} - 1 \right) \times 10,000 \tag{5.4}$$

Figure 5.1: Average ETF $\Delta$Premiums




*Note:* The figure displays the average $\Delta$Premiums from Jan 2012 to Dec 2022. The outbreak of COVID-19 in March-April 2020 is highlighted in green.

## 5.2 Explanatory Variables

Table 5.2 below provides an overview of all the variables used to investigate the hypotheses.

Table 5.2: Data Description

| Data | Description | Measurement | Concept |
|---|---|---|---|
| ΔPremium | Day-to-day change in ETF premium | In bps | Dependent Variable |
| ΔPrice | Day-to-day change in ETF price | In bps | Additional Dependent Variable |
| ΔNAV | Day-to-day change in ETF NAV | In bps | Additional Dependent Variable |
| Surprise | Surprising change in effective federal fund rate | In bps | Hypotheses 1 |
| VIX | Proxy for aggregated bond market illiquidity | Index | Hypotheses 2 |
| AUM | Assets under management | Standardized | Hypotheses 3 |
| FOMC | FOMC announcement days | Dummy | Hypotheses 4 |
| Post-Covid | Post-Covid period | Dummy | Hypotheses 5 |
| One day lag of premium | Size Premium on the previous day | In bps | Control Arbitrage Mechanism |

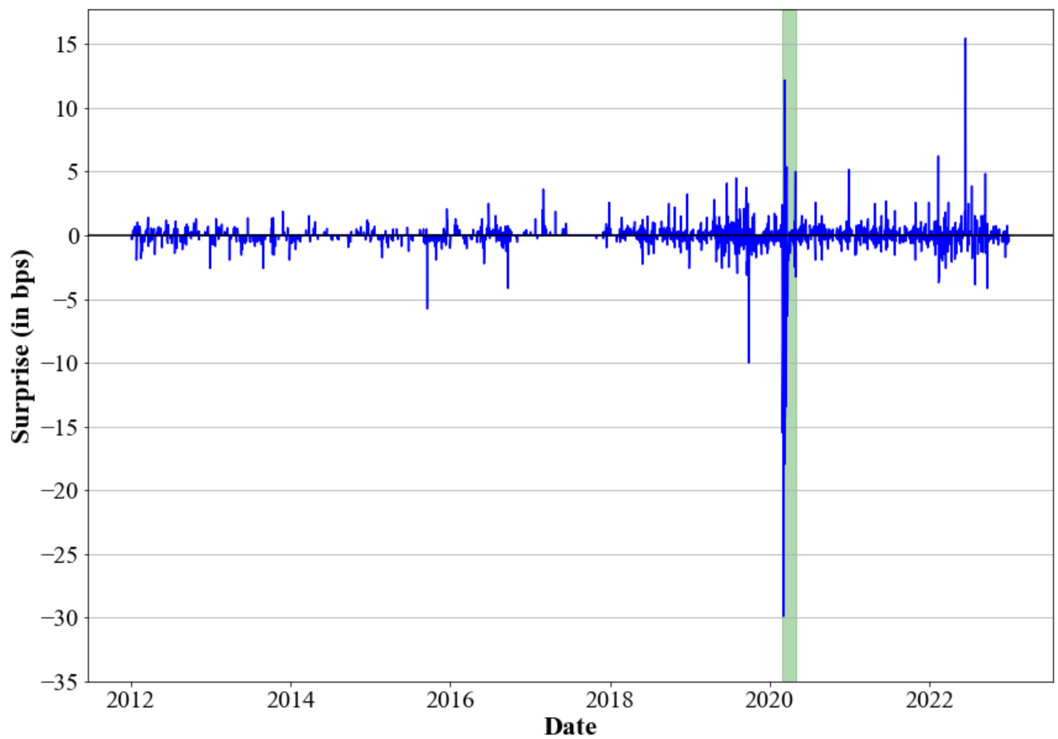
The main independent variable on which we test our hypotheses is, as discussed in the hypotheses part, the surprising change in the effective federal funds rate measured using the Kuttner (2001) method, which takes advantage of changes in the federal funds future contracts. Data on the closing prices of the federal funds futures contracts are obtained from Bloomberg. Since we need the prices of the contracts during each month where the contracts are maturing and the prices on the last day of the previous month, we must look at 132 different contracts.

In Figure 5.2, we can observe the time series of the extracted surprises. There are several interesting findings to be made. First, most of the surprises lie between ±5 bps, though we can observe some larger outliers. As with the ΔPremium observations, we find the most striking outliers during the initial Covid month in March and April 2020 (highlighted green). We can observe surprises far below -10 and one larger than +10 on several days during this period. These observations confirm that excluding the two Covid months from the analysis is a good idea. Additionally, to these Covid-outliers, we observe two outliers larger than 10 bps in absolute terms, one observation in late 2019 and one negative outlier in mid-2022. We must consider the outliers in our analysis, as they can potentially function as leverage points that can severely bias our findings.

In addition to the outliers, it can also be observed that the surprises are happening more often during the last years of our sample. This trend likely stems from escalating market uncertainty due to Covid-19 and more pronounced increases in the Federal Reserve's target rate. In comparison, we observed that the surprises were fewer and weaker during the first few years of our sample, a period characterized exclusively by zero lower-bound interest rates.

We employ the CBOE Volatility Index (VIX) closing values obtained from Yahoo Finance to test our second hypothesis. We use the VIX to proxy for the general bond market illiquidity. While the VIX primarily measures the implied volatility in the stock market, Bao et al. (2011) find that the VIX is also signifi-

Figure 5.2: Surprises



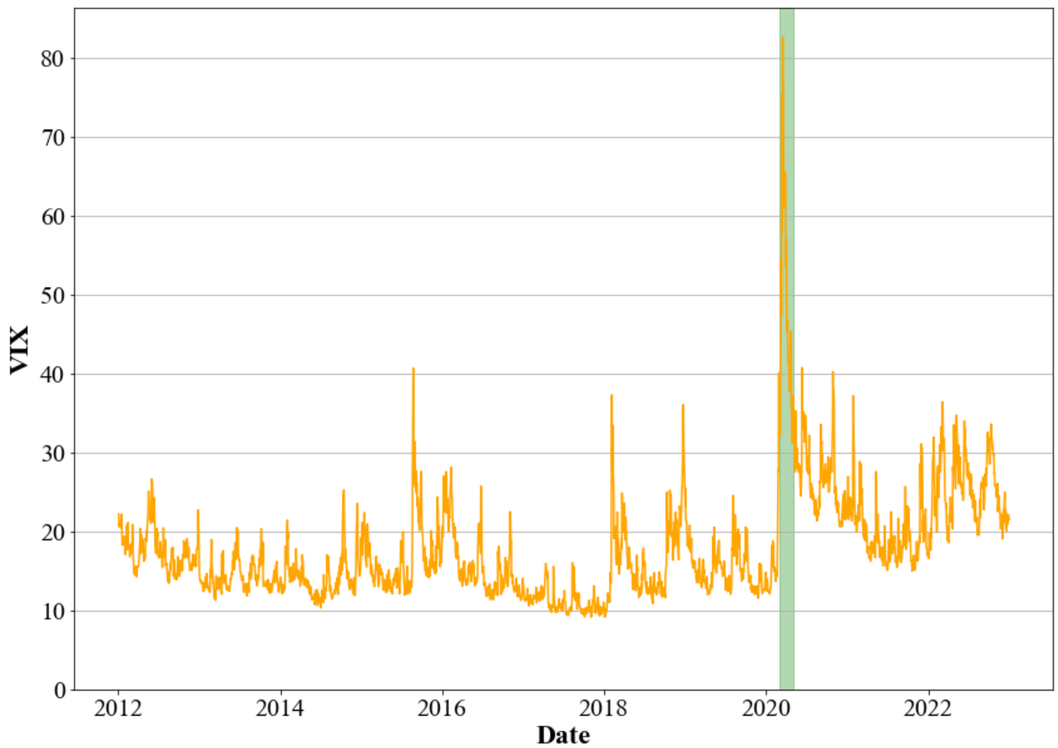

*Note:* The figure displays the federal funds rate surprises from Jan 2012 to Dec 2022. The outbreak of COVID-19 in March-April 2020 is highlighted in green.

cantly and positively related to the illiquidity of corporate bonds. After publishing their influential paper, the VIX has been used as a proxy for the bond market illiquidity in several studies on corporate bonds (e.g., Goldstein et al. (2017), Javadi et al. (2018), Pan and Zeng (2017)).

Figure 5.3 plots the time series of the VIX from 2012 to 2022. As with $\Delta$Premium and the surprises, we observe the most extreme outliers during the initial Covid-19 period in March-April 2020. In contrast to the rest of the sample period, where the VIX rarely exceeded 40, the VIX reached values well above 80 and usually hovered above 40 during the Covid-months. This finding further underscores the importance of omitting the Covid period from our analysis. Strikingly, after the initial Covid shock, the VIX stays elevated on average compared to the pre-Covid time.

To test the hypothesis on ETF size, we have extracted data on the asset under management (AUM) of each bond at each point in time. Since its introduction, the bond ETF market has steadily increased in size. We can observe this surge in popularity in Figure 5.4, a time plot of the aggregated AUM of the whole sample. While the aggregated AUM was below $200 billion in 2012, it quadrupled by 2022,

Figure 5.3: VIX

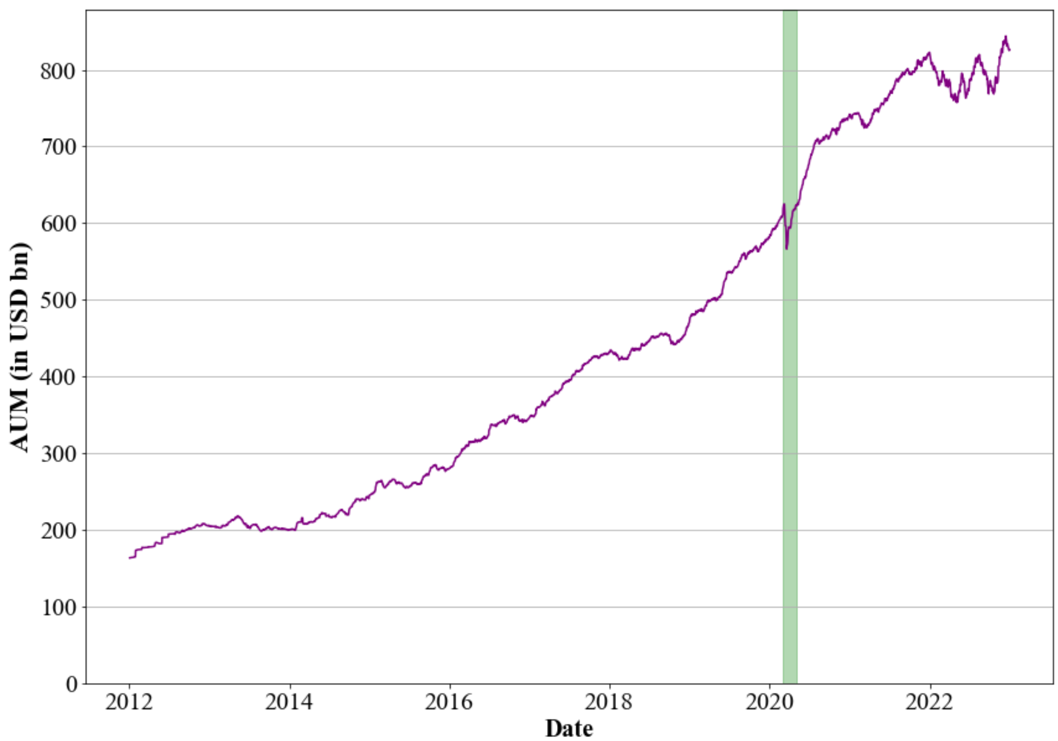



*Note:* The figure displays CBOE Volatility Index (VIX) closing values from Jan 2012 to Dec 2022. The outbreak of COVID-19 in March-April 2020 is highlighted in green.

reaching over \$800 billion. Due to this large growth of the bond ETF market, we cannot include AUM measured in dollars in our regression, as the current much larger observations would dominate the estimates. Instead, we standardize AUM by subtracting the mean on day $t$ from each observation and dividing it by the standard deviation on day $t$:

$$\text{AUM Stand.} = \frac{\text{AUM}_{\text{ETF},t} - \mu_{\text{AUM},t}}{\sigma_{\text{AUM},t}} \tag{5.5}$$

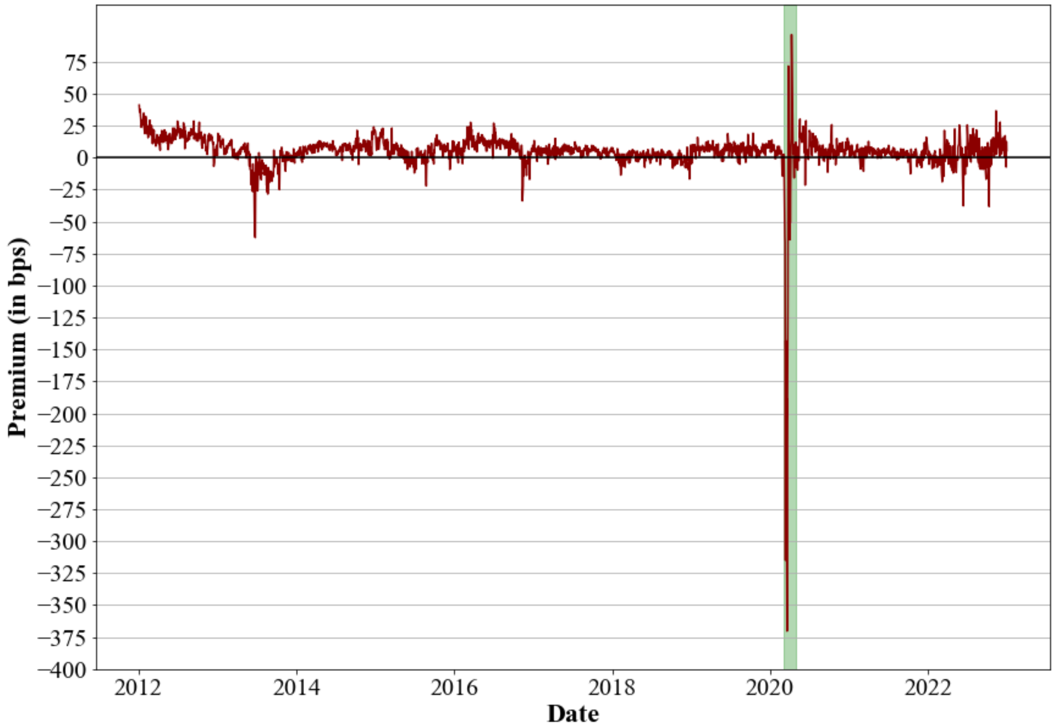
Figure 5.4: AUM




*Note:* The figure displays the aggregated asset under management (AUM) of the 65 bond ETFs in our sample from Jan 2012 to Dec 2022. The outbreak of COVID-19 in March-April 2020 is highlighted in green.

In addition to the variables described, we specify dummies for FOMC meetings and the post-Covid time. We define the post-Covid period as the period that starts after May 2020. We specify these dummies to examine our hypotheses that the relationship between Surprise and $\Delta$Premium significantly differs during these times. Furthermore, we include a one-day lag of the premium to control for arbitrage pressure on the premiums. The average premiums per day can be seen in Figure 5.4. As with $\Delta$Premium, on most days, the average premium of all ETFs seems to be within a range of $\pm 50$ bps and, usually, within a range of $\pm 25$bps. Noteworthy exceptions to this pattern are the Taper Tantrum and the

Figure 5.5: Average Premiums




*Note:* The figure displays the average Premiums from Jan 2012 to Dec 2022. The outbreak of COVID-19 in March-April 2020 is highlighted in green.

Covid-19 period. The Taper Tantrum corresponds to a short period during the summer of 2013, where a demand shock led to significant persistent discounts in ETFs (Dannhauser & Hoseinzade, 2022). However, the observations during the Covid shock in March-April 2020 are still the most extreme. During the Covid-period, we observe several substantial average positive premiums and even more extreme average discounts. The average discounts are up to -375 bps on some days and therefore distinguish a lot from the remaining timespan.

## 5.3 Descriptive Statistics

We will now have a closer look at the variables and discuss the descriptive statistics of our variables and the correlation matrix in the following. Owing to the observed extreme outliers during March and April 2020, we have decided to exclude this period from the continued analysis.[2] Consequently, the following descriptive statistics include the data from all days except the two Covid-months.

Table 5.3 shows the descriptive statistics for the different variables used in

[2]We also exclude the last trading day of February 2020, (i.e. February 28th)

our analysis. Besides the continuous variables, the dummy variables for FOMC announcements and the post-Covid period are included. For these categorical variables, the statistics of primary interest is the mean, which shows the share of the total sample that corresponds to each of those events/periods. For instance, 3% of the days in our sample correspond to a day of an announcement by the FOMC.

Table 5.3: Descriptive Statistics - All Variables

| **Variable** | **Count** | **Mean** | **Std** | **Min** | **25%** | **50%** | **75%** | **Max** |
|---|---|---|---|---|---|---|---|---|
| ΔPremium | 176995 | -0.02 | 15.69 | -307.04 | -5.39 | 0.00 | 5.29 | 484.35 |
| ΔPrice | 176995 | -0.23 | 42.70 | -660.09 | -12.21 | 0.00 | 13.29 | 523.26 |
| ΔNAV | 176995 | -0.21 | 40.68 | -663.46 | -10.23 | 0.66 | 11.25 | 520.59 |
| Surprise | 2723 | 0.01 | 0.71 | -10.00 | 0.00 | 0.00 | 0.00 | 15.47 |
| VIX | 2723 | 17.34 | 5.58 | 9.14 | 13.19 | 15.82 | 20.37 | 40.79 |
| AUM stand. | 176995 | 0.00 | 0.99 | -0.74 | -0.57 | -0.43 | 0.15 | 5.13 |
| FOMC | 2723 | 0.03 | 0.175 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| Post Covid | 2723 | 0.25 | 0.43 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Premium | 176995 | 5.56 | 23.66 | -583.09 | -1.35 | 3.96 | 12.33 | 396.00 |

Considering the variables ΔPremium, Premium, and the returns of both the ETF and the NAV, we observe that all their distributions have somewhat fat tales. For instance, ΔPremium has a min of -307.04bps and a max of 484.35bps, even after omitting the Covid-months. This finding shows that large changes in the premiums also occur during more normal times. For ΔPrice and ΔNAV, however, we observe that they have less fat tails as their outliers are less extreme compared to standard deviations. Further, we can spot that, on average, Δprice and ΔNAV go down (mean of -0.23 and -0.21, respectively). This observation is most likely due to interest rates being at the lower zero bound at the beginning of our sample in 2012, which caused higher bond prices than at the end of 2022 when interest rates are hiking again. We can observe that premiums are, on average, 5.56 bps. This could indicate that investors are, on average willing to pay a positive premium for the ETF in exchange for access to liquidity.

The surprise variable is also characterized by extreme outliers compared to its standard deviation. Noteworthy is that all the observations are zero between the 25th and 75th percentile. This means that for more than half of the sample, no surprises were recorded at all. As mentioned before, the days of the extreme values will get dummies to mitigate the risk of leverage points.

We are primarily interested in analyzing the interplay between the surprises and ΔPremiums over time. However, to get a comprehensive understanding, it is also valuable for our analysis to characterize the ΔPremiums and premiums on

FOMC and non-FOMC dates by comparing the descriptive statistics. In addition, we compare the pre-Covid and post-Covid periods to assess the potential differences between the two periods. The results are displayed in Table B.1, together with the absolute values of these variables. We add the absolute values since positive and negative ΔPremiums and premiums tend to cancel each other out, and absolute values allow us to observe when premiums were larger on average.

We observe that on FOMC days, ΔPremium tends to be more positive (mean of 1.25bps vs. -0.06bps), with a greater standard deviation (17.96bps vs 21.23bps) than on non-FOMC days. The same is the case for the level of the premiums. A possible explanation for this discrepancy can be found in Table B.2, which shows the descriptive statistics for the surprises on FOMC days and non-FOMC days. The surprises are, on average, slightly more negative on FOMC days (-0.06bps), while they tend to be slightly positive (0.012bps) on non-FOMC days. Following our assumption that negative surprises increase the value of the underlying and that the ETF price reacts stronger to the surprises than the NAV, it could help to explain the observed deviations. Still, the observations are too small to conclude. Furthermore, it can be seen that the surprises are more common on FOMC days compared to non-FOMC days (at least on 50% of FOMC days vs. less than 50% on non-FOMC days). Hence, following the same narrative, it can be assumed that more frequent surprises lead to, in absolute terms, more significant ΔPremiums and larger premiums on average.

When comparing the pre-Covid with the post-Covid period, we observe that the movements in premiums are slightly larger in absolute terms post-Covid (9.64bps) than pre-Covid (9.28bps). However, the level of the premiums is more significant in the pre-Covid period than post-Covid (14.74bps vs. 11.91bps). This finding could suggest that premiums were more persistent before Covid than after Covid.

Table 5.4 shows the Pearson correlation matrix, including the correlations between the different dependent variables, the non-binary independent variables, as well as the absolute values for ΔPremium, and Surprise.

We first examine the three dependent variables ΔPremium, ΔPrice, and ΔNAV. We first observe that ΔPrice and ΔNAV have a correlation of 0.93, which is not unexpected considering the two variables are tied together by arbitrage. What is interesting, however, is that ΔPrice has a moderate correlation with ΔPremium at 0.31, while the correlation between ΔNAV and ΔPremium is with its -0.06, close to zero. This result implies that changes in ETF premiums are primarily due to changes in the ETF price.

As for the remaining variables, Surprise, VIX, AUM, and Premium lag (absolute values excluded), we do not see any significant correlations between them and the dependent variables, except the correlation between ΔPremium and Premium lag, which is -0.33, indicating that premiums tend to return to zero. The correlation between Surprise and ΔPremium is also minuscule, indicating that the surprises are not the primary reason premiums change during the day. Still, based on the observed correlation, it cannot be concluded that the surprises do not impact the premiums. Additionally, we do not observe any strong correlations among the explanatory variables.

To measure the correlation of VIX with the two variables Surprise and ΔPremium, we include the absolute values of the two variables. We need the absolute variables since VIX is always positive, while the other two can be both negative and positive. Assuming that greater values of VIX, which proxies the illiquidity of the bond market, are positively correlated with both positive and negative changes in the premiums, it makes sense to check the correlation between VIX and |ΔPremium|. Similarly, the VIX can be positively correlated with both positive and negative surprises since VIX also measures the general volatility in the market, which could lead to more significant surprises, both negatively and positively. The correlation between VIX and |Surprise| and |ΔPremium| shows that these are positive, with 0.12 and 015, respectively. The correlations for the absolute values are indeed larger than those between the relative variables, which are -0.01 and 0.01, respectively, but still very small. Therefore, it can be concluded that there are no multicollinearity issues in the data.

Table 5.4: Correlation Matrix

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| ΔPremium (1) | 1 | | | | | | | | |
| ΔPrice (2) | 0.31 | 1 | | | | | | | |
| ΔNAV (3) | -0.06 | 0.93 | 1 | | | | | | |
| Surprise (4) | 0 | -0.09 | -0.09 | 1 | | | | | |
| VIX (5) | -0.01 | -0.02 | -0.02 | 0.01 | 1 | | | | |
| AUM (6) | 0 | -0.01 | -0.01 | 0.01 | 0.16 | 1 | | | |
| Premium_lag (7) | -0.33 | -0.04 | 0.09 | -0.01 | -0.03 | 0.04 | 1 | | |
| \|ΔPremium\| (8) | 0.01 | -0.01 | -0.02 | 0.01 | 0.12 | -0.09 | -0.07 | 1 | |
| \|Surprise\| (9) | 0.02 | 0.01 | 0.01 | 0.17 | 0.15 | 0.06 | -0.02 | 0.03 | 1 |

# Chapter 6

# Results

## 6.1 Choosing the Right Estimator

In this section, we will present and discuss the results of our analysis. As discussed in the methodology part, we start our analysis by running the complete model using POLS, entity FE, and RE to choose the best estimator for the remaining analysis. Table 6.1 below shows the results of these three regressions. In addition to the variables displayed, all regressions include dummies for the two large surprises detected in the data section before. The outlier-dummies are included to prevent possible leverage points from biasing the findings but are not displayed as they are of no particular interest for the analysis.

When comparing the results of the fixed effect estimator with the pooled OLS estimator, we observe that the coefficients are usually similar for most of the variables. However, when conducting the F-test for the joint significance of the ETF dummies in the fixed effects regression, we find a t-statistic of 83.56. The corresponding p-value is $< 0.01$, which implies that one can reject the null hypothesis that these are jointly insignificant, and hence using the entity fixed effect estimator is preferred over pooled OLS.

Next, we will compare the results of the fixed effects estimator with the random effects estimator. Should the two estimators be similar, the random effects estimator should be used as it is the most efficient estimator of the two. We compare the two statistically using a Hausman test whose null hypothesis is that the estimates of the FE and RE estimators are not different from one another. The t-statistic of the test, which can be seen at the bottom of table 6.1, equals 6120.05 and corresponds to a p-value $< 0.01$. Hence, the null hypothesis is rejected, and the estimates are significantly different, requiring us to use the fixed effect estimator.

Table 6.1: Full Model - Comparison between Pooled OLS, Fixed Effects and Random Effects Estimator

| | *Dependent variable: $\Delta Premium$* | | |
|---|---|---|---|
| | POLS | FE | RE |
| | (1) | (2) | (3) |
| Surprise | -0.017 | -0.030 | -0.017 |
| | (0.226) | (0.223) | (0.226) |
| VIX | -0.064*** | -0.068*** | -0.064*** |
| | (0.008) | (0.008) | (0.008) |
| VIX_x_Surprise | -0.009 | -0.006 | -0.009 |
| | (0.013) | (0.013) | (0.013) |
| AUM_stand. | 0.368*** | -0.133 | 0.368*** |
| | (0.035) | (0.113) | (0.035) |
| AUM_x_Surprise | -0.102** | -0.098** | -0.102** |
| | (0.050) | (0.049) | (0.050) |
| FOMC | 1.229*** | 1.232*** | 1.229*** |
| | (0.201) | (0.198) | (0.201) |
| FOMC_x_Surprise | -0.483*** | -0.499*** | -0.483*** |
| | (0.146) | (0.144) | (0.146) |
| Post_Covid | 0.138 | 0.081 | 0.138 |
| | (0.108) | (0.107) | (0.108) |
| PostCovid_x_Surprise | -0.458*** | -0.495*** | -0.458*** |
| | (0.156) | (0.154) | (0.156) |
| Premium_lag | -0.222*** | -0.275*** | -0.222*** |
| | (0.001) | (0.002) | (0.001) |
| Constant | 2.245*** | | 2.245*** |
| | (0.134) | | (0.134) |
| F-test for Poolability | | 83.56 | |
| Hausman-test | | | 6120.05 |
| Observations | 176,995 | 176,995 | 176,995 |
| $R^2$ | 0.114 | 0.140 | 0.114 |
| Adjusted $R^2$ | 0.114 | 0.139 | 0.114 |

*Note:* The table displays the results of running the complete model on Pooled Regression (POLS), Fixed Effect Estimator (FE), and Random Effect Estimator (RE). Displayed are also the F-test for Poolability, and the Hausman-test used to test whether FE and RE provide same estimates. The statistical significance of the coefficients is indicated as follows: *p<0.1; **p<0.05; ***p<0.01.

## 6.2 Changes in Premiums

Having found that the entity fixed effect estimator is the preferred estimator for our model, the remainder of the analysis is conducted using this estimator. In Table 6.2, we display the complete FE model, including some variations, in which we exclude some of the regressors. Again, the regressions include dummies for the two surprises whose coefficients are not displayed here. Further, we conduct a Breusch-Pagan test and a Breusch-Godfrey test to test both for heteroskedasticity and autocorrelation in the residuals of the complete model. Both tests have significant p-values, indicating evidence for both heteroskedasticity and autocorrelation. Therefore, we use clustered standard errors in all the specifications, which account for both heteroskedasticity and autocorrelation. The resulting standard errors are larger than normal standard errors, and the conclusions based on these are, therefore, more conservative.

Looking at the results of the full model in column (1), we find that the coefficient of Surprise, although slightly negative, does not seem to impact $\Delta$Premiums significantly. Hence, we find no evidence for the first hypothesis stating that the federal funds rate surprises negatively impact ETF premiums. This result could be due to two different reasons: First, the surprises actually do not impact the underlying bonds or the ETF. This would imply that the surprises cannot be considered a fundamental shock to bonds. However, Kuttner (2001) finds that surprises, in fact, impact interest rates, which suggests that another explanation is more likely: Namely, that the surprises impact the NAV and the ETF to the same extent, and no change in the premiums is found. This would imply that the prices of bonds are as quick as the ETF price in incorporating the fundamental shocks. The result indicates that the ETF perhaps does not necessarily promote price discovery.

Besides finding no significant effect of the surprises in general, we also do not find evidence for our hypotheses 2 and 3. The interaction terms' coefficients between Surprise, VIX, and AUM are insignificant, respectively. Therefore, neither the illiquidity of the market nor the ETF size seems to alter the impact of the Surprise on $\Delta$Premium. With respect to ETF size, we can, therefore, not shed more light on the opposing findings of Dannhauser and Hoseinzade (2022) and Madhavan and Sobczyk (2016). Considering the bond market illiquidity, we assumed that as it increases, the impact of Surprise on $\Delta$Premium would increase since the APs would arbitrage less. According to the coefficient, however, the APs seem to keep ETF and NAV together in response to a surprise regardless of the overall bond market liquidity.

However, a coefficient that does show significance is the main effect of VIX on ΔPremium, which is negative. Although the main effects are not our primary interest in the analysis, we can still interpret them. The coefficient indicates that discounts tend to form on days when the bond market is more illiquid. This finding aligns somewhat with the fire sale theory of Shim and Todorov (2022). They find that during the initial Covid months, when the bond markets got very illiquid, the APs tended not to arbitrage the gap between ETFs and underlying away when the ETF prices dropped. Their findings suggest that the APs feared triggering a fire sale by arbitraging the discounts that could significantly impact the value of the remaining bonds in the APs' portfolios. It is debatable whether the fear of fire sales also holds during more normal times, but on the other hand, it is possible that the APs also arbitrage discounts less when the bond market is more illiquid in general.

In contrast to hypotheses one, two, and three, we find evidence for hypotheses four and five regarding the FOMC announcement days and the post-Covid period, as the interaction terms with the Surprise are significant. Table 6.2 shows that the FOMC x Surprise interaction term is significant at the 1% level, and the Post-Covid x Surprise is significant at the 5% level. Considering first the role of FOMC announcement days, we see that on these days, Surprise negatively impacts the premiums, which is also the relationship we expected for Surprise in general. A positive Surprise will lead to discounts, while a negative Surprise will lead to positive premiums. The size of the coefficient also tells us that for a positive Surprise of 10 bps, the premium will go down by about 4.99 bps. Vice versa, for a negative Surprise of the same size, it goes up by about 4.99 bps. Whether this is due to increased staleness in the NAV due to faster price discovery in the ETFs on these days can be seen once we run the regressions on ΔPrice and ΔNAV.

The effect of the post-Covid period on the relationship between Surprise and ΔPremium is also negative and similar in size to the one of the FOMC interaction term. Hence, after the initial Covid period starting in May 2020, the surprises seem to impact premiums significantly, as expected. Again, to observe whether this is due to faster price discovery in the ETFs or greater staleness in the NAV, we must observe the individual effect both on price and NAV separately.

Concerning Premium lag, its coefficient is significantly negative, as expected. Positive premiums should experience a negative change in the premium as arbitrage will push it to zero, while discounts should experience a positive change for the same reasons.

The intention of running regressions (2), (3), and (4) is to investigate the impact of excluding the FOMC and post-Covid interaction terms and their dummies from the regression. In regression (2), both are missing, while regression (3) excludes post-Covid, and regression (4) excludes FOMC. Looking at the results, we can see that, for the most part, the coefficients of the other variables only change marginally. However, one interesting exception is the coefficient of the interaction term between VIX and the Surprise. The coefficient becomes significantly negative when not controlling for the post-Covid period in regression (2) and (3). The result implies that with larger bond market illiquidity, the impact of Surprise actually does increase, which is what we assumed in hypothesis two.

However, since the interaction term of VIX is only significant when dropping the post-Covid interaction term from the regression, it is very likely that VIX only captures the effect previously observed during the post-Covid period. As we have seen before, VIX has been, on average greater post-Covid than pre-Covid. One explanation of this observation is that the interaction term absorbs the effect of the post-Covid period. Therefore, this does not fully serve as evidence for hypothesis two.

It is also worthwhile to discuss the adjusted R2 of our regressions. The complete model has an adjusted R2 of 13.9%, implying that it can explain about 13.9% of the variance in the movements of the premiums. Although it is not particularly large, it is not surprising. The underlying bonds and the ETF most likely experience a great variety of liquidity and fundamental shocks each day, not due to surprising changes in the federal funds rate. Hence, it can be expected that when using daily data on the ETFs, a model able to explain most of the variation in $\Delta$Premium between days would need many more factors.

Table 6.2: Different Specification of Fixed Effect Estimator

| | *Dependent variable:* $\Delta Premium$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Surprise | -0.030 | 0.245 | 0.291 | -0.070 |
| | (0.291) | (0.198) | (0.202) | (0.291) |
| VIX | -0.068*** | -0.064*** | -0.064*** | -0.069*** |
| | (0.021) | (0.022) | (0.022) | (0.021) |
| VIX_x_Surprise | -0.006 | -0.036*** | -0.033*** | -0.010 |
| | (0.018) | (0.011) | (0.011) | (0.018) |
| AUM_stand. | -0.133 | -0.133 | -0.133 | -0.133 |
| | (0.421) | (0.417) | (0.418) | (0.421) |
| AUM_x_Surprise | -0.098 | -0.098 | -0.098 | -0.098 |
| | (0.061) | (0.060) | (0.060) | (0.061) |
| FOMC | 1.232*** | | 1.264*** | |
| | (0.226) | | (0.231) | |
| FOMC_x_Surprise | -0.499*** | | -0.445*** | |
| | (0.133) | | (0.132) | |
| Post_Covid | 0.081 | | | 0.096 |
| | (0.281) | | | (0.282) |
| PostCovid_x_Surprise | -0.495** | | | -0.472** |
| | (0.229) | | | (0.229) |
| Premium_lag | -0.275*** | -0.275*** | -0.275*** | -0.275*** |
| | (0.031) | (0.031) | (0.031) | (0.031) |
| Observations | 176995 | 176995 | 176995 | 176995 |
| $R^2$ | 0.139 | 0.139 | 0.139 | 0.139 |
| Adjusted $R^2$ | 0.139 | 0.139 | 0.139 | 0.139 |

*Note:* The table displays the results of the FE estimator. Model (1) displays the complete model with all the variables included. Model (2) displays the model excluding the FOMC dummy, the interaction term between FOMC and Surprise, the Post-Covid dummy, and the interaction term between post-Covid and Surprise. Model (3) excludes the Post-Covid dummy and the interaction term between Post-Covid and Surprise. Model (4) excludes the FOMC dummy and the interaction term between FOMC and Surprise. Clustered standard errors are reported in parentheses. The statistical significance of the coefficients is indicated as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

## 6.3 Price Discovery

As we are not only interested in the change of the premiums but also in whether they are caused by price discovery in the ETFs, we also run the complete model with $\Delta$Price and $\Delta$NAV as the dependent variables. Doing so allows us to see how the ETF and the NAV react differently to the fundamental shock implied by Surprise. The difference in their reaction is also the source of the changes in the premiums. Table 6.3 contains the results of these regressions. Regression (1) is again the complete model with $\Delta$Premium as the dependent variables, while regression (2) and (3) show the results for $\Delta$Price and $\Delta$NAV as the dependent variables, respectively.

Table 6.3 shows that ETF prices and NAV are significantly impacted by the Surprises with coefficients of -6.11 and -6.07, respectively. This result shows that the surprises are indeed fundamental shocks, and that the surprises do have a directional impact on the bonds and ETFs, as expected. However, according to the results, the two variables are not impacted significantly differently by it, which is why we do not see any impact on the premiums. This could be due to the NAV incorporating the new information stemming from the fundamental shock as quickly as the ETF price does, at least when measured daily. If that is the case, it indicates that ETF price and NAV tie together well and that the bond ETF market is efficient.

Moving on to the interaction term between the FOMC dummy and Surprise, we observe that the impact of the Surprise is muted on FOMC announcement days. For both the price and NAV, we can observe that the coefficients of the FOMC interaction terms are positive, implying that the impact of a 1 bps surprise on FOMC announcement days is equal to -1.061 bps (-6.11+5.049) on the prices and -0.521 bps (-6.069+5.548) on the NAV. The fact that the impact of Surprise on NAV is muted more is why we observe a significant impact on the premiums on FOMC days. The result indicates that the NAV is staler than the price. Therefore, the ETF seems to affect the price discovery on FOMC days.

Interestingly, we observe that the impact of Surprise on $\Delta$Price and $\Delta$NAV is smaller on FOMC days compared to non-FOMC days. This indicates that some of the manners in which the FOMC announcements impact the markets counteract the surprises' impact on interest rates. For instance, one possible explanation could be the impact of FOMC announcement on credit risk, as discussed earlier. Following Smolyansky and Suarez (2021), a surprising hike in the target rate on FOMC announcement days leads to lower credit spreads on bonds as confidence in the market increases. Consequently, interest rates may go up due to the surprise, while credit spreads go down due to the same surprise. These two effects countering each other could explain the dampened effect of the Surprise.

Turning our attention to the post-Covid interaction term, we observe that the reason for the significance is slightly different. The impact of Surprise on both price and NAV is negative and significant, which implies that the impact of Surprise on both is amplified for the post-Covid period. When adding the coefficients to the main effects of Surprise, the price goes down by -7.956 bps (-6.11 + (-1.846)) for a 1 bps surprise while the NAV goes down by -7.419 bps (-6.069 +(-1.350)) in response to same surprise. Again, the NAV is relatively staler than the ETF, indicating that the ETF promotes price discovery. These findings align with our expectations that, in the aftermath of Covid-19, surprises have a stronger impact on both ETF price and NAV. Further, these fundamental shocks are due to the relative staleness of the NAV. However, our approach does not allow us to identify the causes behind the staleness in NAV. One possible explanation can be that the increased market uncertainty during this time may lead to greater reactions to fundamental shocks.

Finally, it is interesting to look at the coefficients of the lag of the premium. Several things can be observed. For a positive premium the previous day, the price tends to go down while the NAV tends to go up. This observation makes sense since APs arbitrage the premium, imposing downward pressure on the price and upward pressure on the NAV, and vice versa in a discount scenario. What is particularly interesting, however, is that the coefficient corresponding to a change in NAV is more than twice the size of the ETF price coefficient in absolute terms. If the movement of price and NAV were solely due to arbitrage, one would expect that price and NAV would change to a similar degree. Hence, the larger movement in the NAV points to what Madhavan and Sobczyk (2016) find regarding NAV catching up with the ETF. The finding indicates that the movements in the ETF prices are, to some degree, due to changes in the fundamentals of the underlying, to which the NAV needs more time to adjust than the ETF price. Therefore, it functions as further evidence for the price discovery hypothesis.

Table 6.3: Comparison of $\Delta$Premium, $\Delta$Price and $\Delta$NAV

| | $\Delta$Premium | $\Delta$Price | $\Delta$NAV |
|---|---|---|---|
| | (1) | (2) | (3) |
| Surprise | -0.030 | -6.110*** | -6.069*** |
| | (0.291) | (0.803) | (0.760) |
| VIX | -0.068*** | -0.004 | 0.063 |
| | (0.021) | (0.089) | (0.075) |
| VIX_x_Surprise | -0.006 | -0.015 | -0.009 |
| | (0.018) | (0.030) | (0.020) |
| AUM_stand. | -0.133 | -0.171 | -0.032 |
| | (0.421) | (0.296) | (0.308) |
| AUM_x_Surprise | -0.098 | 0.428 | 0.529 |
| | (0.061) | (0.349) | (0.366) |
| FOMC | 1.232*** | 6.564*** | 5.328*** |
| | (0.226) | (0.682) | (0.647) |
| FOMC_x_Surprise | -0.499*** | 5.049*** | 5.548*** |
| | (0.133) | (0.605) | (0.631) |
| Post_Covid | 0.081 | -2.648*** | -2.730*** |
| | (0.281) | (0.965) | (0.913) |
| PostCovid_x_Surprise | -0.495** | -1.846*** | -1.350*** |
| | (0.229) | (0.512) | (0.401) |
| Premium_lag | -0.275*** | -0.085*** | 0.190*** |
| | (0.031) | (0.013) | (0.025) |
| Observations | 176995 | 176995 | 176995 |
| $R^2$ | 0.139 | 0.012 | 0.02 |
| Adjusted $R^2$ | 0.139 | 0.012 | 0.02 |

*Note:* The table displays the results of running the full model on $\Delta$Premium (1), $\Delta$Price (2), and $\Delta$NAV(3). Clustered standard errors are reported in parentheses. The statistical significance of the coefficients is indicated as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

# Chapter 7

# Conclusion

With this thesis, we wanted to investigate how fundamental shocks in the form of surprising federal funds rate changes can impact bond ETF premiums. Recent literature discusses whether premiums are caused by price discovery or whether they are due to non-fundamental liquidity shocks. We wanted to add to the literature by using surprising federal funds rate changes as fundamental shocks to the ETF and its NAV to test whether premiums can result from price discovery in the ETF.

We conducted the empirical analysis utilizing ETF fixed effects on a panel of 65 U.S. bond ETFs from 2012 to 2022 and examined how the surprising federal funds rate changes under different conditions impact the ETF premiums. Further, we examined how the ETF price and the NAV were impacted separately by the surprises. Our primary finding reveals that, on normal days, the surprises do not significantly impact ETF premiums. This is attributable to ETF price and NAV being impacted by the surprises to the same degree. This finding indicates that there is no extra price discovery in the ETF and that the NAV seems to incorporate the new information as quickly as the ETF price.

By using interaction terms to test for different characteristics and situations under which the surprise may impact premiums, we find that the surprises impact premiums negatively on FOMC announcement dates and during the period after the initial Covid shock, i.e., the period from May 2020 onwards. Further, when we analyze the individual impact on ETF price and NAV, we see that in both cases, the price is more strongly impacted by the surprises, serving as evidence for price discovery in the ETFs.

Notably, after the Covid outbreak, our findings show that the surprises impacted both NAV and ETF prices more than the baseline observations. The results show an increased reaction to the surprises in asset pricing after Covid.

Given the liquidity mismatch between ETF price and NAV, the increased impact of the surprises could lead to observable price discrepancies. This finding suggests that the ETF can function as a tool for price discovery.

Our findings also reveal price discrepancies on FOMC days. However, the model provides some puzzling results. The impact of the surprises on ETF price and NAV are both attenuated compared to the baseline observations. A possible reason for the subdued impact can be that FOMC announcements affect the market in many different and possibly opposing ways, such as affecting credit risk. Since most bond ETFs hold bonds representing broad indices, the asset class incorporates many of these opposing factors, which can cause a muted impact. Still, the results show that the NAV is staler relative to the ETF price, which suggests that the ETF can function as a price discovery tool on FOMC days. However, using the approach at hand does not allow us to explain why the effect is different.

Our analysis also finds that the daily observed price discrepancies tend to go to zero, mainly because the APs arbitrage them away. However, the NAV interestingly moves more than the ETF price. This finding suggests that the NAV generally tends to follow the ETF price, a fact that Madhavan and Sobczyk (2016) associate with price discovery.

Given these results, there is only partial evidence that the fundamental shocks in the shape of surprising federal funds rate changes impact ETF premiums daily. This makes it difficult to give clear recommendations to investors. Our model shows that the Surprises impact ETF price and NAV equally strongly in regular periods, indicating that small fundamental shocks are incorporated equally quickly in the ETF price and underlying securities. Therefore, the ETF does not provide any advantage in price discovery, and investors can use the NAV as an indicator of the true value of the underlying.

On the other hand, finding that the surprises significantly impact premiums post-Covid has two significant implications. First, it implies that ETF and NAV are quicker to depart from each other during periods characterized by uncertainty and more volatility. The apparent price discrepancy is due to ETF price and NAV showing different sensitivities to fundamental shocks. As a consequence, the efficiency of the bond ETF market is negatively impacted. However, assuming that the premiums partially originate from price discovery and that the NAV typically trails the ETF, bond ETFs can provide investors with insights into the intrinsic value of the underlying securities.

It is important to acknowledge some limitations of our results. First, we cannot conclusively state that federal funds surprises are the sole drivers of ETF premiums. We capitalize on a reduced-form model, not a formal structural model derived from theory. Hence, we cannot give any firm conclusions about causality. Second, our model measures daily changes in premiums, potentially excluding a comprehensive measurement of the shocks we analyze. We premised our approach on the assumption that, given the illiquidity of the underlying bonds, the APs take time to arbitrage, causing persistent premiums. However, the results suggest that the arbitrage process often goes quicker than our model can capture. Our analysis can suffer from biased results since we cannot pinpoint the exact time of the shocks.

The last point also forms our first suggestion for future research. The frequency of the data we apply can lead to missed observed impacts. For that reason, it would be beneficial to replicate this study using high-frequency data. Doing so would allow a more precise time-estimation of the surprises and better capture the initial impact of the surprises on NAV and ETF prices around these surprises.

A further suggestion would be to investigate the channels through which FOMC announcements impact bond ETFs and the price discrepancies. We have seen that on these days, the surprising federal fund rate changes have a muted impact on both ETF and NAV, which we associate with the FOMC announcements impacting bond ETFs in various ways. Hence, it would be interesting to investigate these further.

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# Appendix A

# List of ETFs

Table A.1: List of ETFs in Sample - Part 1

| Ticker | Rating | Name | Sponsor | AUM 2012 (in mil) (Rank) | AUM 2022 (in mil) (Rank) |
|---|---|---|---|---|---|
| **Investment Grade** | | | | | |
| AGG | Investment Grade | iShares Core U.S. Aggregate Bond ETF | BlackRock | 15 135 (4) | 82 827 (1) |
| BND | Investment Grade | Vanguard Total Bond Market ETF | Vanguard | 16 495 (3) | 81 864 (2) |
| VCIT | Investment Grade | Vanguard Intermediate-Term Corporate Bond ETF | Vanguard | 2 260 (19) | 42 114 (3) |
| VCSH | Investment Grade | Vanguard Short-Term Corporate Bond ETF | Vanguard | 3 352 (14) | 41 149 (4) |
| BSV | Investment Grade | Vanguard Short-Term Bond ETF | Vanguard | 8 287 (9) | 38 558 (5) |
| LQD | Investment Grade | iShares iBoxx $ Investment Grade Corporate Bond ETF | BlackRock | 21 968 (2) | 34 242 (6) |
| TIP | Investment Grade | iShares TIPS Bond ETF | BlackRock | 22 833 (1) | 30 362 (7) |
| MUB | Investment Grade | iShares National Muni Bond ETF | BlackRock | 3 007 (16) | 27 448 (8) |
| SHY | Investment Grade | iShares 1-3 Year Treasury Bond ETF | BlackRock | 9 846 (7) | 25 023 (9) |
| MBB | Investment Grade | iShares MBS ETF | BlackRock | 5 338 (10) | 22 266 (10) |
| IGSB | Investment Grade | iShares 1-5 Year Investment Grade Corporate Bond ETF | BlackRock | 9 394 (8) | 21 765 (11) |
| TLT | Investment Grade | iShares 20+ Year Treasury Bond ETF | BlackRock | 3 343 (15) | 21 576 (12) |
| IEF | Investment Grade | iShares 7-10 Year Treasury Bond ETF | BlackRock | 4 754 (12) | 19 836 (13) |
| BIL | Investment Grade | SPDR Bloomberg 1-3 Month T-Bill ETF | SSGA | 1 258 (22) | 19 273 (14) |
| SHV | Investment Grade | iShares Short Treasury Bond ETF | BlackRock | 2 501 (18) | 19 010 (15) |
| SCHP | Investment Grade | Schwab U.S. TIPS ETF | Schwab | 466 (40) | 16 846 (16) |
| VGSH | Investment Grade | Vanguard Short-Term Treasury ETF | Vanguard | 184 (56) | 15 125 (17) |
| VMBS | Investment Grade | Vanguard Mortgage-Backed Securities ETF | Vanguard | 210 (52) | 14 363 (19) |
| BIV | Investment Grade | Vanguard Intermediate-Term Bond ETF | Vanguard | 3 570 (13) | 12 846 (20) |
| STIP | Investment Grade | iShares 0-5 Year TIPS Bond ETF | BlackRock | 344 (44) | 11 749 (21) |
| IEI | Investment Grade | iShares 3-7 Year Treasury Bond ETF | BlackRock | 2 653 (17) | 11 169 (22) |
| VGIT | Investment Grade | Vanguard Intermediate-Term Treasury ETF | Vanguard | 114 (61) | 10 340 (23) |
| IGIB | Investment Grade | iShares 5-10 Year Investment Grade Corporate Bond ETF | BlackRock | 5 021 (11) | 10 077 (24) |
| SCHO | Investment Grade | Schwab Short-Term U.S. Treasury ETF | Schwab | 219 (51) | 9 106 (25) |
| FLOT | Investment Grade | iShares Floating Rate Bond ETF | BlackRock | 204 (53) | 9 053 (26) |
| SUB | Investment Grade | iShares Short-Term National Muni Bond ETF | BlackRock | 548 (37) | 8 496 (27) |
| SCHZ | Investment Grade | Schwab U.S. Aggregate Bond ETF | Schwab | 289 (47) | 7 563 (28) |
| SPSB | Investment Grade | SPDR Portfolio Short Term Corporate Bond ETF | SSGA | 1 098 (24) | 7 479 (29) |
| USIG | Investment Grade | iShares Broad USD Investment Grade Corporate Bond ETF | BlackRock | 1 287 (21) | 6 731 (31) |

Table A.2: List of ETFs in Sample - Part 2

| Ticker | Rating | Name | Sponsor | AUM 2012 (in mil) (Rank) | AUM 2022 (in mil) (Rank) |
|---|---|---|---|---|---|
| **Investment Grade** | | | | | |
| SCHR | Investment Grade | Schwab Intermediate-Term U.S. Treasury ETF | Schwab | 183 (57) | 6 473 (32) |
| SPAB | Investment Grade | SPDR Portfolio Aggregate Bond ETF | SSGA | 514 (39) | 6 371 (33) |
| SPIB | Investment Grade | SPDR Portfolio Intermediate Term Corporate Bond ETF | SSGA | 284 (48) | 5 603 (34) |
| SPTL | Investment Grade | SPDR Portfolio Long Term Treasury ETF | SSGA | 54 (65) | 5 558 (35) |
| SHM | Investment Grade | SPDR Nuveen Bloomberg Short Term Municipal Bond ETF | SSGA | 1 558 (20) | 4 827 (36) |
| BLV | Investment Grade | Vanguard Long-Term Bond ETF | Vanguard | 702 (33) | 4 595 (38) |
| VCLT | Investment Grade | Vanguard Long-Term Corporate Bond ETF | Vanguard | 857 (28) | 4 565 (39) |
| CWB | Investment Grade | SPDR Bloomberg Convertible Securities ETF | SSGA | 825 (29) | 4 512 (40) |
| TFI | Investment Grade | SPDR Nuveen Bloomberg Municipal Bond ETF | SSGA | 1 136 (23) | 3 947 (41) |
| SPTI | Investment Grade | SPDR Portfolio Intermediate Term Treasury ETF | SSGA | 195 (54) | 3 822 (42) |
| VGLT | Investment Grade | Vanguard Long-Term Treasury ETF | Vanguard | 73 (64) | 3 780 (43) |
| TLH | Investment Grade | iShares 10-20 Year Treasury Bond ETF | BlackRock | 556 (36) | 3 527 (44) |
| SPIP | Investment Grade | SPDR Portfolio TIPS ETF | SSGA | 708 (32) | 2 954 (46) |
| GVI | Investment Grade | iShares Intermediate Government/Credit Bond ETF | BlackRock | 820 (30) | 2 471 (47) |
| PZA | Investment Grade | Invesco National AMT-Free Municipal Bond ETF | Invesco | 769 (31) | 2 118 (48) |
| TDTT | Investment Grade | FlexShares iBoxx 3-Year Target Duration TIPS Index Fund | FlexShares | 358 (43) | 2 016 (49) |
| BAB | Investment Grade | Invesco Taxable Municipal Bond ETF | Invesco | 972 (26) | 1 850 (51) |
| ITM | Investment Grade | VanEck Intermediate Muni ETF | VanEck | 514 (38) | 1 745 (52) |
| IGLB | Investment Grade | iShares 10+ Year Investment Grade Corporate Bond ETF | BlackRock | 302 (46) | 1 576 (53) |
| STPZ | Investment Grade | PIMCO 1-5 Year US TIPS Index ETF | PIMCO | 991 (25) | 1 422 (55) |
| EDV | Investment Grade | Vanguard Extended Duration Treasury ETF | Vanguard | 189 (55) | 1 289 (56) |
| MUNI | Investment Grade | PIMCO Intermediate Municipal Bond Active ETF | PIMCO | 161 (59) | 796 (58) |
| TDTF | Investment Grade | FlexShares iBoxx 5-Year Target Duration TIPS Index Fund | FlexShares | 241 (50) | 736 (59) |
| SPLB | Investment Grade | SPDR Portfolio Long Term Corporate Bond ETF | SSGA | 98 (63) | 692 (60) |
| LTPZ | Investment Grade | PIMCO 15+ Year US TIPS Index ETF | PIMCO | 308 (45) | 690 (61) |
| CORP | Investment Grade | PIMCO Investment Grade Corporate Bond Index ETF | PIMCO | 246 (49) | 687 (62) |
| AGZ | Investment Grade | iShares Agency Bond ETF | BlackRock | 381 (42) | 641 (63) |
| ZROZ | Investment Grade | PIMCO 25+ Year Zero Coupon US Treasury Index ETF | PIMCO | 118 (60) | 476 (64) |
| PLW | Investment Grade | Invesco 1-30 Laddered Treasury ETF | Invesco | 166 (58) | 472 (65) |
| **High Yield** | | | | | |
| HYG | High Yield | iShares iBoxx $ High Yield Corporate Bond ETF | BlackRock | 14 949 (5) | 15 110 (18) |
| JNK | High Yield | SPDR Bloomberg High Yield Bond ETF | SSGA | 11 523 (6) | 7 478 (30) |
| BKLN | High Yield | Invesco Senior Loan ETF | Invesco | 624 (35) | 4 629 (37) |
| HYD | High Yield | VanEck High Yield Muni ETF | VanEck | 668 (34) | 3 134 (45) |
| HYMB | High Yield | SPDR Nuveen Bloomberg High Yield Municipal Bond ETF | SSGA | 108 (62) | 1 856 (50) |
| HYS | High Yield | PIMCO 0-5 Year High Yield Corporate Bond Index ETF | PIMCO | 392 (41) | 1 470 (54) |
| PHB | High Yield | Invesco Fundamental High Yield® Corporate Bond ETF | Invesco | 885 (27) | 798 (57) |

# Appendix B

# Additional Descriptive Statistics

Table B.1: Descriptive statistics $\Delta$Premium, $|\Delta\text{Premium}|$, Premium, $|\text{Premium}|$. For FOMC and Non-FOMC Days as well as Pre-Covid and Post-Covid (in bps)

| Variable | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| **FOMC Days** | | | | | | | | |
| $\Delta$Premium | 5590 | 1.25 | 17.96 | -179.45 | -4.87 | 0.62 | 6.82 | 140.46 |
| $\|\Delta\text{Premium}\|$ | 5590 | 10.80 | 14.40 | 0.00 | 2.29 | 5.82 | 13.24 | 179.45 |
| Premium | 5590 | 6.94 | 25.53 | -333.73 | -1.48 | 4.69 | 14.11 | 242.54 |
| $\|\text{Premium}\|$ | 5590 | 15.79 | 21.23 | 0.00 | 3.51 | 8.81 | 19.57 | 333.73 |
| **Non-FOMC Days** | | | | | | | | |
| $\Delta$Premium | 171405 | -0.06 | 15.61 | -307.04 | -5.40 | 0.00 | 5.24 | 484.35 |
| $\|\Delta\text{Premium}\|$ | 171405 | 9.32 | 12.52 | 0.00 | 2.04 | 5.32 | 11.68 | 484.35 |
| Premium | 171405 | 5.50 | 23.55 | -583.10 | -1.35 | 3.94 | 12.26 | 396.00 |
| $\|\text{Premium}\|$ | 171405 | 13.99 | 19.73 | 0.00 | 3.08 | 7.67 | 17.13 | 583.10 |
| **Pre-Covid** | | | | | | | | |
| $\Delta$Premium | 133250 | -0.03 | 15.12 | -284.38 | -5.56 | 0.00 | 5.50 | 374.46 |
| $\|\Delta\text{Premium}\|$ | 133250 | 9.28 | 11.94 | 0.00 | 2.22 | 5.53 | 11.78 | 374.46 |
| Premium | 133250 | 5.99 | 24.82 | -583.09 | -1.40 | 4.40 | 13.15 | 396.00 |
| $\|\text{Premium}\|$ | 133250 | 14.74 | 20.84 | 0.00 | 3.29 | 8.13 | 17.97 | 583.09 |
| **Post-Covid** | | | | | | | | |
| $\Delta$Premium | 43745 | 0.01 | 17.31 | -307.04 | -4.87 | 0.00 | 4.72 | 484.35 |
| $\|\Delta\text{Premium}\|$ | 43745 | 9.64 | 14.38 | 0.00 | 1.76 | 4.81 | 11.51 | 484.35 |
| Premium | 43745 | 4.18 | 19.46 | -417.92 | -1.26 | 3.27 | 9.91 | 164.33 |
| $\|\text{Premium}\|$ | 43745 | 11.91 | 15.94 | 0.00 | 2.61 | 6.62 | 14.76 | 417.92 |

Table B.2: Descriptive statistics Surprise and |Surprise|. Both for FOMC and Non-FOMC Days (in bps)

| Variable | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| **FOMC Days** | | | | | | | | |
| Surprise | 86 | -0.06 | 1.53 | -5.77 | -0.26 | 0.00 | 0.00 | 4.50 |
| \|Surprise\| | 86 | 0.80 | 1.29 | 0.00 | 0.00 | 0.26 | 0.98 | 5.77 |
| **Non-FOMC Days** | | | | | | | | |
| Surprise | 2637 | 0.01 | 0.66 | -10.00 | 0.00 | 0.00 | 0.00 | 15.47 |
| \|Surprise\| | 2637 | 0.26 | 0.61 | 0.00 | 0.00 | 0.00 | 0.35 | 15.47 |