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공학석사 학위논문

Environmental, Social and Governance Exchange-Traded Funds: Do They Attract More Cash Flows Than Their Conventional Counterparts?

사회책임투자 상장지수펀드의 투자유도효과에 관한 연구

2020년 08월

서울대학교 대학원
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이 논문을 공학석사학위논문으로 제출함

2020 년 08 월

서울대학교 대학원

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바라노브스키의 석사 학위논문을 인준함

2020 년 08 월

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부위원장 이정동 (인)

위 원 백철우 (인)

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논문제목 : Environmental, Social and Governance Exchange-Traded Funds: Do They Attract More Cash Flows Than Their Conventional Counterparts?

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Abstract

Environmental, Social and Governance Exchange-Traded Funds: Do They Attract More Cash Flows Than Their Conventional Counterparts?

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The integration of environmental, social and governance (ESG) factors into the investing process is underpinned by the growing popularity of sustainable development strategies and global concerns regarding the environment. However, scholars are not in agreement about whether ESG investing obliges an investor to sacrifice financial returns, does not affect the performance of financial entities, or can improve it. Such investing can be done using different financial instruments. This study deals with one of those instruments – exchange-traded funds or ETFs. These funds are one of the most prospective investment vehicles because of their special properties. Moreover, ESG ETFs are being popularised, and they demand attention from both practitioners and academia. However, existing studies concerning ESG ETFs are rather scarce, and they focus on performance measured by risk-return characteristics.

This paper addresses that gap in the literature and investigates a special financial issue that has not been discovered in the case of ESG ETFs – whether such funds can attract more financial flow than their conventional counterparts – which may reflect investors' demand for ESG ETFs. In particular, this study examines the relationship between the inflows to such funds and their compliance with ESG criteria, using two types of regression models. First, it exploits cross-sectional data on bond and equity ETFs traded in the U.S., and it investigates the relationship between higher ESG scores and higher inflows. Second, the study uses historical data on U.S. bond and equity ETFs in 2- and 3-year periods, and it applies pooled OLS and mixed effects models to panel data samples of ESG and non-ESG ETFs distinguished by a dummy variable.

The positive relationship between financial flows and ESG score was partially proved: a statistically significant and positive coefficient of variables representing ESG scores was observed in the case of the equity ETF model. However, its value was too modest to draw any meaningful conclusions. In the model for bond ETFs, no such evidence was found. This might be because of the small size of the sample and other methodological weaknesses. On the contrary, in all specifications operating different samples of panel data dummy variables representing ESG labelling had relatively high, positive and statistically significant coefficients. To be precise, on average, compliance of ETFs with ESG criteria may promise 2.1-3.5% of additional inflows. This is in line with other ESG fund literature, e.g. studies dealing with mutual funds.

This result gives a strong market signal to ETF providers, other market participants and policy makers; it contributes to the dilemma regarding the financial impact of ESG factors, and it opens up many directions concerning financial properties and other specificities of ESG ETFs. Several implications for the broader literature on exchange-traded funds also are identified and discussed. At present, there are still many limitations to this type of research. However, as more ESG ETFs emerge – those limitations can be overcome. This paper provides a strong background for further studies in this area, and it suggests possible improvements for later studies.

Keywords: Exchange-Traded Funds, ESG, financial flows, regression analysis
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1. Introduction

The era of the industrial revolution extremely damaged the environment. Industrial growth caused a huge negative effect on all the components of the natural system: air, soil, water and bio-diversity in general (Patnaik, 2018). In the 1970s the whole world started to pay attention to environmental issues, which were inherited from decades of intensive economic growth. Countries began a process which united the whole world behind the goal of resisting the depreciation of the environment. One result was the Stockholm Declaration of the United Nations (UN), in which increasing the quality of the environment was proclaimed as the key issue that affects the economic development of all countries. To preserve the environment, efforts and responsibility from all institutions in all levels are needed (United Nations, 1973). Such a shift in values led to several economic processes, e.g. in the U.S. the concept of 'societal marketing' emerged and became widespread (Radu, 2016). An important phase of understanding the severity of environmental issues came from the world-famous work *Limits to Growth,* published by members of the Rome Club in 1972. Their computer model projected that the world economy would collapse based on circumstances relevant at that time (Meadows *et al.*, 1997). After that, the entire world started to reflect on environmental problems, making attempts to find solutions for given conditions of nature. Such solutions were generated by UN and captured in the famous report, 'Our Common Future', which established the concept of sustainable development. This was defined as a particular kind of development, one that helps to meet present goals without reducing the ability to follow generations to meet future goals (United Nations, 1987). It can be interpreted in the following way: the economic dimension is no longer the only goal for countries, environmental and societal dimensions should also be satisfied when designing economic policies. This approach linked economic outputs with environmental and social indicators and made it impossible to ignore the negative influence of economic activities on society and nature. These efforts were later reinforced during several summits, starting with Earth Summit in 1992 and continuing with subsequent summits every 10 years – the World Summit on Sustainable Development in 2002, The Future We Want in 2012. Arguably, the main outcome of these meetings has been The United Nations Millennium Declaration in 2000 (United Nations, 2015a) and Transforming Our World: the 2030 Agenda for Sustainable Development in 2015 (United Nations, 2015b). These documents set up the Sustainable Development Goals (SDGs) – eight to be achieved by 2015 and 17 by 2030. These goals or Grand Challenges are designed as sets of particular targets, which should be achieved by the humanity during following 15 years. For example, Goal 14.1 is 'By 2020, conserve at least 10 percent of coastal and marine areas, consistent with national and international law and based on the best available scientific information'. Strict formulations including benchmarks should foster and direct the efforts of the global society to reach SDGs and ensure the prosperity of the environment and society as the whole.

However, although SDGs are important statements, which unite countries under the aim of a better world, probably the most influential outcome of the concept of sustainable development is not the creation of SDGs, but the appearance of many notions related to sustainability and addressing different elements of economic development. The best examples are the green economy and green growth strategies, which were formulated as a response to the financial crisis of 2008. Such notions are solely focused on the relationship between economic growth and activities limiting the negative influence of economic prosperity on the environment. Scientists (Kazstelan, 2017) put these concepts into the following logical chain. The strategy of green growth by demanding the best-available technologies create the circumstances for the green economy to appear. Henceforth, policies based on the pillars of the green economy delineate the sustainable development path for the country. This way of thinking gave birth not only to the wide set of different policies on international and national levels, but it also produced a new paradigm in the business sector, where Corporate Social Responsibility (CSR) has been an important notion for decades. Tendencies to publish non-financial reporting and operate responsibly started to prevail in all industries (Calace and Vukić, 2017). The influence of green trends on the financial markets is of particular interest for this study.

The financial side of sustainable development was always in the focus. Green growth and the green economy demand huge financing flows, according to the Paris Agreement (UN, 2015). Signatories of that declaration agreed to ensure financial flows in sufficient amounts to limit the increase in the global average temperature to no more than 2 °C above pre-industrial levels and attempt to limit the temperature increase at 1.5 °C above pre-industrial levels. Such measures suggest the need for $1-2 trillion of financial flows every year extracted from the world economy. The famous report Towards a Green Economy (OECD, 2015) argued that public and private investments are the main pillars of growth in income and employment within the strategy of the green economy. Therefore, the conditions arose for the emergence of a responsible investment movement, oriented on fostering the green economy and sustainable development. This led to related notions, particularly in the financial sphere.

Orientating financial flows to green strategies is implemented through compliance with the Principles of Responsible Investing (PRI). The UN launched the PRI in 2006, and 1600 participants signed onto these principles to manage over $70 trillion AUM (UNEP, 2019). Within this initiative, institutional investors agreed to act in the best long-term interests of beneficiaries. To do so, they aimed to integrate environmental, social and governance (ESG) factors into their investment processes. ESG investing appeared in 2005.

The ESG factors are at the core of the current study, and they will be further discussed in the following sections. ESG investors have more preference for companies and financial entities with good ESG profiles. ESG investing became even more popular when several studies (Khuram et al., 2016) pointed out that such investing can be financially more justifiable, although other studies disputed this insight (Humphrey and Tan, 2014). The obvious issue is how to persuade investors and other participants in financial markets that this particular investment complies with ESG criteria. This gave birth to a separate segment of financial markets – green finance. It is more oriented toward environmental issues, but it incorporates ESG factors and is suitable for the analysis.

It is hard to define the concept of green finance properly. In fact, green financial instruments emerged before the notion was captured in the literature. (The first green bond was issued in 2007 by the European Investment Bank (Climate Bonds Initiative, 2018)). Green finance combines financial institutions, economic growth and environmental dimension, and it is treated as the key element of both green growth and the green economy. The renewal of obsolete funds and the transition to best-available technologies contributed to both increasing their productivity and improving environmental conditions, as the amount of emissions of harmful substances is being reduced. This helps to improve the quality of growth — improving working conditions, reducing mortality rates, and maintaining the state of natural capital. In addition, technological progress promoted by such funds opened up new sources of energy for the economy, created opportunities for saving energy in other sectors, and contributed to scientific research in the field of natural sciences. However, in the financial sense, green finance is the system of specific financial instruments that allow investors to promote ESG factors and particularly green investments – investments in environmental goods and services or against the negative impacts on the climate and nature (Lindenberg, 2014). These instruments might be of any format, the whole range of green financial instruments comprises financing tools like green loans, green sukuk, ESG investment funds and green bonds. Such instruments are similar to their conventional counterparts except for the fact that all proceeds are dedicated to green projects (CBI, 2017). It can be mentioned that a wide range of financial instruments complying with ESG criteria have emerged throughout the last decade. However, the financial nature of such instruments does not dramatically differ from classical financial instruments. In fact, ESG investments are conducted through conventional financial instruments, which operate in the usual way, but finance projects and assets which are earmarked as complying with ESG factors. This delineates the multidisciplinary area of study, integrating ESG-specific literature and studies regarding the peculiarities of certain financial instruments. This work investigates ESG investing as it applies to exchange-traded funds (ETFs). These financial instruments appeared at the end of the 20^{th} century and gained popularity through a move toward passive investing. An ETF is a suitable financial tool to discover the specificities of ESG investing and trace its influence on the financial performance of a certain instrument.

Therefore, the goal of this study is to investigate the features of ESG ETFs. In particular, we address the specific issue of financial flows by comparing ESG and non-ESG (conventional) ETFs. After applying regression analysis to cross-sectional and panel data, we come to several conclusions concerning the ability of ESG ETFs to attract more flows than their conventional counterparts. The study is relevant for ETF providers, other market participants and policy makers. Moreover, it contributes to the financial literature regarding ETFs and multidisciplinary topics around the use of investment funds for ESG investing.

2. Theory and Hypothesis

2.1. The Basics of Investment Funds and Passive Investing

The industry of investment funds has been growing rapidly for several decades, reaching the value of $54.9 trillion of total assets with over 122,000 funds worldwide at the end of 2019 (Figure 1).

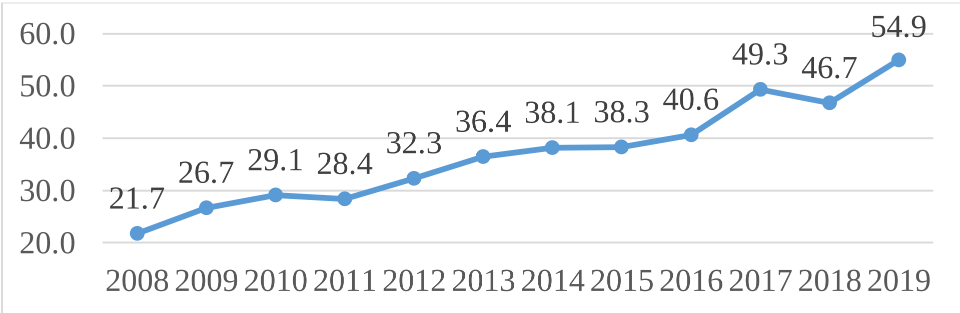

Figure 1. Total assets of open-end investment funds worldwide, $ trillions. Source: Investment Company Institute (2020) 'Investment Company Factbook: A Review of Trends and Activities in the Investment Company Industry', pp. 1-329.

An investment fund is a capital asset simultaneously owned by many investors and exploited to buy securities together while each investor maintains ownership and control of his shares (Chen, 2020c). Pooled investing vehicles have existed in the United States since the beginning of the 19th century. The Boston Personal Property Trust is the first known investment fund in the U.S. In Europe, pooled investing dates from the beginning of the 18th century (Hougan *et al.*, 2015). Investment funds provide a more convenient way to diversify risks, achieve greater investment opportunities, use the benefits of economies of scale, pay lower fees and get better management expertise than investors can enjoy by investing on their own. Any investor willing to buy securities does not need to reflect on the precise number and quantity of individual stocks. Instead, s/he buys shares of funds, which holds some securities, already chosen by the fund manager. Funds may include a broad selection of underlying securities (e.g. SPY holds stocks of the biggest U.S. companies in different industries), or they may be devoted to a specific area (e.g. BGRN invests only in specific green bonds).

There are different types of funds in markets today. Usually one would name mutual funds, exchange-traded funds, market money funds and hedge funds. However, very often the two last types are omitted in articles since they are just special cases of mutual funds that operate in the same way (money market funds are based on very short-term debt products traded between governments and banks, while hedge funds are oriented to institutional investors and offer less federal regulations) (Chen, 2020c). Thus, the main distinction should be between mutual funds and exchange-traded funds (ETFs). They occupy the biggest market shares and crucially alter in nature.

Mutual funds are the oldest financial funds in existence. They are controlled by professional managers who choose appropriate stocks, bonds or other securities to invest in, trying to beat the market and generate an absolute return (Ben-David and Franzoni, 2017). When any investor buys a share of a mutual fund, s/he buys a part of the fund's portfolio value. This share has a price – its net asset value (NAV) – which is calculated by dividing the total value of the underlying holdings by the total number of shares outstanding. Orders to buy and sell shares of mutual funds are satisfied at the end of the trading day at the current NAV (Hougan *et al*., 2015). However, different types of funds may vary their procedures for purchasing and redeeming shares.

Investors may gain returns in following ways: 1) income is derived from dividends on stocks and interest on bonds, which are paid to investors in the form of a distribution or are reinvested; 2) the prices of underlying securities may rise and create a capital gain for the fund, which is paid out in a distribution; 3) capital gain is not paid out, but leads to an increase in the price of the shares of the mutual funds, which can be sold to other investors at those higher prices. In response, mutual fund managers set an expense ratio – the sum of the management fee and administrative cost – usually between 1% and 3% (Hayes, 2020).

It is vital to distinguish two types of mutual funds: open-end funds and closed-end funds. The first type is more popular. It operates in the way described above, and it is traditionally treated as a 'mutual fund'. The purchase of shares of the fund is conducted between the investor and the fund company. The number of shares is limitless, and it changes as new investors arrive. However, the per-share price is adjusted on a daily basis so there are no fluctuations in the value of an individual's shares. In contrast, closed-end funds issue a specific number of shares through an Initial Public Offering (IPO) and do not issue additional shares when new investors come. This predetermines trading of shares with a premium or discount to their NAV, depending on the demand in the secondary market (Parker, 2019). Closed-end funds are very similar to another type of funds, exchange-traded funds or EFTs, which are at the focus of this study.

ETFs dramatically differ from mutual funds. They were developed as a solution for investors who wanted more flexibility with their portfolios. That is why many ETFs are just counterparts of existing mutual funds (e.g. the Vanguard 500 Index Fund vs. the Vanguard S&P 500 ETF) (Chen, 2020c). Similar to close-end funds an ETF has a fixed number of shares and is traded on an exchange throughout the business day like stocks. This allows for many daily price changes and the existence of a premium or a discount. There is a comprehensive description of the trading peculiarities of EFTs in the next sub-section. What is crucial for this discussion is that such funds are usually not operated by fund managers who try to conduct a stock-picking process. Instead, they just track the market index on which they are based and fully comply with the index's composition. Therefore, ETFs are traditional vehicles for so-called passive investing. Let us briefly discuss this important global trend in financial markets. For decades passive investing has been slowly stealing the ground from actively managed funds (Figure 2). This process reached a meaningful milestone in 2019: index-based equity passive mutual funds and ETFs topped the active equity funds in the U.S. That is, the inflow to passive U.S. stock funds was $88.9 billion, while outflow from active funds reached $124.1 billion in the January–July period. This made the volume of total assets in U.S. equity funds equal to $4.271 trillion, compared with $4.246 trillion in the case of passive ones (Gittelsohn, 2020).

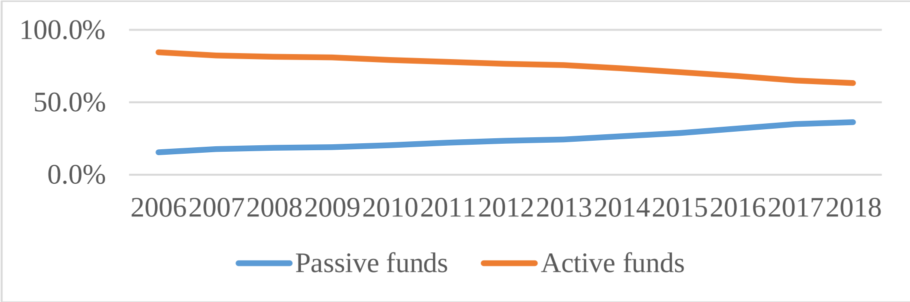

Figure 2. Market shares of U.S. passive and active funds, in percent.
Source: Kerzérho, R. (2019) 'The Passive Vs. Active Fund Monitor'. PWL Capital. pp. 1-14.

The highlighted process has its own rationale. From the very first papers investigating the performance of mutual funds (Sharpe, 1966) to more recent ones (Carhart, 1997), scholars have questioned whether actively managed funds provide better performance, usually measured in terms of Jensen's Alpha. Simultaneously, the modern portfolio theory was introduced by Markowitz in the 1950s, enriched by Sharpe in the 1960s and popularised by Burton Malkiel in his book *A Random Walk Down Wall Street* in 1973. This theory held that to 'buy the market' was better than to pick individual securities. This influenced the financial industry greatly, and institutional investors started to follow market indexes with their portfolios. This gave rise to the 'conventional wisdom' that active managers cannot outperform the market. This opinion was based on several findings by leading scientists – Sharpe, Carhart, Fama and French: 1) the average fund underperforms after fees; 2) the performance of the best funds does not persist; 3) some fund managers are skilled, but few have skills in excess of cost (Cremers, Fulkerson and Riley, 2019). Still, there are adepts of actively management funds who promise that their returns are better, both in the academic sphere (Nanigian, 2019) and in industry. For instance, Michael

Burry, famous for his forecast of the financial crisis in 2008, argued that passive investing creates another stock and bond bubble when inflows to indexes exceed those to individual securities. On the other hand, the R&D director of Capital Group, Steve Deschenes, argued that investments in passive index funds are vulnerable to all downturns, while ‘Strong active managers can provide less volatility and a smoother ride’ (Gittelsohn, 2020). However, global trends have appeared: passive investing is gaining popularity and the main financial instrument driving this movement is the exchange-traded fund.

2.2. Exchange-Traded Funds as the Disruptive Invention

Besides being the most influential innovation in the financial industry in recent decades, exchange-traded funds are one of the most impressive inventions (Deville, 2008). These funds originated in another computer-based innovation from the 1980s, ‘program trading’, which gave investors the possibility of selling all the shares of a single index in one pocket. The first successful attempt to package all the shares of an index was the Toronto Index Participation Shares launched in 1990 but shut down later on. The honour of the first ETF traded in the U.S. goes to SPY, which is designed to track the S&P 500 index and remain the biggest ETF in the world.

Soon enough, ETFs occupied a large share of financial markets. In fact, today, ETFs are responsible for more than $6 trillions of assets under management or more than 10% of the entire investment funds industry (Figure 3).

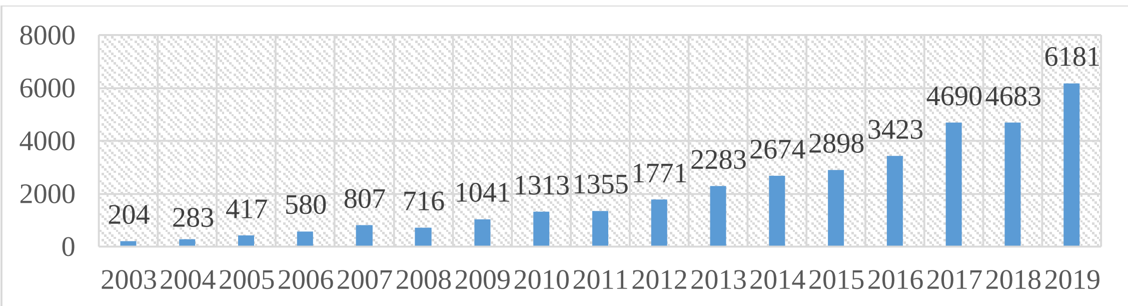

Figure 3. Amount of assets owned by ETFs globally, $ billions.
Source: Investment Company Institute (2020) ‘Investment Company Factbook: A Review of Trends and Activities in the Investment Company Industry’, pp. 1-329.

There are several advantages of ETFs, which make them so promising for investors around the world. These advantages come from the very nature of exchange-traded funds. An exchange-traded fund is an investment fund which often tracks a market index and consequently holds a portfolio of the kinds of securities contained in that index (Chen, 2020c). There are two fundamental ways to replicate an index, so there are two types of ETFs. Physical ETFs, common in the U.S. market, attempt to replicate the portfolio of an index by holding all the stocks in that index or their representative samples with the same weights. Synthetic ETFs, typical in Europe, enter into derivative contracts like total return swaps on the tracked index (Ben-David and Franzoni, 2017). Unlike a mutual fund, which is bought or sold only once each day, an exchange-traded fund is always listed on some exchange and the price of its shares change during the day like any other security, such as a stock. In this sense, an ETF is similar to a closed-end fund. However, the creation and redemption of shares in an ETF make it very close to an open-end fund. This mechanism creating and redeeming shares throughout the trading day was probably the most ground-breaking invention. It is the reason for the success of ETFs and it still ensures their distinctive features.

The market price of an ETF sometimes deviates from the NAV of its underlying securities. This is called tracking risk or tracking error. Potential sources of these tracking errors are transaction costs and fees, leading to underperformance; mistakes in replicating the index, such as having different weights or omitting some stocks; timing issues when changes are made to the index that have not been made in the related ETF; non-concurrent trading hours between an ETF and its underlying stocks, especially in the case when underlying securities are from a foreign market (Hehn, 2005).

These tracking errors are eliminated by two main market participants, who benefit from such activity. Authorised participants (APs) are large institutional investors, who have an arrangement with ETF providers or fund issuers or fund sponsors (these terms are used interchangeably) to create new shares in the primary market and redeem them from the provider. This usually happens ‘in kind’. That is, when the ETF provider publishes the list of securities it wants to hold at the start of the trading day, APs buy this creation basket in the market and exchange it for some amount of ETF shares with the fund sponsor. Then they sell the ETF shares in the secondary market, where they are traded freely afterwards (Hougan et al., 2015). Such a process can also be conducted in reverse. This is the principal way to maintain the price of an ETF close to its NAV. When the total of the underlying securities costs more than the ETF, APs buy shares of the ETF and exchange them for the underlying stocks, which they then sell in the secondary market, making a profit on this arbitrage. When an ETF’s price is higher than the NAV of the underlying securities, APs exchange the underlying securities that they hold for shares in the ETF, which they sell in the market. Thus, downward pressure on the price of expensive assets occurs at the same time as upward pressure on cheap assets, so the price of the ETF and its NAV stay close to each other (Ben-David and Franzoni, 2017). When APs exchange securities, they pay all costs associated with trading and fees paid to fund sponsors. That is why price discrepancies must be greater than transaction costs for APs to operate. A creation or redemption process is usually done in huge blocks called creation units, which range from 30,000 to 100,000 ETF shares, but are mostly equal to 50,000 shares (Deville, 2008).

The second mechanism for keeping the price of an ETF close to its NAV other is the activity of secondary market arbitrageurs. Such traders take a long or short position in the ETF and the opposite position in the main components of the index at the same time, hoping that price differences will be eliminated. Such activity assumes the risk of widening discrepancies. It is usually conducted by hedge funds or other market makers (Ben-David and Franzoni, 2017). Overall, these mechanisms are specific to exchange-traded funds, involve various participants and ensure the smooth performance of ETFs, which track indexes with minimum price discrepancies. That is why ETFs are major vehicles for index-oriented passive investments. In practice, however, they are not always passive, just as mutual funds are not obliged to be active. There are special cases of passive mutual funds (around ¼ of all funds) and active ETFs (around 1/8 of all ETFs) (Kerzérho, 2019).

Trading with ETFs has advantages beyond the ability to track an index closely, which distinguish them from mutual funds. First, ETFs have lower costs for investors. There are two reasons for that. First, they are mostly passive, so they avoid the costs associated with a manager's efforts to manage them. And second, they are exchange-traded, which means individual investors can buy them only through brokerage firms, which carry all costs connected with recording the customer, preparing prospectus documents, etc. As a result, ETFs are even less expensive to operate than passive mutual funds (Table 1).

Table 1. Expense ratios for Canadian mutual funds and ETFs

	Active	Passive
ETFs	0.64%	0.24%
Mutual Funds	1.74%	0.68%
ETFs + Mutual Funds	1.67%	0.31%

Source: Kerzérho, R. (2019) 'The Passive vs. Active Fund Monitor'. PWL Capital. pp. 1-14.

The second advantage of ETFs is the full access they have to all market segments. Because of the exchange-traded nature of ETFs, they provide the entire range of investment opportunities to any investor with a brokerage account, regardless of the size of the investor's holdings and the time horizon. Moreover, inverse ETFs allow investors to take short positions to satisfy those willing to earn on price decreases. The next advantage of ETFs is their superior transparency. U.S.-based mutual funds must disclose their portfolio on a monthly basis, but they have the ability to lag for 60 days. This leaves investors unaware of the details of a fund's portfolio within the quarter. In contrast, most

ETFs disclose their portfolios daily, and actively managed ETFs are required by law to do this (Hougan et al., 2015). This gives investors an opportunity to adjust their investment strategies with no lack of information. Another advantage of ETFs is their exchange-traded nature. On the one hand, this allows investors who trade with ETFs to apply all the various market tools (margining, optioning, etc.), which they typically use in the case of ordinary stocks. On the other hand, this makes ETFs a very important source of price information. For markets that are not liquid by nature, like fixed-assets markets or poorly priced markets in times of crises, ETFs may become the only source of liquidity, while also being the only way to investigate prices. For example, when the Egyptian stock market shut down during the Arab Spring, related ETFs were the only vehicles traded and revealing delivered prices to markets (Hougan *et al*., 2015). The final reason to choose ETFs over other investment vehicles is their tax efficiency. Mutual funds expose investors to taxes at the time that they pay capital distributions. However, ETFs have less portfolio turnover, since shares circulate on the secondary market, so they do not expose investors to tax liabilities. The creation and redemption processes are usually conducted in creation units, not in cash, and a creation unit is not a taxable event. In fact, an investor buying shares of both the S&P 500 Index and SPY will have an after-tax return of 6.77% for the mutual fund with periodical capital gain distributions and 7.12% for the ETF with an obligation to pay taxes only when the shares are actually sold (Hougan *et al*., 2015).

However, there are some disadvantages of ETFs which investors should be aware of. First, broad access to various markets by trading with ETFs may expose investors to many risks if they do not understand a portfolio’s features. Commodity ETFs, leverage ETFs and inverse ETFs are convenient trading tools. However, one should clearly understand the nature of such products. The next drawback is the obligation of investors to pay transaction costs, which are not imposed when trading with mutual funds. The exchange-traded nature of these funds incurs commissions, bid-ask spreads and premiums or discounts to NAVs, and for some investors, such costs may be more than they are willing to pay. Finally, if we consider the U.S. market, ETFs might not be an attractive option for 401(k) investors in current circumstances. Tradability and tax efficiency are not relevant for pension plans, and most plans do not have brokerage services for exchange access, so investors in these plans cannot trade ETFs (Hougan *et al.*, 2015). However, it is still valid to say that ETFs gave ground-breaking abilities for individual investors to trade using any investment strategies in any market at any time.

It came as no surprise, therefore, that with such innate flexibility, different kinds of ETFs emerged in the market. One could find an enormous number of ETFs, depending on the domestic or foreign market, which are either broadly based or attached to a particular industry or sector, type of underlying security, and usage of various trading tools like leverage.

The following is a brief review of some kinds of ETFs, based on different types of underlying securities to delineate the choice of particular ETFs for this study. The most common ETFs are equity ETFs. These ETFs finance stock markets and occupy the biggest share of the global ETF industry. Very large funds like SPY are equity-based. The next type is the fixed-asset ETF or, more precisely, bond ETFs. In general, these securities are designed to decrease the volatility of the portfolio, while adding to income. As in the case with equity ETFs, bond indexes and consequently bond ETFs may have any focus. Investors should choose among them according to their investment goals (Ashworth, 2020). These two types of ETFs create the basis for the ETF market (around 40% in the U.S. according to Hougan *et al.*, 2015), and they will serve as the object of this study. However, these instruments are rather different in their nature. So, before reviewing other kinds of ETFs, the details of these differences should be highlighted.

Discrepancies between equity and bond ETFs come from the markets of their underlying securities – stock and bond markets. A stock represents the share of a company and generates returns for investors as a result of price changes or dividends. A bond, on the other hand, is a debt instrument, which ensures regular coupon payments (usually every six months) (Chen, 2020a). By combining in the portfolio many bonds with different periods of coupon payments, the ETF can generate monthly returns with less risk. That is why bonds and bond ETFs are often used to compensate for the risks associated with the stock market, and this is especially relevant for indexes that rely on government or municipal bonds. Consequently, equity and bond ETFs are suitable for opposite investing goals and different investor pools (institutional investors prefer debt instruments). Moreover, unlike stocks, which are traded on exchanges, bonds are usually traded over-the-counter (OTC). So, prices are negotiated privately, which limits price transparency. As a result, bond ETFs rely only on estimates of bond prices, so there is more deviation between their prices and their NAVs than in the case of equity ETFs (Chen, 2020a). Overall, share and debt instruments are innately different, so ETFs that hold them also vary a lot in their basic characteristics, that is why in this work bond and equity ETFs are intentionally separated to avoid bias in calculations and interpretation.

As for the other types of ETFs, they are less popular, but still important for the market. Commodity ETFs invest both in commodities themselves and in the stocks of producers of commodities, so the choice between them is done by the investor, who should understand why s/he enters this market. A good way to compensate for the risk of currency depreciation is to buy shares of a currency ETF, which can invest in dollars or any other currencies and hedge risks. Real Estate ETFs contain shares of real estate investment trusts (REITs). They provide an opportunity to get a high yield, since 90% of incomes are paid to shareholders. This is convenient in periods when interest rates and inflation are very low. However, their volatility may be considerable higher than in the case of other types of funds, such as bond ETFs (Ashworth, 2020).

All in all, an unlimited number of different ETFs can be found in the market, depending on various characteristics. However, the one specific type of ETFs we are interested in has emerged recently and incorporated sustainability trends, which were highlighted above. These ETFs are called ESG ETFs, and they are discussed further in the next sub-section. xxx

2.3. Environmental, Social and Governance Exchange-Traded Funds: Main Properties and Description of the Market

ESG investing has been developing since the 1990s, being propelled by increasing environmental and value-based concerns. Such investing became serious when the Principles of Responsible Investing were promulgated. That dramatically fostered popularisation of ESG factors worldwide (Inderst and Stewart, 2018). As a result, ESG investments have grown rapidly, so today they are responsible for a meaningful part of financial markets (Figure 4).

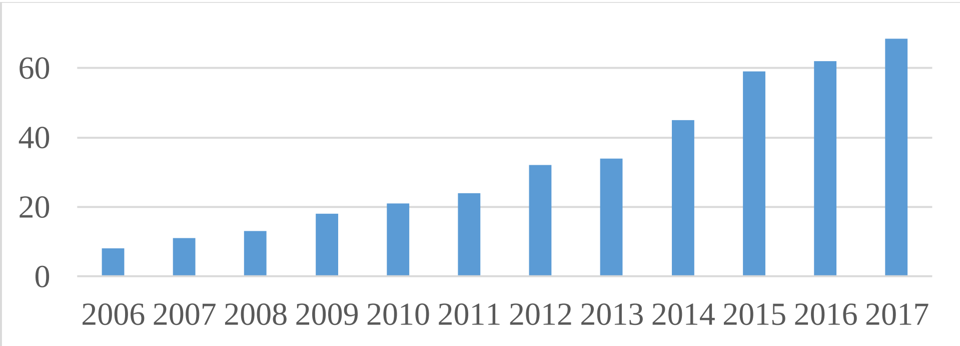

Figure 4. Assets under management owned by signatories of PRI, $ trillions.
Source: UNEP (2019) ‘Principles for Responsible Investment’, pp. 1-12.

ESG criteria are standards for a company’s business processes, which responsible investors use to screen investments (Chen, 2020b). These standards can be sub-divided according to the issuers. The ‘E’ element comprises climate change, carbon emissions, pollution, resource efficiency and biodiversity. ‘S’ refers to human rights, labour standards, health and safety, diversity policies, community relations and development of human capital. The ‘G’ element comprises corporate governance, corruption, the rule of law, institutional strength and transparency (Inderst and Stewart, 2018). However, it is impossible to create a comprehensive list, since the values to address vary in time and across countries.

There are several drivers responsible for the growing popularity of ESG investing. First, regulations in some countries have come into play. For instance, the EU has established several rules: The Non-Financial Reporting Directive obliges large EU corporations to disclose data on their ESG activities, while the Sustainability Disclosure Regulation requires financial institutions that label their products as ESG to disclose additional data (Ingman, 2020). Second, many investors, especially young ones, consider compliance with ESG criteria an absolute necessity (UNCTAD, 2019). Third, rising concerns about investors' long-term risks are satisfied through sustainable investments. A survey by BNP Paribas showed that 52% of respondents considered improved long-term returns among their top-three motivations for incorporating ESG into their investments (Spencer, Kearns and Denys, 2019). In addition, more and more studies discount earlier concerns that sustainable investments are associated with lesser returns, and many studies have shown that ESG investments might outperform conventional investing in terms of the risk-return relationship (Dunn, Fitzgibbons and Pomorski, 2017; Nordea, 2017). An investigation of the returns of ESG investments is one of the peripheral goals of this study. Finally, improved ESG data in parallel with technological improvements have extended the transparency in markets while creating the basis for index providers and fund sponsors to respond to the demand for sustainable investments (UNCTAD, 2019). Therefore, a large amount of ESG-related financial instruments like green bonds and green loans emerged and became well-known investment vehicles. Obviously, these trends could not pass by exchange-traded funds, hence ESG ETFs were created.

The number of ETFs that comply with ESG criteria increased from 39 to 221 in a decade, while the number of assets under management rose five fold (Figure 5).

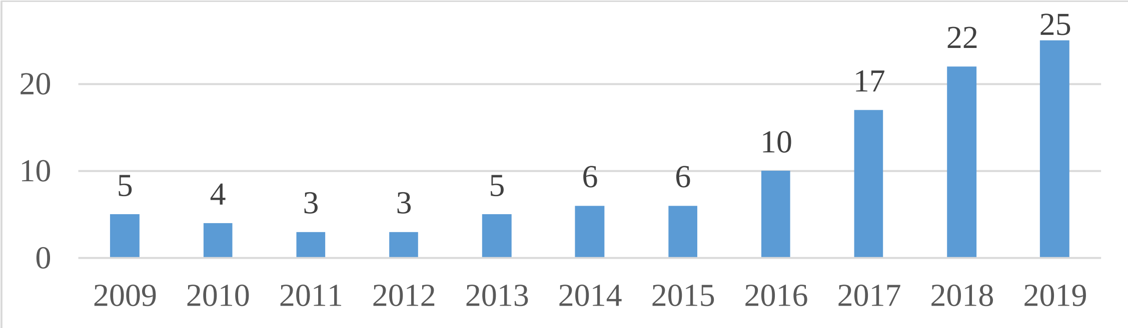

Figure 5. ESG ETFs worldwide: assets under management, $ billions.
Source: UNCTAD (2019) 'Leveraging the Potential of ESG ETFs for Sustainable Development', pp. 1-24.

Most ETFs are located in developed countries, Europe and the U.S. account for 56% and 41% of assets under management (AuM), respectively. Of all ESG ETFs, 55% track MSCI sustainability indexes (others track indexes by Bloomberg, Solactive, S&P, etc.). Moreover, 46% are issued by UBS or iShares (others are issued by BNP Paribas, DWS, etc.), and 90% of ESG ETFs are devoted to three scopes: climate change, gender equality, affordable and clean energy, while only 10% track emerging market indexes (UNCTAD, 2019). Overall, the market for ESG ETFs has been rather small, and any trends are hard to identify.

For the ESG ETF market to evolve, it must address the issue of the procedures for labelling funds as complying with ESG criteria. UNCTAD defined four ways to integrate ESG factors into the structure of ETFs. Most funds bear ESG in their names and address a broad range of issues. That is called a general integration strategy. The best-in-class or positive screening strategy embraces the ETFs that select the best-performing companies in terms of sustainability. The ESG theme strategy is applied when funds are focused on a particular topic like gender equality or if they are focused on a precise E, S or G element. Finally, exclusion screening allows funds to exclude from their portfolio companies that violate some standards (UNCTAD, 2019). UNCTAD has emphasised the lack of standards and official criteria in the market, which leads to conflicts between different

ESG ratings and scores. Moreover, inconsistent data regarding assets seriously limit investors' ability to distinguish one fund from others.

We have investigated various providers of ESG ratings and found heterogeneous principles in different countries for labelling ETFs as ESG. However, this work does not aim to characterise the ESG ratings available in markets to that extent. Instead, in this study, we use two particular approaches to address the issue of the financial flows to ESG ETFs. The first approach deals with the ESG score, owned by MSCI, called the MSCI Fund ESG Quality Score. It is based on assessments of companies in terms of their abilities to deal with long-term ESG risks. This includes a detailed analysis of their core business, the location of their assets, outsourced production and so forth.

The construction of a precise ESG score is done in three steps. In the first step, all securities in the fund's portfolio are assessed according to the ESG Ratings Final Industry-Adjusted Score or the Government-Adjusted ESG Score. The method for constructing these ratings is dense, but it is important to note that MSCI's approach does not allow bias, which may occur when traditional sectors, which are less inclined to innovations, can achieve lower ratings than novel sectors using best-available technologies and causing a lower negative environmental impact on default. MSCI uses more than 80 metrics to investigate the most significant ESG risks and opportunities for the particular industry within GICS sub-industry classifications by assigning key issues to each sector. The risk associated with a given industry arises when a company is likely to incur substantial costs because of that risk, and opportunities emerge when a company can capitalise on them in a particular industry. Therefore, regardless of how technologically advanced and green an industry is, MSCI approaches each industry individually and assigns key issues using a complicated quantitative model to avoid overweighting. Companies in the same industry tend to face similar risks and opportunities, while they may be completely different across industries, so this requires an adjustment. Weighting each of the 37 key issues accounts for the contribution of the industry (relative to all other industries) to the negative or positive impact on the environment or society. The weighting also accounts for the timeline within which risks associated with the precise industry are assumed to be eliminated. Finally, specific companies are assessed with two kinds of metrics: defining the level of exposure the company has to industry-specific risks and determining the level of management of such risks. These measures are combined to find a company's ESG score (0-10) and ESG rating (CCC-AAA) (MSCI, 2019b). All such scores for each security are aggregated, weighted according to weights in portfolio, normalised and averaged. In the second step, the adjustment base is calculated by subtracting Fund ESG Trend Negative and Fund ESG Laggards from Fund ESG Trend Positive (%). In the third step, the Fund Weighted Average ESG Score is adjusted by multiplying it by 1 + Adjustment Base. The overall score ranges from 0 to 10 (MSCI, 2019a). This study utilises this score as the variable for distinguishing funds with higher exposure to ESG criteria from funds with lower exposure. In particular, we assume that funds with higher MSCI Fund ESG Quality Scores perform better in terms of ESG factors and attract more inflows because of overall ESG trends in the financial markets, described above.

The second approach to address the issue of the financial flows to ESG ETFs simply distinguishes between ESG and non-ESG ETFs according to the list of 'Socially Conscious' funds constructed by Jon Hale, the head of sustainability research at Morningstar, one of leading financial services companies in the market. This list is published by Schwab (Schwab Charles, 2020). Unfortunately, the method used to select such funds is available only for premium users of Morningstar Direct (Liu, 2020). For that reason, we will present this list and provide the short descriptions made by Schwab. Funds are included in the list if they identify themselves as selectively investing based on the following principles. They make investments based on environmental concerns, human rights or religious values. For instance, they may intentionally invest in environmentally friendly companies or firms with good employee relations. This includes investments according to exclusion criteria: companies from military, alcohol, tobacco or gambling industries are avoided (Schwab Charles, 2020). Although a certain method is not available for such funds, it is very unlikely that there is any cheating or ambiguity in the selection procedure conducted by Morningstar. Moreover, the description and the number of funds selected are very close to those identified by UNCTAD (2019). Therefore, we have assumed that ETFs on this list are ESG ETFs and they attract more financial flows than non-ESG ETFs close to them in financial characteristics.

Stemming from this, we constructed two hypotheses to guide the research.

H1: A higher ESG score for an ETF is associated with more cash flows available for this ETF.

To check this hypothesis, we use cross-sectional aggregated data on bond and equity ETFs, and we use the MSCI ESG Quality Score of each fund as the influencing variable.

H2: Compliance of an ETF with ESG criteria significantly and positively affects the inflows to the ETF.

To explore this hypothesis, we use historical panel data for ESG ETFs from the Schwab list and their conventional counterparts, selected by the special method. We use a dummy variable to distinguish between two groups of funds. The process of this analysis and the results of the investigation are presented in the next sections.

3. Literature Review

The literature discussing ESG ETFs derives from two streams of academic papers that explore broader research issues: the literature about ETFs as a special financial instrument and studies regarding ESG factors, green finance and sustainability in its whole sense.

Business analyses and statistics have been available since the first ‘true’ ETF, the S&P 500 Trust ETF (SPDR) was introduced in 1993 (Tarassov, 2016). However, it took almost a decade for the pioneer academic works on ETFs to emerge. *The Exchange-Traded Fund Manual* by Gary Gastineau was one of the first books to study the development of ETFs in the financial market and their advantages over mutual funds. In addition, it gave investors an understanding of how to choose the best available ETFs (Gastineau, 2002). In the following years, authors have tried to highlight the main properties of ETFs compared to their predecessors (Gastineau, 2003; Hehn, 2005; Simon, 2007). During that time, numerous papers discussing a broad range of financial nuances appeared, and some authors attempted to aggregate the studies regarding ETFs. Deville (2008) divided all the studies published before 2006 into four groups based on their research questions: 1) the ability of the ETF structure to deliver effective index fund pricing; 2) comparisons with index mutual funds; 3) the influence of ETFs on their underlying assets and their derivatives, and 4) other related issues. A later but quite similar classification of literature was done by Charupat and Miu (2013). They highlighted three main strands of literature concerning ETFs. The first one investigated price efficiency by comparing the NAVs and the market prices of funds. The second strand of the literature analysed the performance of ETFs by investigating tracking errors. The last strand studied the effects on the constituent stocks of the indexes and their derivatives, giving accents to change in trading characteristics in the case of stocks and reinforcing arbitrage activities after introducing ETFs in the case of derivatives. One special sub-category of papers deals with the price discovery process, i.e. speed with which instruments react to new information. The issue of informational efficiency implied by the creation of ETF also was discussed by Ben-David and Franzoni (2017). Authors identified studies that found parallel effects: on the one hand, information was impounded into underlying assets more efficiently when they were included in ETFs; on the other hand, securities become more volatile to non-fundamental factors. Quite a different collection of papers, devoted to novel forms of ETFs such as actively managed ETFs, leveraged ETFs and smart-beta products, was embraced by Madhavan (2014). However, one of the most extensive reviews of relevant literature was done by Tarassov (2016). He used Scholar.google.com to find and analyse the 127 papers on the first 50 pages of a request for ‘Exchange traded funds’. Then he classified those studies in a matrix that had columns for the years 2001–2015 and six areas of study: 1) comparison with index mutual funds in terms of tax effectiveness, performance, tracking errors, etc.; 2) investigation of effects on underlying assets through analysis of arbitrage, hedging and liquidity; 3) effectiveness of ETFs that follow foreign indexes; 4) development of ETFs outside the U.S.; 5) recently emerged alternatives to ETFs that track equity indexes (these were similar to the ones noted by Madhavan, 2014); 6) effective portfolio construction using ETFs. Although that literature review was rather holistic, the universe of studies on ETFs is much broader, and it has many nuances that might be very important for practitioners or for further academic work. Two of those issues were the embedding of ETFs into global trends of sustainability and the integration of ESG factors into the process of investing with ETFs.

The literature regarding sustainable development and ESG factors relied on the notion of Corporate Social Responsibility (CSR) or Corporate Social Performance (CSP). It is impossible to identify the date when those phenomena appeared because concerns about societal effects are inevitable for any commercial activity. However, the terms CSR and CSP in connection with businesses were popularised in the 1920s (Bilson, 2010). CSR may be seen as the situation when a firm voluntarily conducts any activity (including investing) with regard to or aimed at minimise the negative effects on the environment and the society (or causing positive ones) (Lindberg, 2018). The reasonableness of applying such an approach to commercial activities has been challenged by a great deal of academic and business literature through several decades. In classical economic perceptions (such as Friedman, 1970), any operations that pursue the interests of society rather than following financial corporate goals, extract money from companies and predetermine financial losses for all types of stakeholders. In contrast, stakeholder-agency approach (Freeman and McVea, 2001) promised better financial performance as the result of adapting the firm to the exterior circumstances such as environmental policies and trends. The position that is based on natural resources goes further to claim that by constraining the negative impact on the environment the firm may gather unique capabilities, which can increase its corporate performance (Hart, 1995). Thus, controversial reasoning for integrating environmental and social targets into a firm's strategies has attracted many scientists to prove or disprove the consequences proposed for different economic sectors.

Enlightenment came mostly from the financial sector, as any goal that involves climate change requires a great deal of investment, according to the Paris Agreement (UN, 2015) and other conventions. As a result, notions like socially responsible investing (SRI), PRI and ESG investing appeared and directed financial flows into the new environmentally and socially responsible scopes. Unfolding the differences in meanings of these terms might lead to the following conclusions. SRI is the oldest notion, it aims at lowering 'sin' investments into industries associated with harm for society, such as alcohol and tobacco. ESG factors involve pursuing responsible investments allocated in three main directions – environment, society and governance (Khuram et al., 2016). The main point about ESG factors is that their integration, unlike the case of SRI, implies higher financial returns (Knoepfel, 2005). However, some researchers remain sceptical about higher financial returns associated with ESG investing. Thus, a separate group of papers studying this issue emerged.

Manrique and Martí-Ballester (2017), among others, investigated the effect of corporate environmental performance (CEP) expressed by a variable with parameters, extracted from Thomson Reuters ASSET4 ratings on returnx on assets (ROA) and Tobin's Q. For the sample of 2982 companies in 2008-2015, it was found that CEP had a positive statistically significant effect on both short-term and long-term financial performance. However, this effect was weaker for developed countries than for developing countries. Friede et al. (2015) went deeper and discovered distinct dimensions of ESG activities, i.e. E, S and G factors in combinations and separately. For such an analysis, the authors reviewed 3718 primary studies on the period between 1970 and 2014. That study found that around 90% of papers discovered a nonnegative relationship between corporate financial performance and ESG-factors. Furthermore, 62.6% of vote-count studies and 47.9% of meta-analyses investigated the positive correlation, which had a coefficient value of around 0.15. The results for distinct ESG factors were very consistent with those for combinations of factors. Revelli and Viviani (2015) collected 120 studies about integrating of SRI into investing, published between 1972 and 2012. Not only did they find no costs associated with SRI portfolio, but they also found that the level of performance strongly depended on the methods chosen by researchers to capture the ability of fund managers to generate performance. Experts at Summit Consulting (2017) conducted a literature review that embraced both academic literature (including meta-analyses) and business reports. They concluded that, although many individual investors are sceptical about ESG investing, academic literature proved that ESG investments performed at least as well as their non-ESG counterparts, when properly compared. From such findings, one cannot unequivocally claim the existence of a positive ESG-CFP relationship. However, such a correlation should not be dismissed out of hand. It should also be noted that, besides the possible increase in financial performance, an investor may be attracted to invest responsibly for non-pecuniary reasons. For instance, Hartzmark and Sussman (2017) claimed that people are interested in environmentally friendly assets as elements of their portfolio because they shared altruistic values, because such investing may be part of image and promotion, or, finally, because they strive to avoid societal disdain, which has become common. Any noted intentions might be the reason for responsible investing, which is usually conducted by using many funds like ETFs, including ESG and green ones.

This leads to the analysis of literature covering the special range of papers involving both the peculiarities of ETFs and the application of those specificities to ESG investing.

The literature regarding ESG ETFs is rather scarce, since the number of such instruments in the market is quite small. Most studies continued to discuss the financial performance of such funds and compare it to conventional counterparts. Meziani (2016) created a sample of 21 available ESG ETFs and showed that such funds added considerably to systematic risk while demonstrating low risk-adjusted returns. In contrast, Reiser and Tucker (2015) found that higher financial returns were associated with integrating ESG factors into investment strategies. However, for their sample of passive ESG ETFs and index funds, they found that higher fees eliminating the benefits of better performance. Authors also point to vague disclosures and wide-range voting patterns as problems to be addressed for both active and passive ESG funds. Moreover, ETFs have had some tracking errors, which should be at least lowered. However, in the case of ESG ETFs, it has been problematic to lower tracking error and achieve strong ESG scores. Winegarden (2019) recommended that institutional investors with fiduciary responsibilities not invest in ESG funds (though he did not distinguish ETFs from other funds). This was because such funds could not match the returns of broad-based index funds like the S&P 500 index fund. Of 18 ESG funds with 10-year records, only one outperformed the S&P 500 benchmark in 5-year periods. In addition, all the funds had higher expense ratios. This is in line with Meziani (2020) who questioned the legitimacy of investing in ESG ETFs by ones, obeying ERISA. However, in this updated study the scientist found some promising improvements of ESG ETFs: they were no longer overpriced compared to the market and they had been significantly improved in terms of generated returns and associated risk. Nevertheless, they still lagged behind SPY, reinforcing the doubts around ESG investing. ESG literature also contains some works that investigated peripheral issues. In some papers, special methods have been used to challenge specific topics. Rehman and Vo (2019) used wavelet transformations to discover co-movement between the six most-traded SRI funds. Scholars have concluded that combining SRI funds in one portfolio did not lead to any diversification benefits, so more asset classes should be added. van Duuren, Plantinga and Scholtens (2016) even used qualitative methods of analysis. They conducted an international survey of 126 ESG fund managers and unfolded some insights from the industry. It appeared that many conventional fund managers attempted to integrate some elements of responsible investing in their strategies. They used such elements mostly to mitigate risks or for red flagging. Moreover, there were serious differences between countries, as European investors are much more positive about the future of SRI and ESG than their U.S. colleagues. In general, ESG-related studies have gradually attracted more scientists, and new issues are being investigated. One approach has been to separate the E, S and G dimensions for deeper analysis. That approach leads to the strand of literature that deals with certain components like E one, i.e. with so-called green exchange-traded funds. Such instruments are not the primary objects of this study, but they should be briefly reviewed for a better understanding of current trends in the sphere of green finance.

Since the number of green ETFs has been very modest so far, papers discussing green ETFs are published very rarely, which makes analysing them quite simple. The first and most-cited work was by Sabbaghi (2008) who investigated 15 green ETFs and shed light on several points. First, market-wide returns for green ETFs were generally uncorrelated over time. This signalled the existence of a weak form of market efficiency. Second, cumulative returns were positive before 2008, but afterwards, they became negative. This showed that green ETFs are vulnerable to movements in the general stock market, and it undermined their role as hedging instruments. Finally, volatility effects were stable over time. Later, Sabbaghi used the same sample of funds to compare their returns with the S&P 500 index (Sabbaghi, 2011). He found that green ETFs outperformed the index prior to 2008, but underperformed afterwards which complies with the first research, moreover, their betas exceeded the value of 1, that indicates about high volatility. Using Sabbaghi’s sample, Tsolas and Charles (2015) conducted an analysis using a combination of DEA slacks-based models and regression analysis to identify funds suitable for value investors, rank top-performers among them and investigate fund-specific factors as determinants of DEA ratings. Mallett and Michelson (2010) compared SRI funds, green funds and index funds in terms of returns and found no significant difference between these three classes of assets, although the sample sizes were rather small. Only six green funds were included. The event study method also was applied to green ETFs (Wallace and McIver, 2019). Scholars have analysed the reaction of green and polluting ETFs on environmental announcements. They found that, in general, abnormal returns are equal for both groups of funds. However, when polluting and green firms reacted to the same announcement, their returns went in opposite directions.

The ARFIMA-FIGARCH model has been used to determine that green ETFs did not have any long memory of returns, so any market predictions should be done with caution (Chen and Diaz, 2016). Finally, there are studies that subdivided green ETFs even further and analysed fund investing in particular environmental areas. For example, it was discovered that a portfolio comprising both clean and conventional energy ETFs functioned better, in terms of returns and risk, than two separate portfolios, taking into account of the energy shocks of 2008 and 2014 (Alexopoulos, 2018). Rompotis (2016) assessed four water ETFs in terms of returns and systematic risks, while Tularam and Reza (2016) investigated the idiosyncratic risk of water investments under different regimes. Overall, the studies of green ETFs have not comprehensively covered features of these instruments, and they suffer from small sample sizes. Thus, new research with wider samples of funds and broader ranges of questions is needed.

It is clear that attempts to study ETFs separately, based only on E, S or G components, have not been very successful, since the numbers of funds with such distinct features are quite low, so any data analysis will be of relatively low quality. Instead, it is more interesting to look at ESG ETFs in terms of their financial properties, which are the usual objects of study in the literature on ETFs, but have not been applied to ESG ETFs.

One such issue is the investigation of financial flows going through such funds, understanding the funds' determinants and comparing them with other classes of funds. The problem of financial flows is very relevant for investment funds, especially for issuers of funds and fund managers. In a general sense, fund inflow or outflow is the number of shares created or redeemed, respectively, which can be treated as the investors' demand, since new shares outstanding should be bought by someone (Clifford, Fulkerson and Jordan, 2014). Such cash inflow is transcribed into the profit for fund managers by imposing management fee. That is why raising inflows to a mutual fund or ETF is the main purpose for ETF providers to own the investment fund. While returns are of the highest relevance for investors, cash inflows are the main point of interest for fund managers. Hence, they are extensively studied by scholars from different sides. Consequently, research devoted to the inflows and outflows of mutual funds and ETFs has emerged, and it is reviewed below.

There are two strands of literature about the flows into mutual funds (Cao, Chang and Wang, 2008). The first one deals with micro-level funds and the relationship between the performance of an individual fund and flows into or out from it. For instance, Chevalier and Ellison (1995) and Sirri and Tufano (1998) identified the causality between net fund flows and returns of funds in previous periods. However, returns are not implied by inflows. Frazzini and Lamont (2005) investigated the dumb money effect: reallocating money between different mutual funds reduces the wealth of investors in the long run. Moreover, scholars exploit flows as a measure of individual investors' sentiment for stocks, and they have concluded that high sentiment today promises low returns in the future. The second strand of research comprises papers on fund flows at the macro-level. Warther (1995) argued that the macro-level completely differs from the micro-one, since flows between funds on the micro-level offset each other, so only aggregated flow into all funds are examined. Warther found that flows into funds are related to both concurrent and subsequent monthly returns, while subsequent flows affect market returns negatively. Edelen and Warner (2001) stated that daily flows were also associated with the previous day's returns and concurrent returns, but returns were not associated with subsequent flows. Such phenomena are also relevant for developing countries (Froot, O'Conell and Seasholes, 1998). More recently, a broader spectrum of questions has been investigated. Cao, Chang and Wang (2008) found a negative correlation between fund flows and market volatility. Inflows imply a decrease in future volatility of the market and vice versa. Chen, Goldstein and Jiang (2007) showed that funds with illiquid assets are more vulnerable to outflows than funds with liquid assets. However, this phenomenon does not apply to funds held by large institutional investors. Cashman et al. (2014) investigated investors' behaviour based on mutual flows. They concluded that persistence in mutual fund flows is important, that the characteristics of the flows vary by the type of funds, and investors react to performance within a window shorter than a year. Ivkovich and

Weisbenner (2013) paid attention to individual investors' selling decisions. They found that individual investors have a propensity to sell funds with incurred losses. Expenses and loads associated with funds are the main determinants of selling decisions. In addition, by analysing inflows, outflows and net flows separately, they found that inflows were affected by the relative performance of the funds, while outflows were inspired by absolute performance in the previous year. Thus, the range of issues covered by related papers is rather broad, and authors have used different methods to explore them.

The literature covering the specificities of ETF flows is not as developed, although there are papers revealing many insights in this area. It is important to study ETFs separately from mutual funds because they have different fee structures, trading peculiarities and tax features (Agapova, 2011). Many arguments are related to the creation/redemption mechanism involving APs, described in Sections xx and yy. In an early study, Kalaycıoğlu (2004) began with the hypothesis that flows into ETFs were not based on the skills of the fund manager but on investors' beliefs about the underlying index. Using a sample of only five ETFs based on the most popular indices, Kalaycıoğlu found a negative relationship between ETF flows and market returns. However, he denied that ETF flows put price pressure on market returns. Agapova (2011) compared aggregated flows into t index funds and ETFs and found that these instruments were imperfect substitutes for each other and also that the difference was provided by the clientele effect. Cheng, Massa and Zhang (2013) found that outflows represented the reaction of investors to overinvestments by the ETFs in stocks of affiliated banks to boost the prices of those stocks so that conflicts of interest were created. ETF flows are also different from mutual fund flows in the sense that they do not show persistence (Broman and Shum, 2013). Moreover, those scholars have shown that liquidity affection predicts future ETF flows in terms of price impact, share creation and turnover pillars even after unexpected shocks. In more recent studies, authors have delved more deeply into issues of liquidity, i.e. they have discovered that relative liquidity increases net flows, inflows and outflows, but it specifically encourages short-term demand. Clifford, Fulkerson and Jordan (2014) have shown that ETF flows are the same as mutual fund flows in that they chase returns. This has added to the debate whether return chasing in funds is based on a search for skilled managers. Wang and Xu (2019) addressed the issue of volatility and found that the daily flow of ETFs positively affected both the total of the underlying assets and their fundamental volatility on the next trading day. Staer (2017) addressed the questions whether price pressure and price reversal patterns on underlying stocks were related to inflows to ETFs. Scholars have found that ETF flows are positively correlated to underlying returns, while lagged flows are negatively correlated. This implies that the effect of the price pressure is transitory. In contrast to previous studies, Oztekin (2018) used a sophisticated meta-classification modelling approach to identify the determinants of inflows and outflows of ETFs. He concluded that management fees, standard creation and redemption fees, the number of fund holdings and total returns were the most influential fund-level contributors to flows. In total, many studies were built on analogues to investigate mutual funds and used similar methods to discover this wide range of issues. In this regard, it is reasonable to look at papers dealing with SRI or ESG and see how that research is related to the questions raised by this study.

Studies of ESG-related fund flows generally examine SRI mutual funds. The essence of such studies has been to find differences in relation to past returns in the cases of SRI and conventional funds. For instance, Benson and Humphrey, (2008) stated that SRI funds were less sensitive than conventional funds to current and past returns in monthly and annual perspectives. Bollen (2007) compared SRI and conventional funds in the U.S. and concluded that SRI funds were less sensitive than conventional funds to negative returns, but more sensitive to positive ones. This was also the conclusion of Renneboog, Ter Horst and Zhang (2011) although they found no smart money effect.

Białkowski and Starks (2016) investigated money flows attracted by SRI funds and conventional ones. They found that SRI funds on average attracted more flows and that this situation was robust even after scandals and corporate environmental disasters. These differences are implied by non-financial considerations. These postulates were confirmed by Hartzmark and Sussman (2017). Funds with low sustainability ratings were associated with more net outflows, while funds with high sustainability ratings were considered to have more net inflows. Moreover, sustainability has been mentioned as positively predicting future performance. All these studies come to the conclusion that responsible investments are less oriented to commercial gains. So, SRI funds are less affected by past returns than are conventional funds. Unfortunately, these results cannot be directly extrapolated to ETFs because of the structural differences noted above. Thus, additional investigation is needed to find similar or differing results in the case of exchange-traded funds. This paper addresses this gap and explores one of the main issues, differences in the determinants of fund flows in application to ESG ETFs and their counterparts.

4. Methodology and Approach

4.1. Common Methods in Fund Literature

Regression analysis is a common method to investigate the determinants of financial flows of different kinds of funds. Since there are no studies that specifically examine ESG ETFs, we provide examples from the literature on ETF flows and ESG mutual fund flows to illustrate how this method can capture both the specificities of the instrument and of ESG criteria, which usually distinguish the observed funds, both ESG funds and conventional ones.

Agapova (2011) exploited pooled OLS and SUR regressions to investigate the substitution effect between exchange-traded funds and conventional index funds in panel data for the period, 2000-2004. Aggregated monthly flows were the dependent variables in models with both types of instruments, while lagged flows, lagged returns, expenses and the logarithm of total assets served as the independent variables. Agapova also included year and index dummies in the model. We also use dummy variables in our research. The scientist concluded that ETFs and index funds were substitutes for each other because of the negative value of one of the parameters responsible for such meaning. A pooled OLS regression with fixed effects for time, sector funds and style was used by Broman and Shum (2013) to find the relationships between different types of liquidity and ETF monthly inflows. Scientists found higher flows for ETFs with higher relative liquidity (which investors use to decide whether to buy an ETF that tracks a particular index or to buy its constituents) in spreads, price impacts, turnover and share creation activity. This analysis required four different panels with 165 ETFs. In parallel with Agapova (2011) expenses, total assets and other fund characteristics like age of the fund were used as control variables. Later on, scholars focused more on the influence of relative liquidity on funds' flows, and they extended their analysis to include more data and to use different dependent variables – inflows, outflows and net inflows (Broman and

Shum, 2018). Clifford, Fulkerson and Jordan (2014) also utilised different measures of fund flow while dividing control variables into three groups – fund characteristics (e.g. age, size, expense ratio); trading characteristics unique to ETFs (e.g. standard deviation of daily volume, average daily spread, share turnover), and return variables, responsible for capturing different measures of prior return (12-month return, standard deviations of returns, etc.). In our study, we intend to follow that set of variables. However, because of limited access to data, we can replicate that study only partially, although main controls are still covered. These are discussed next.

Integrating ESG criteria into studies of investment funds is usually done by dividing the funds into two groups and analysing the groups separately. However, the first studies were focused only on green instruments. For instance, Sabbaghi (2008) utilises a special method – t-GARCH – to examine long-memory characteristics of the funds. The scientist applies it to green ETFs without any comparison and came to the following conclusion: returns are generally not correlated over time and green ETFs are not immune to market movements. In later research, Sabbaghi used the same sample of green ETFs and compared returns with S&P 500 returns using a CAPM analysis. Green ETFs outperformed S&P 500 in the 2005-2008 period, but they were vulnerable to market volatility. More recent studies have compared ESG-related instruments with their counterparts. Chen and Diaz (2016) constructed two samples – five green ETFs and five non-green ETFs – and applied the ARFIMA-FIGARCH models. Regardless of being green or not, most ETFs showed non-stationarity and non-invertibility. This became another argument for the efficient market hypothesis, which states that securities always trade at fair value and exhibit all necessary market information (Fama, 1970). Białkowski and Starks (2016) constructed samples of panel data comprising 117 Socially Responsible Investing (SRI) funds and their counterparts, using a 1-to-1 and a 1-to-5 match. Scholars have implemented different methods, and they have undertaken different kinds of analysis, including panel data regressions with fund flows as the dependent variables and fund characteristics, such as expenses and assets as the influencing variables. What is important, they have analysed all funds simultaneously, making the SRI funds the dummy variable and observing its significance and coefficient. Authors have shown that SRI funds attract more flows than conventional funds for all sub-samples, varying in the degree to which a fund is investing in a responsible manner. These results are also robust for the whole time-period, 1999-2011, even after environmental disasters. In our study, we also use a dummy variable to separate ESG funds from conventional ones. Moreover, following Białkowski and Starks (2016) we have construct samples for regression analysis, using the matching procedure described in Section xx. Stemming from features utilised in other papers, we have created the following models to examine our hypotheses.

4.2. Cross-sectional Regression Model

The first model that we exploit addresses the first hypothesis regarding the significance of the ESG score for fund flows. For this portion of the analysis, we exploit a cross-sectional model, using aggregated data from ETFdb.com. Cross-sectional models have not been used in many studies of fund flows, as panel data allows a researcher to have more observations and they increase the reliability of the model. However, we regard this model as a preliminary tool to provide the first glance at the relationship between fund flows and the compliance of their portfolios with ESG criteria. Therefore, we created a model with the following variables (Table 2).

Table 2. Variables for a regression model with cross-sectional data

Flow_Assets	**The ratio of one-year fund flow divided by total assets of the fund, %**
ESG_Score	MSCI ESG score, 1 to 10
ER	Expense ratio set by the fund, %
Return	Aggregated annual return for the previous year, %
Log_Volume	Logarithm of a fund's average traded volume, $
SD	Standard deviation of a fund's returns, %

Age	Age of fund, months
Volatility	Volatility of the fund for last 200 days, compared to its peer group in ETFdb.com, %

Source: devised by author in Microsoft Excel.

The dependent variable is the ratio of yearly fund flows divided by the fund's total net assets (TNA), represented in per cents. We have chosen this ratio as the dependent variable for the following reason. In some papers (Clifford, Fulkerson and Jordan, 2014) net flows, inflows and outflows are used with no additional calculations. However, to exploit such an approach, the sample should contain funds with values that are close to total assets, such that an increase in inflows may be generalised to all ETFs in money values. This study comprises funds with ESG scores or funds labelled ESG, which may be very young and small, especially compared to well-known ETFs like SPY. In this sense, the overall increase in inflows caused by any regressor is hard to interpret when represented by money values, since for some funds a certain amount of inflow may be substantial, while for others it is insignificant. Dividing by TNA yields the value of a coefficient, which accounts for differences in total assets and shows the increase in inflows equally relevant for all funds in the sample. In addition, we do not distinguish between inflows and outflows because of a lack of data. The ESG_Score is the main object of study, it mirrors the score given by MSCI to each fund, using the method described in Section xx. It can vary between 1 and 10, and it is expected to have positive coefficients in the model. The Expense ratio is normally set by the fund managers; it is represented in per cents. This variable is expected to have negative coefficients, as in other studies, since investors tend to buy less costly securities (Cashman et al., 2012; Das et al., 2018). The variable representing return is given as the aggregated return for the last year in per cents, it is assumed to have positive coefficients, as financial return is the main motivation for investors to buy any security. The same is true in similar studies (Clifford, Fulkerson and Jordan, 2014; Das et al., 2018). The average traded volume of a fund denotes the overall activity of the security (Nickolas, 2020). It is expected to have a positive value in the model. SD and volatility are both responsible for capturing the risk of the security. They tend to have negative coefficients in the models constructed by other authors (Clifford, Fulkerson and Jordan, 2014) because investors operating in passive markets do not seek riskier options. Moreover, in the period when ESG market funds were emerging, compliance with ESG criteria was associated with lower volatility. In time, however, this effect converged, so investors in responsible funds behave in the same manner as conventional investors (Białkowski and Starks, 2016). Finally, the age of a fund is given in months since the inception date. It may have positive or negative signs, according to the specificities of a sample. Some studies have found a positive relationship between fund flows and the age of a fund (Broman and Shum, 2018; Das et al., 2018), while others discover negative relationships (Clifford, Fulkerson and Jordan, 2014; Białkowski and Starks, 2016). We do not include the variable representing the total assets of funds, since the dependent variable already contains that information.

As a result, we come to the following cross-sectional regression equation, investigating the relation between fund flows and influencing variables:

$$Flow\_Assets_i = Intercept + \beta_1 * ESG\ Score + \beta_2 * ER + \beta_3 * Return + \beta_4 * Log\ Volume + \beta_5 * SD + \beta_6 * Age + \beta_7 * Volatility. \quad (1)$$

4.3. Panel Data Model

The second portion of analysis was conducted using regressions with panel data, which came from the Bloomberg database. These models are aimed at answering the main questions of the study – whether ESG ETFs attract more financial flows than conventional ETFs. Such an analysis requires the following set of variables (Table 3).

Table 3. Variables for a regression model with panel data

Flow_TNA	**The ratio of monthly fund flow divided by total assets of the fund**
ESG	Dummy variable, 1 – the fund is ESG, 0 – otherwise
ER	Expense ratio set by the fund, %

Return	Aggregated monthly return lagged for one month, %
Holdings	Number of securities owned by the fund
Price_NAV	Price of the ETF to the fund's Net Asset Value, %
Age	Age of the fund, months
Spread_Price	Ratio of the ETF's price spread to its price, %
Log_Turnover	Logarithm of share turnover, $

Source: devised by author in Microsoft Excel.

The dependent variable is the monthly ratio of fund flows, divided by total net assets. It is similar to the one used in the cross-sectional model except that it comprises panel data, i.e. extended to a lasting time period. Once again, dividing flows by TNA allows a researcher to eliminate the obvious differences in assets between old, well-known funds and newly created ones. ER and age do not differ from their use in the cross-sectional model, even though age changes over time. The return variable is intentionally lagged for one period (one month), following the method of other papers (Clifford, Fulkerson and Jordan, 2014; Białkowski and Starks, 2016). The number of underlying securities is represented by the variable Holdings. We assume a positive value of the coefficient, since Oztekin (2018) argued that investors are concerned about small numbers of holdings, as it is hard to keep the right proportion and offset management fees when the holdings are few. Price_NAV and Spread_Price both come from the tradable nature of ETFs. Since such funds may be traded at a premium, which is described in previous sections, the ratio of the market price to the book value of the fund may represent a very meaningful source of inflows, particularly to ETFs. Likewise, the bid-ask spread denotes the liquidity of the fund. Theoretically, it should have a negative sign, since liquid funds are traded more and have narrower spreads. The logarithm of turnover represents the total amount traded in securities currency. It also shows the liquidity of the fund and should have a positive sign of the coefficient in the model. With these variables we created models with samples comprising bond ETFs and equity ETFs.

In our study, we exploit two types of regression models dealing with panel data. The pooled OLS method is used when data on different individuals is pooled together with no provision for individual differences, which may lead to different coefficients (Hill, Griffiths and Lim, 2011). We assume, that in our case such a model will have low explanatory power, since differences should occur across funds and time periods. However, we start with this method to achieve more robustness in the chosen specifications. From our set of variables, we can construct the following equations for bond and equity ETFs:

$$Flow\_Assets_{i,t} = Intercept + \beta_1 * ESG_{i,t} + \beta_2 * ER_{i,t} + \beta_3 * Return_{i,t} + \beta_4 * Holding_{i,t} + \beta_5 * Price\ NAV_{i,t} + \beta_6 * Age + \beta_7 * Spread\ Price_{i,t} + \beta_8 * Log\ Turnover_{i,t}. \quad (2)$$

In practice, individual differences often exist and should be captured. There are two main ways to account for such differences. A fixed effects model captures individual differences in the intercept parameter by introducing dummy variables for each individual, while a random effects model assumes that individuals are randomly selected in the sample and adds the special term, analogous to random errors, which assumes zero mean, constant variance and absence of correlations across individuals (Hill, Griffiths and Lim, 2011). Normally, a Hausman test is used to choose between these models and to achieve better specification. That test compares coefficient estimates for the fixed effects model and the random effects model by identifying the correlation between random effect and explanatory variables. If such correlations exist, the random effects estimator becomes inconsistent, and the fixed effects model has a better specification. As will be seen, applying the Hausman test to all models shows the need for fixed effects modelling. However, since we use a cross-sectional dummy variable as the main object of our study (ESG vs. non-ESG), we cannot fix effects in the cross-sectional dimension, only in the time series. Hence, we use the mixed effects model, which allows using fixed effects and random effects simultaneously.

Such models are particularly useful in some areas of study like medicine. In matrix form the mixed model has the following specification:

$$y = XB + ZU + \varepsilon \ (3)$$

where y is the vector of responses, X is the known design matrix for fixed effects, B is the unknown vector of fixed effects, Z is the known design matrix for the fixed effects, U is the unknown vector of random effects, and ε is the unobserved factor of random errors (Mclean, Sanders and Stroup, 1991). Applied to our variables, regression models have the following equation:

$$\begin{aligned} Flow\ Assets = {} & Intercept_t + \beta_1 * ESG_{i,t} + \beta_2 * ER_{i,t} + \beta_3 * Return_{i,t} + \beta_4 \\ & * Holdings_{i,t} + \beta_5 * Price\ NAV_{i,t} + \beta_6 * Age_{i,t} + \beta_7 * Spread\ Price_{i,t} \\ & + \beta_8 * Log\ Turnover_{i,t} + v_{it} \ (4) \end{aligned}$$

where v_{it} is the sum of components, u_i responsible for individual random effects and e_{it} is random error (Hill, Griffiths and Lim, 2011).

This equation is applied to different samples of data – bond and equity ETFs, two or three years observed, one-to-one or one-to-two samples. The data exploited for the analysis are described in Chapter 5.

5. Data

5.1. Cross-sectional data

Since we have two types of models in our analysis, aimed at discovering two hypotheses, the data we used, also came from various sources. The first portion of data is related to the cross-sectional model, which addresses the first hypotheses. We have chosen a commercial database from ETFdf.com. This site is one of the leading in providing relevant information regarding ETFs including data on financial flows. The obvious drawback of such a database is the absence of historical data, i.e. all information is cross-sectional and has the aggregated form, e.g. a YTD fund flow, a 1-year fund flow, a 3-year fund flow and a 5-year fund flow. Such an approach to aggregate the data does not allow to lag variables or conduct any time-series analysis. Nevertheless, the database covers the vast majority of ETFs traded on U.S. exchanges, a total of 2289 unique funds. The database provides access to more than 60 variables, which might be used to filter out unnecessary funds. This set included traditional financial fund characteristics such as total assets, price, average volume, expense ratio and returns aggregated for different periods, as well as less common variables like RSI value, class of liquidity and sustainability score. In our analysis, we focused on certain fund characteristics, used in other papers: fund flows, total assets, expense ratio, inception data, return, volume, standard deviation, volatility and ESG score. That is why we had to refrain from using most of the available variables and narrow the set to the features we are interested in.

To get the sample of funds, close in their financial specificities, we should have filtered out many of them according to the following logic. First, we removed all the funds that were not equity funds or bond funds, such as multi-asset funds, real estate funds and commodity funds. These types of ETFs have special kinds of underlying securities, so they cannot be mixed with equity or bond ETFs because of different financial properties. Next, we eliminated all ETFs that were related to groups of inverse, leveraged, Smart

Beta or currency hedged funds. We did this for inverse and leveraged ETFs, since they must adjust their exposures to the benchmark indices at the end of the trading day in order to maintain a constant leverage ratio. Therefore, they have different returns compared to conventional ETFs (Charupat and Miu, 2013). Moreover, inverse ETFs are based on short positions, which makes them distinct in behaviour from other types of funds. Smart Beta ETFs do not passively track a particular index. Instead, they choose and weight stocks to invest in, according to their own rules. That is why such funds have different scales of risk and should be excluded. Finally, since we are focused on the U.S. market, ETFs investing in different markets and using currency hedging mechanisms also were removed. After we excluded the ETFs that lie outside of our interest, we could focus on the variables we have chosen. Some of them required additional calculations, e.g. to create certain ratios and logarithms or to define the age of funds from their inception date. Many of the ETFs lacked one or more of these variables, so they were not included in further analysis. After filtering out all the funds with outlying characteristics or omissions in data, we arrived at two samples comprising 163 bond ETFs and 897 equity ETFs with certain characteristics. Bond ETFs had the descriptive statistics of the chosen variables listed in Table 4.

Table 4. Descriptive statistics for bond ETF cross-sectional data sample

	Mean	Median	Maximum	Minimum	Std. Dev.
FLOW_ASSETS	0.0949	0.121	0.979	-1.59	0.366
ESG_SCORE	5.032	5.040	6.710	2.090	1.232
SD	0.019	0.011	0.162	0.002	0.024
ER	0.003	0.002	0.010	0.000	0.002
AGE	100.344	97.000	213.000	19.000	43.285
RETURN	0.057	0.046	0.746	-0.121	0.117
VOLATILITY	0.167	0.156	0.561	0.002	0.100
LOG__VOLUME	12.140	12.429	17.553	3.638	2.567

Source: devised by author in Eviews.

It should be noted that cross-sectional fluctuations of the ratio of funds' flows and their assets are very small because of the aggregated character of the data. Hence the values have been multiplied by millions for better representation. Other variables have a wide range. For example, the oldest fund is 213 months old, while the youngest is just 13 months. We can assume several problems in the models arising from small variations of dependent variables such as a low level of the explanatory power of the model or inadequate coefficients. Such concerns may also be drawn from the correlation analysis (Table 5).

Table 5. Correlations between variables in bond ETFs cross-sectional data sample

	FLOW_ASSETS	ESG_SCORE	SD	ER	AGE	RETURN	VOLATILITY	LOG__VOLUME
FLOW_ASSETS	1.000	-0.037	-0.123	-0.185	-0.223	-0.012	-0.112	0.072
ESG_SCORE	-0.037	1.000	0.143	-0.457	0.366	0.562	-0.372	0.138
SD	-0.123	0.143	1.000	0.102	0.353	0.723	0.573	0.091
ER	-0.185	-0.457	0.102	1.000	-0.204	-0.252	0.342	-0.365
AGE	-0.223	0.366	0.353	-0.204	1.000	0.310	0.041	0.516
RETURN	-0.012	0.562	0.723	-0.252	0.310	1.000	0.249	0.112
VOLATILITY	-0.112	-0.372	0.573	0.342	0.041	0.249	1.000	-0.027
LOG__VOLUME	0.072	0.138	0.091	-0.365	0.516	0.112	-0.027	1.000

Source: devised by author in Eviews.

Most of the variables, including the ESG score, have negative correlations with the dependent variable. This contradicts most of the assumptions above on signs of coefficients in the regression model. This situation may be because of the small number of observations affected the quality of the model. This statement may be indirectly proved by observing the equity ETFs sample. Several relationships between the independent variable are associated with high correlation values (> 0.5), which creates the possibility for multicollinearity.

The sample of equity ETFs comprises many more observations, and it has the following descriptive statistics (Table 6).

Table 6. Descriptive statistics for equity ETFs cross-sectional data sample

	Mean	Median	Maximum	Minimum	Std. Dev.
FLOW_ASSETS	-0.136	-0.0398	33.4	-12.6	1.48
ESG_SCORE	5.249	5.415	9.470	0.480	1.423
SD	0.050	0.036	0.549	0.007	0.043
ER	0.004	0.004	0.024	0.000	0.002
AGE	123.095	114.500	327.000	5.000	63.203

	Mean	Median	Maximum	Minimum	Std. Dev.
RETURN	-0.171	-0.150	0.503	-12.660	0.442
VOLATILITY	0.503	0.475	2.254	0.105	0.156
LOG__VOLUME	11.200	10.933	18.920	4.234	2.481

Source: devised by author in Eviews.

From this table, we might derive several conclusions. First, the standard deviation of the dependent variable was higher than in the case of bond ETFs. Moreover, the maximum value was much bigger, which showed that the equity ETFs sample comprised funds that were far more attractive to the market. This is despite the fact that the mean value was negative and lower than in the case of bond ETFs. In addition, equity ETFs are generally older, have bigger expenses, are much more volatile and have higher ESG scores. Interesting enough, equity funds are less profitable than bond ETFs, and they even showed negative 1-year returns. This result might be related to the outbreak of coronavirus, which inflamed volatility and risk across all financial markets starting in February, while the data were gathered at the end of March (Catala, 2020).

The equity ETF sample was assumed to have more adequate correlations with the dependent variable (Table 7).

Table 7. Correlations between variables in equity ETFs cross-sectional data sample

	FLOW_ASSETS	ESG_SCORE	SD	ER	AGE	RETURN	VOLATILITY	LOG__VOLUME
FLOW_ASSETS	1.0000	0.0673	0.0499	-0.0507	0.0122	0.0175	0.0604	0.0475
ESG_SCORE	0.0673	1.0000	-0.0734	-0.1568	-0.0140	0.2080	-0.1760	0.0496
SD	0.0499	-0.0734	1.0000	-0.2056	0.4097	0.0160	0.3804	0.2012
ER	-0.0507	-0.1568	-0.2056	1.0000	-0.1036	-0.0998	0.2340	-0.2909
AGE	0.0122	-0.0140	0.4097	-0.1036	1.0000	-0.0025	0.1205	0.4394
RETURN	0.0175	0.2080	0.0160	-0.0998	-0.0025	1.0000	-0.1419	0.0591
VOLATILITY	0.0604	-0.1760	0.3804	0.2340	0.1205	-0.1419	1.0000	0.1551
LOG__VOLUME	0.0475	0.0496	0.2012	-0.2909	0.4394	0.0591	0.1551	1.0000

Source: derived by author in Eviews.

Correlations with the dependent variable comply with the imposed theoretical assumptions. Moreover, the ESG score variable had the strongest influence on the fund flows, which permits predicting a significant coefficient in the regression model. In addition, there are no high correlation coefficients between influencing variables, which reduces the possibility of multicollinearity in the model. In general, the model with equity ETFs was seen to be much more reliable, so it became the main object of our analysis of the relationship between the ESG score and funds flows.

5.1. Panel Data

We tested our main hypothesis with monthly panel data, following other studies of investment funds. All data came from the Bloomberg database, which is one of the most used databases in financial literature. It contains historical data on dozens of securities including mutual funds and ETFs, and it has hundreds of variables. Unfortunately, unlike narrowly focused fund databases like CRSP Survivor-Bias-Free US Mutual Fund, the Bloomberg database does not offer some specific fund features, such as fund flows divided by inflows, outflows and net inflows. That would have made this analysis broader and easier. Nevertheless, we managed to gather data on the following fund features: monthly aggregated day-to-day total return, net asset value, last price, average bid-ask spread, fund total assets, fund flow, current shares outstanding, turnover (traded volume). Despite the value of current shares outstanding, which we used to check the relevance of fund flows (change in the number of current shares outstanding denotes inflow or outflow of the fund, depending on increase or decrease in this amount), all other characteristics were used to construct additional variables involved in the regression analysis and described in Section xx.

To use our models, we had to gather data on four different samples: bond ESG ETFs, bond non-ESG ETFs, equity ESG ETFs, equity non-ESG ETFs. Filters to create cross-sectional samples were used to exclude all ETFs that had underlying securities other than bonds and equities, and then to distinguish these two kinds of funds. To further delineate the border between ESG and non-ESG funds we exploited the list of all ESG mutual funds and ETFs existing in the first quarter of 2020. This list was derived from Morningstar's 'Socially Conscious' data and published by the Charles Schwab Company (Charles

Schwab, 2020). It divides ESG funds into groups such as International Equity ETFs and Sector Equity ETFs. However, such distinctions exceeded the detail we needed for our analysis. That is why all equity and bond ETFs were aggregated in two plain groups, consisting of 84 equity ESG ETFs and 27 bond ESG ETFs. We excluded several funds in our dataset that did not have cross-sectional data from ETFdb.com, since some of those data – like age or expense ratio – would also be also used in the panel data analysis. For these funds, historical data was derived from the Bloomberg database. Nevertheless, some equity funds were not contained in the dataset, so the sample of ESG ETFs was shortened to 80 funds. Then, non-ESG counterparts were identified for both groups of funds. This required identifying the providers (issuers) of these funds and finding non-ESG ETFs that they issued, to parallel the ESG funds. As a result, data on 139 bond non-ESG funds and 317 equity non-ESG funds were extracted. Although our datasets did not include an exhaustive number of funds available from those issuers (student access to Bloomberg database has its limitations), the final number of funds was certainly sufficient to identify suitable counterparts for the ESG funds to use in our analysis.

The next phase was to define the proper time period for analysis. Extracted data were given for the period from March 2016 to March 2020. Many studies, such as Białkowski and Starks (2016) and Das et al. (2018), used periods of 10 years or more in their analyses of ESG mutual funds. However, such an analysis was not possible in or the case of ESG ETFs, as many of them appeared only a few years or only several months ago. As a result, we restricted our time period to two years (2018.03-2020.03) for bond ETFs, and to two years and three years (2017.03-2020.03) for equity ETFs so that there would be enough observations for an adequate regression model. We analysed equity EFTs for both a 2-year and a 3-year time period, and this contributed to the robustness of the analysis. After filtering out funds with less than two years of history, we ended up with 15 bond ESG

ETFs and 42 equity ESG ETFs. These two samples were the basis for our analysis, and the rival samples of non-ESG funds stemmed from them.

To create samples of non-ESG counterparts, we had to go through several steps. First, we once again checked the issuers. of ESG ETFs. Then we tried to find appropriate counterparts for each ESG ETF, and we construct two samples of matching funds – a 1-to-1 sample (1-1) and a one-to two sample (1-2). This helped us to achieve more robustness in the samples by varying the number of matched funds. In some cases, the procedure was straightforward. For instance, Nuveen has issued one bond ESG ETF and one non-ESG ETF issued. Because there were no other funds against which to match these funds, they were matched with each other in the 1-1 sample. However, many ESG ETFs providers did not have non-ESG counterparts to the funds in our samples. These included J.P. Morgan, and simultaneously some issuers, e.g. IShares, have many non-ESG funds both in bond and equity samples. In such cases, we had to match more than one or two funds to IShares ESG ETFs to have an equal number of funds in both samples. The matching procedure followed the methodology of Białkowski and Starks (2016), but we did not use Fama-French-Carhart factors as matching variables. Instead, despite total assets, we exploited age, expense ratio and the number of holdings to match funds:

$$Match_{ij} = \frac{(TNA_i - TNA_j)^2}{\sigma^2_{TNA}} + \frac{(Age_i - Age_j)^2}{\sigma^2_{Age}} + \frac{(ER_i - ER_j)^2}{\sigma^2_{ER}} + \frac{(Holdings_i - Holdings_j)^2}{\sigma^2_{Holdings}} \quad (5),$$

where σ is the cross-sectional deviation. The matched fund had the lowest matching rank among others. Hence, funds with the lowest ranks were matched according to the number of ESG funds in the portfolio of a given issuer. As a result, we had the following distribution of ETF providers in the final bond ETF sample (Table 8). For a better understanding of which funds could be included in the ESG sample, the full names of bond ESG ETFs are listed in Appendix A.

Table 8. Issuers of bond ETFs in panel data samples

ISSUER	ESG	NON-ESG 1-1	NON-ESG 1-2

INSPIRE INVESTING	1	0	0
ISHARES	2	3	8
SAGE ADVISORY	1	0	0
J.P. MORGAN	3	0	0
NUVEEN	1	1	1
HARTFORD FUNDS	2	0	0
VANECK	1	2	2
INVESCO	3	3	13
DWS	1	6	6
TOTAL	**15**	**15**	**30**

Source: devised by author in Microsoft Excel.

As it can be seen in Table 8, the 1-1 sample had a rather balanced distribution of issuers across funds, while the 1-2 sample was mostly constructed from funds issued by IShares and Invesco. The equity ETF sample had a similar issue. The vast majority of funds in the 1-2 sample were issued by four ETF providers: Invesco, IShares, State Street SPDR and First Trust (Table 9).

Table 9. Issuers of equity ETFs in panel data samples

ISSUER	ESG	NON-ESG	NON-ESG
COLUMBIA THREADNEEDLE INVESTMENTS	4	1	1
ISHARES	7	9	21
STATE STREET SPDR	5	7	15
FLEXSHARES	1	4	4
INSPIRE INVESTING	2	0	0
GLOBAL X	2	3	6
NUVEEN	5	0	0
ETF MANAGERS GROUP	1	1	1
VANECK	2	0	0
FIRST TRUST	4	5	12
INVESCO	7	10	22
STRATEGY SHARES	1	1	1
TORTOISE CAPITAL	1	1	1
TOTAL	**42**	**42**	**84**

Source: devised by author in Microsoft Excel.

This situation, when several issuers prevail in the sample was not unpredictable since those companies also occupy the biggest positions in the investment funds market in general.

Another issue which should be noted is the possibility of industrial bias. It may be assumed that novel ESG funds invest in technologically advanced companies with bigger concerns for sustainable strategies and innovations. So, higher flows to those ESG funds might be based, not on the ESG nature of those funds, but on better portfolio management, which focused on more prospective industries and companies. This can be found by econometric analysis. To eliminate such risks, we conducted a simple statistical analysis: by gathering data on the Yahoo!Finance service we conducted an industrial breakdown of the portfolios of funds in the equity ESG and 1-1 non-ESG samples. The results of this analysis showed that there were no major differences between samples. That is, the ESG funds invested in the same industries as non-ESG funds, but with a lower intensity, since the total assets of novel ESG funds were generally lower than the total assets of well-known non-ESG ETFs. The actual outcomes of that analysis are given in Appendix B.

Samples were characterised with several specificities. This can be inferred from the descriptive statistics, which were intentionally divided into the samples of ESG and non-ESG funds (Table 10).

Table 10. Descriptive statistics of the bond ETF panel data samples

	FLOW _TNA	ER	LOG__TU RNOVER	PRICE _NAV	SPREAD _PRICE	HOLDING S	AGE	RETUR N
Bond ESG ETFs								
Mean	0.04	0.003	16.28	1.001	0.01	1036.6	47.4	0.45
Median	0.01	0.003	16.28	1.001	0.00	225.0	25.0	0.32
Maximum	0.89	0.006	22.63	1.015	0.14	9749.0	149.0	4.16
Minimum	-0.22	0.001	9.54	0.982	0.00	55.0	3.0	-2.21
Std. Dev.	0.10	0.001	2.12	0.003	0.01	2387.5	47.2	0.95
Bond non-ESG ETFs 1-1								
Mean	-0.01	0.003	14.92	1.00	0.60	464.6	55.1	0.29
Median	0.00	0.002	14.58	1.00	0.00	285.0	44.0	0.22
Maximum	0.64	0.007	21.98	1.015	22.93	2009.0	212.0	6.53
Minimum	-1.79	0.000	5.28	0.979	0.00	1.0	2.0	-4.06
Std. Dev.	0.15	0.002	2.53	0.004	11.51	556.2	49.9	1.52
Bond non-ESG ETFs 1-2								
Mean	0.01	0.002	16.75	1.00	0.30	417.3	61.4	0.28
Median	0.00	0.002	17.17	1.00	0.00	236.5	50.0	0.24
Maximum	0.64	0.007	22.95	1.015	22.93	2596.0	212.0	6.53
Minimum	-1.79	0.000	5.28	0.976	0.00	1.0	2.0	-9.32
Std. Dev.	0.11	0.002	2.86	0.003	8.14	581.9	44.8	1.36

Source: devised by author in Eviews

For the bond ESG ETFs, the dependent variable had higher values for the mean, median, minimum and maximum than their non-ESG counterparts. This provided a preliminary glimpse into the greater demand for ESG funds in the market. It is worth noting that the mean and median for returns were also higher for ESG ETFs. This led us to studies that investigated the performance of ESG ETFs and mutual funds, and they had the same result (Tularam and Reza, 2016; Das et al., 2018). However, the maximum value was lower for such funds, which underscores the heterogeneity of results and leads to that strand of the literature that has not found strong evidence for the prevailing of returns from ESG funds (Revelli and Viviani, 2015; Alexopoulos, 2018). In general, ESG ETFs were younger and had more underlying securities in their portfolios, yet they were less volatile in terms of the price spread. It should be noted that the price-to-NAV ratio did not fluctuate very much, and its values were similar in all three samples. However, as can be seen from the correlation analysis, price-to-NAV was the variable with the second-most influence (Table 11).

Table 11. Correlations in models with bond ETF panel data samples

Bond ETFs 1-1 sample									
	FLOW _TNA	ESG	ER	LOG__TUR NOVER	PRICE_ NAV	SPREAD _PRICE	HOL DING	AGE	RETU RN
FLOW_TNA	1.000	0.180	-0.014	0.146	0.116	-0.005	-0.003	-0.094	0.049
ESG	0.180	1.000	-0.038	0.280	0.204	-0.037	0.163	-0.079	0.063
ER	-0.014	-0.038	1.000	0.080	0.080	0.014	0.214	-0.125	-0.047
LOG__TUR NOVER_	0.146	0.280	0.080	1.000	0.059	-0.036	0.103	-0.047	0.073
PRICE_NAV	0.116	0.204	0.080	0.059	1.000	-0.013	0.021	-0.219	0.078
SPREAD_PR ICE	-0.005	-0.037	0.014	-0.036	-0.013	1.000	-0.016	0.004	-0.012
HOLDING	-0.003	0.163	0.214	0.103	0.021	-0.016	1.000	-0.051	-0.012
AGE	-0.094	-0.079	-0.125	-0.047	-0.219	0.004	-0.051	1.000	0.030
RETURN	0.049	0.063	-0.047	0.073	0.078	-0.012	-0.012	0.030	1.000
Bond ETFs 1-2 sample									
	FLOW _TNA	ESG	ER	LOG__TUR NOVER	PRICE_ NAV	SPREAD _PRICE	HOL DING	AGE	RETU RN
FLOW_TNA	1.000	0.144	-0.013	0.101	0.141	-0.005	0.002	-0.049	0.083
ESG	0.144	1.000	0.108	-0.085	0.107	-0.021	0.197	-0.143	0.064
ER	-0.013	0.108	1.000	-0.178	0.009	0.017	0.180	-0.129	-0.043

LOG__TURNOVER	0.101	-0.085	-0.178	1.000	0.033	-0.039	0.040	0.118	0.041
PRICE_NAV	0.141	0.107	0.009	0.033	1.000	-0.013	-0.003	-0.131	0.078
SPREAD_PRICE	-0.005	-0.021	0.017	-0.039	-0.013	1.000	-0.012	0.000	-0.009
HOLDING	0.002	0.197	0.180	0.040	-0.003	-0.012	1.000	0.001	0.002
AGE	-0.049	-0.143	-0.129	0.118	-0.131	0.000	0.001	1.000	0.047
RETURN	0.083	0.064	-0.043	0.041	0.078	-0.009	0.002	0.047	1.000

Source: devised by author in Eviews.

Overall, the correlations of influencing variables with the dependent variable were in line with our assumptions about their signs. The weakest affection on the flow-to-TNA ratio was caused by the spread-to-price ratio and the number of holdings. Those variables were supposed to be insignificant in the model. On the contrary, the price-to-NAV ratio, the logarithm of turnover and the ESG dummy variable had the highest values of correlation with the dependent variable. This allowed us to assume that there are significant and positive coefficients for those variables in the model. There was no evidence to suspect multicollinearity in the model since there were no correlation values above 0.3.

Almost the same conclusions might be drawn from observing the data for equity ETFs (Table 12).

Table 12. Descriptive statistics for equity ETF 2-year panel data samples

	FLOW_TNA	ER	LOG__TURNOVER	PRICE_NAV	SPREAD_PRICE	HOLDING	AGE	RETURN
Equity ESG ETFs								
Mean	0.015	0.005	16.19	1.000	0.09	183.2	79.1	0.33
Median	0.001	0.004	16.17	1.001	0.00	91.0	47.0	0.83
Maximum	0.875	0.011	21.46	1.019	35.34	725.0	182.0	25.55
Minimum	-3.471	0.002	11.48	0.973	0.00	1.3	13.0	-14.41
Std. Dev.	0.155	0.002	1.58	0.004	1.44	200.5	54.4	4.90
Equity non-ESG ETFs 1-1								
Mean	-0.009	0.004	17.34	1.000	0.02	183.1	96.9	0.09
Median	0.000	0.004	17.35	1.000	0.00	92.0	83.0	0.79
Maximum	0.556	0.012	22.07	1.018	8.71	1173.0	189.0	15.32
Minimum	-2.713	0.001	10.63	0.984	0.00	2.0	23.0	-17.12
Std. Dev.	0.172	0.002	1.95	0.003	0.35	249.9	48.4	4.66
Equity non-ESG ETFs 1-2								
Mean	-0.005	0.004	17.83	1.000	0.03	215.4	109.5	0.12
Median	0.000	0.005	17.94	1.000	0.00	101.0	127.0	0.71
Maximum	0.750	0.012	23.28	1.026	38.90	1688.0	236.0	16.89
Minimum	-2.713	0.001	10.63	0.955	0.00	2.0	18.0	-18.60
Std. Dev.	0.146	0.002	1.82	0.003	0.88	307.8	52.3	4.95

Source: devised by author in Eviews.

ESG ETFs on average attracted more flows while being younger and more profitable than their non-ESG counterparts. However, in contrast to bond funds, equity ESG ETFs were more volatile and had fewer underlying holdings than non-ESG funds. In addition, such funds had less turnover. These observations are discussed in the next sections. These statements are relevant for the 3-year sample as well (Table 13).

Table 13. Descriptive statistics for equity ETFs 3-year panel data samples

	FLOW _TNA	ER	LOG__TUR NOVER_	PRICE _NAV	SPREAD _PRICE	HOLDIN G	AGE	RETU RN
Equity ESG ETFs								
Mean	0.022	0.005	15.97	1.001	0.08	183.2	73.1	0.87
Median	0.000	0.004	16.01	1.001	0.00	85.0	44.0	1.33
Maximum	0.898	0.011	21.46	1.032	35.34	725.0	182.0	25.55
Minimum	-3.471	0.002	11.13	0.973	0.00	1.3	1.0	-14.41
Std. Dev.	0.150	0.002	1.64	0.004	1.24	200.6	54.9	4.29
Equity non-ESG ETFs 1-1								
Mean	0.000	0.004	17.231	1.000	0.04	182.8	90.9	0.70
Median	0.000	0.004	17.254	1.000	0.00	92.0	80.0	1.17
Maximum	0.556	0.012	22.069	1.023	15.65	1173.0	189.0	15.32
Minimum	-2.713	0.001	10.635	0.984	0.00	2.0	11.0	-17.12
Std. Dev.	0.153	0.002	1.920	0.003	0.55	249.5	48.9	4.16
Equity non-ESG ETFs 1-2								
Mean	0.003	0.004	17.70	1.000	0.03	215.3	103.5	0.73
Median	0.000	0.005	17.82	1.000	0.00	101.0	119.0	1.22
Maximum	0.750	0.012	23.28	1.026	38.90	1688.0	236.0	16.89
Minimum	-2.713	0.001	10.63	0.955	0.00	2.0	6.0	-18.60
Std. Dev.	0.132	0.002	1.81	0.003	0.80	307.6	52.8	4.40

Source: devised by author in Eviews.

Correlation analysis showed very different results, compared to the bond ETF outcomes. The ESG was not the most influencing variable, although it had a relatively high value of correlation compared to other variables (Table 14).

Table 14. Correlations in models with equity ETF 2-year panel data samples

Equity ETF 1-1 sample									
	FLOW _TNA	ESG	ER	LOG__TUR NOVER	PRICE_ NAV	SPREAD_ PRICE	HOLDI NG	AGE	RETU RN
FLOW_TN A	1.00	0.07	-0.15	0.03	0.07	0.04	0.10	-0.06	0.12
ESG	0.07	1.00	0.09	-0.31	0.05	0.03	0.00	-0.17	0.02
ER	-0.15	0.09	1.00	-0.21	-0.10	-0.01	-0.53	0.44	0.01
LOG__TUR NOVER	0.03	-0.31	-0.21	1.00	-0.05	-0.07	0.08	0.32	-0.02
PRICE_NA V	0.07	0.05	-0.10	-0.05	1.00	0.02	0.09	-0.12	-0.05
SPREAD_P RICE	0.04	0.03	-0.01	-0.07	0.02	1.00	-0.01	-0.03	0.03
HOLDING	0.10	0.00	-0.53	0.08	0.09	-0.01	1.00	-0.41	-0.03

AGE	-0.06	-0.17	0.44	0.32	-0.12	-0.03	-0.41	1.00	0.06
RETURN	0.12	0.02	0.01	-0.02	-0.05	0.03	-0.03	0.06	1.00
Equity ETF 1-2 sample									
	FLOW _TNA	ESG	ER	LOG__TUR NOVER	PRICE_ NAV	SPREAD_ PRICE	HOLDI NG	AGE	RETU RN
FLOW_TN A	1.00	0.06	-0.15	0.01	0.07	0.04	0.07	-0.07	0.13
ESG	0.06	1.00	0.05	-0.41	0.07	0.02	-0.05	-0.26	0.02
ER	-0.15	0.05	1.00	-0.21	-0.09	0.02	-0.53	0.38	0.01
LOG__TUR NOVER	0.01	-0.41	-0.21	1.00	-0.05	-0.05	0.12	0.39	-0.03
PRICE_NA V	0.07	0.07	-0.09	-0.05	1.00	0.02	0.06	-0.10	-0.05
SPREAD_P RICE	0.04	0.02	0.02	-0.05	0.02	1.00	-0.01	-0.02	0.03
HOLDING	0.07	-0.05	-0.53	0.12	0.06	-0.01	1.00	-0.25	-0.03
AGE	-0.07	-0.26	0.38	0.39	-0.10	-0.02	-0.25	1.00	0.04
RETURN	0.13	0.02	0.01	-0.03	-0.05	0.03	-0.03	0.04	1.00

Source: devised by author in Eviews

The variables with the most influence on the dependent variable were the expense ratio and returns, while the lowest value of correlation was associated with the logarithm of turnover. Overall, the signs of variables complied with our theoretical assumptions, while the ESG had a relatively high and positive correlation value. This promises that it will be a significant and positive coefficient in the regression model. Correlations among independent variables were not high in general. However, there were relatively high values of correlations between expense ratios and the number of holdings, as well as between expense ratio and age. However, weak evidence of multicollinearity might be suspected in the model. The same effects were observed for the 3-year sample. There were high values of correlation between the dependent variable and returns and expense ratio, but there were high values for age and holdings as well (Table 15).

Table 15. Correlations in models with equity ETF 3-year panel data samples

Equity ETF 1-1 sample									
	FLOW_ TNA	ESG	ER	LOG__TU RNOVER	PRICE_ NAV	SPREAD_P RICE	HOL DIN G	AGE	RETU RN
FLOW_TN A	1.00	0.07	-0.12	0.03	0.08	0.03	0.10	-0.10	0.13
ESG	0.07	1.00	0.08	-0.33	0.07	0.02	0.00	-0.17	0.02
ER	-0.12	0.08	1.00	-0.16	-0.10	-0.03	-0.53	0.44	0.01
LOG__TUR NOVER	0.03	-0.33	-0.16	1.00	-0.11	-0.08	0.04	0.38	-0.02
PRICE_NA V	0.08	0.07	-0.10	-0.11	1.00	0.02	0.10	-0.17	0.01

SPREAD_PRICE	0.03	0.02	-0.03	-0.08	0.02	1.00	0.00	-0.05	0.02
HOLDING	0.10	0.00	-0.53	0.04	0.10	0.00	1.00	-0.40	-0.02
AGE	-0.10	-0.17	0.44	0.38	-0.17	-0.05	-0.40	1.00	0.02
RETURN	0.13	0.02	0.01	-0.02	0.01	0.02	-0.02	0.02	1.00
Equity ETF 1-2 sample									
	FLOW_TNA	ESG	ER	LOG__TURNOVER	PRICE_NAV	SPREAD_PRICE	HOLDINGS	AGE	RETURN
FLOW_TNA	1.00	0.06	-0.11	0.01	0.08	0.02	0.08	-0.11	0.13
ESG	0.06	1.00	0.05	-0.42	0.08	0.02	-0.05	-0.26	0.01
ER	-0.11	0.05	1.00	-0.17	-0.09	-0.01	-0.53	0.38	0.02
LOG__TURNOVER_	0.01	-0.42	-0.17	1.00	-0.12	-0.06	0.09	0.44	-0.03
PRICE_NAV	0.08	0.08	-0.09	-0.12	1.00	0.01	0.08	-0.17	0.00
SPREAD_PRICE	0.02	0.02	-0.01	-0.06	0.01	1.00	0.00	-0.03	0.02
HOLDING	0.08	-0.05	-0.53	0.09	0.08	0.00	1.00	-0.25	-0.02
AGE	-0.11	-0.26	0.38	0.44	-0.17	-0.03	-0.25	1.00	0.01
RETURN	0.13	0.01	0.02	-0.03	0.00	0.02	-0.02	0.01	1.00

Source: devised by author in Eviews

To further investigate the differences in financial flows between ESG funds and their counterparts, we constructed Table 16, which makes it possible to observe those differences for the samples directly.

Table 16. Descriptive statistics of the flow-to-TNA ratio in different samples

	Bond ETFs			Equity ETFs 2 year			Equity ETFs 3 year		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
ESG Funds	0.041	0.008	0.102	0.015	0.001	0.155	0.022	0.000	0.150
1-1 sample	-0.005	0.000	0.146	-0.009	0.000	0.172	0.000	0.000	0.153
1-2 sample	0.007	0.000	0.112	-0.005	0.000	0.146	0.003	0.000	0.132

Source: devised by author in Eviews.

In all the samples ESG funds were characterised with higher ratios of flow-to-TNA than their conventional counterparts, and this was mirrored in the values for means and medians. Moreover, those ratios were lower for the 1-1 sample than for the 1-2 sample. We might suspect some selectivity bias, as 1 or 2 samples comprise funds mostly issued by big and well-known issuers. This can create the basis for the attraction of cash flows. However, we still may conclude that our hypothesis regarding higher inflows related to

ESG funds compared to non-ESG ones is preliminarily proven. Descriptive statistics for all samples supported this statement. To further investigate and prove this hypothesis, we conducted regression analyses with the constructed samples and the chosen variables, when ESG funds were indicated by the dummy variable according to the stated methodology. The next chapter reviews the results of this analysis.

6. Findings

6.1. Models with Cross-sectional Data

Assumptions were made in the preliminary analysis which used descriptive statistics and correlation analysis to identify the possible influence of variables. Those assumptions were partially proved by the outputs of the actual models. The first portion of results was related to models that used cross-sectional data. The first model involved data on bond ETFs (Table 17).

Table 17. Output of the regression model with bond ETFs cross-sectional data

Dependent Variable: FLOW_ASSETS				
Included observations: 163				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG_SCORE	-0.0445	0.0378	-1.177	0.241
SD	-0.736	2.24	-0.329	0.743
ER	-32	18.3	-1.751	0.082*
AGE	-0.00279	0.000855	-3.260	0.001***
RETURN	0.543	0.488	1.112	0.268
VOLATILITY	-0.395	0.41	-0.963	0.337
LOG__VOLUME	0.0262	0.0134	1.954	0.053*
C	0.41	0.27	1.515	0.132
R-squared	0.13955	Mean dependent var		9.49E-08
Adjusted R-squared	0.100691	S.D. dependent var		3.66E-07
S.E. of regression	3.47E-07	Akaike info criterion		-26.862
Sum squared resid	1.87E-11	Schwarz criterion		-26.709
Log likelihood	2197.214	Hannan-Quinn criter.		-26.799
F-statistic	3.5912	Durbin-Watson stat		2.1946
Prob(F-statistic)	0.001304			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

All the variables had very small coefficients with the dependent variable, which was multiplied by one million. This does not allow any serious conclusions to be drawn regarding their real affection. However, there were some statistically significant variables: expense ratio, age and the logarithm of volume. They deviate from the results of the correlation analysis, since the standard deviations were not statistically significant, though there was a relatively high value of correlation with the flow-to-assets ratio.

Moreover, the variable representing age had a positive sign, but a very small coefficient. The ESG score appeared not to be significant in the model; it had a coefficient with a very low value. Therefore, we cannot conclude any statistically significant relationship between the ESG score and fund flows in the current specification. Therefore, the first hypothesis of this study is not proved. The model itself had a relatively low value for R-squared, and it was characterised by small explanatory power. To test the model for heteroscedasticity, we applied the Breusch-Pagan-Godfrey test, available in the Eviews Software (Table 18).

Table 18. Output of Breusch-Pagan-Godfrey test for models with bond ETFs

F-statistic	0.704184	Prob. F(7,155)	0.6685
Obs*R-squared	5.023934	Prob. Chi-Square(7)	0.6570
Scaled explained SS	21.71383	Prob. Chi-Square(7)	0.0028***

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: devised by author in Eviews.

Two of three statistics, however, did not reject the null hypothesis about the existence of homoscedasticity in the model, while one statistic strongly rejected the null hypothesis.

The model covering equity data should have more reliable results since it included more observations. In fact, the results of two models vary at a high rate (Table 19).

Table 19. Output of the regression model with equity ETF cross-sectional data

Dependent Variable: FLOW_ASSETS				
Included observations: 896				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG_SCORE	0.0748	0.0362	2.067	0.039**
SD	0.647	1.42	0.455	0.649
ER	-29.8	23.9	-1.250	0.212
AGE	-0.000432	0.000947	-0.456	0.648
RETURN	0.0235	0.115	0.203	0.839
VOLATILITY	0.73	0.38	1.921	0.055*
LOG__VOLUME	0.013	0.0237	0.547	0.584
C	-0.885	0.364	-2.430	0.015**
R-squared	0.013818	Mean dependent var		-1.36E-07
Adjusted R-squared	0.006044	S.D. dependent var		1.48E-06
S.E. of regression	1.48E-06	Akaike info criterion		-24.0055
Sum squared resid	1.93E-09	Schwarz criterion		-23.9627
Log likelihood	10762.48	Hannan-Quinn criter.		-23.9892

F-statistic	1.777484	Durbin-Watson stat	1.99842
Prob(F-statistic)	0.088419		

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

The results of the regression model complied fully with the descriptive statistics and the correlation analysis. The difference in results compared to the model with the bond ETF sample may be related to statistical nuances. (The models had very different numbers of observations – 163 against 896.) In addition, the results may vary because of differences in the nature of these financial instruments, so there should be differences in models with panel data as well. Actually, the ESG score and volatility were the only significant variables in the model. They both had positive, but very low values of coefficients. We have the evidence to conclude that a higher ESG score had a statistically significant and positive influence on higher inflows to ETFs, even though this influence was very modest. The model itself had very little explanatory power, which was mirrored in an R-squared value of less than 2%. As in the case of bond ETFs, we tested the heteroscedasticity in the model with the Breush-Pagan-Godfrey test (Table 20).

Table 20. Output of Breusch-Pagan-Godfrey test for models with equity ETFs

F-statistic	1.364158	Prob. F(7,888)	0.2171
Obs*R-squared	9.532625	Prob. Chi-Square(7)	0.2166
Scaled explained SS	1495.432	Prob. Chi-Square(7)	0.0000***

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: devised by author in Eviews.

Results of the test were similar to those for the bond ETFs model. Two statistics did not reject the null hypothesis of homoscedasticity, while one statistic strongly rejected this hypothesis.

Bond and equity ETFs should not be combined in one sample because they have completely different financial natures. However, the statistical drawbacks of models above, associated with the small number of observations, has led us to try to construct a model that includes both instruments. They are separated by a dummy variable bond with a value of 1 if the ETF holds bonds. The results in Appendix C show that such a model does not provide better quality. (The R-squared was around 2%, similar to the equity sample.) The ESG score was the only significant variable besides the dummy variable that distinguished equity ETFs from bond ETFs. That is, the bond ETFs attracted more inflows than equity ETFs, which was observable in the descriptive statistics. It is obvious that in such specification the equity sample with more observations prevailed and was responsible for the biggest share of outputs. Yet the coefficients were still very small, so no additional insights can be drawn from that model.

Stemming from the results from the models with cross-sectional data, we were not able to state with confidence that a higher ESG score had a positive influence on higher inflows to funds. We did not find evidence for that statement using the bond ETFs sample, but we did find it in the model with equity ETFs. Nevertheless, the model itself suffers from statistical drawbacks so the first hypothesis of this study has been proved only partially. We shall conduct regression analyses with panel data to test the second hypothesis, hoping to achieve more reliable models and provide more valuable proofs of the relationship between ESG criteria and fund flows.

6.2. Models with Panel Data

Results of the regression analysis involving models with panel data provided much more evidence for defining the relationship between the compliance of funds with ESG criteria and their fund flows. These results, in general, were in line with the assumptions made during the preliminary analysis with descriptive statistics and correlation analysis. However, it is noteworthy that they vary when the methods of a pooled OLS model and a model with mixed effects were applied. This creates the space for an upgrade of the models' specifications. The first model dealt with the bond ETF 1-1 sample covering two years (Table 21).

Table 21. Output of the regression model with bond ETFs 1-1 panel data sample, pooled OLS method

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 750				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0345	0.0099	3.4953	0.0005***
ER	-1.7537	2.8443	-0.6166	0.5377
LOG__TURNOVER	0.0055	0.0020	2.8057	0.0052***
PRICE_NAV	2.5517	1.4210	1.7957	0.0730*
SPREAD_PRICE	0.0001	0.0006	0.1380	0.8903
HOLDINGS	0.0000	0.0000	-0.9557	0.3395
AGE	-0.0002	0.0001	-1.8820	0.0602*
RETURN	0.0028	0.0036	0.7751	0.4385
C	-2.6229	1.4216	-1.8450	0.0654*
R-squared	0.0558	Mean dependent var		0.0180
Adjusted R-squared	0.0456	S.D. dependent var		0.1279
S.E. of regression	0.1250	Akaike info criterion		-1.3099
Sum squared resid	11.5692	Schwarz criterion		-1.2544
Log likelihood	500.1953	Hannan-Quinn criter.		-1.2885
F-statistic	5.4746	Durbin-Watson stat		1.8411
Prob(F-statistic)	0.0000			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

The Statistically significant variables were the ESG, the logarithm of turnover, age and intercept. Last two variables had negative signs of coefficients, the rate of change of the conditional mean of the flow-to-TNA ratio with respect to age was about -0,2% (Clifford, Fulkerson and Jordan, 2014; Białkowski and Starks, 2016). Higher turnover of funds' shares was associated with a 0,06% larger value of the low-to-TNA ratio, while a high price-to-NAV ratio was associated with a 250% larger flow-to-TNA ratio. That was an unexpected result. Normally, investors choose securities with a lower price-to-NAV ratio (Hayes, 2020). This outlying result will be explored further in Chapter 7. The ESG dummy variable was the main object of the study, according to this particular model. Being an ESG fund leads to a shift of the conditional mean of flow-to-TNA by 3,45%. That result was statistically significant at the 1% level. The spread-to-price ratio and the number of holdings were not statistically significant, even though they had positive signs.

This complies with Clifford, Fulkerson and Jordan (2014). The model itself had an R-squared of less than 6%, which reflected its small explanatory power.

The model with mixed effects, in general, had similar results, although there were some deviations (Table 22).

Table 22. Output of the regression model with bond ETF 1-1 panel data sample, mixed effects model

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 750				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0318	0.0119	2.6828	0.0075***
ER	-1.5802	3.4418	-0.4591	0.6463
LOG__TURNOVER_	0.0073	0.0023	3.1494	0.0017***
PRICE_NAV	2.3921	1.4478	1.6522	0.0989*
SPREAD_PRICE	0.0001	0.0006	0.1171	0.9068
HOLDING	0.0000	0.0000	-0.8029	0.4223
AGE	-0.0001	0.0001	-1.1180	0.2640
RETURN	0.0082	0.0041	2.0069	0.0451**
C	-2.4951	1.4483	-1.7229	0.0853*
R-squared	0.0950	Mean dependent var		0.0180
Adjusted R-squared	0.0546	S.D. dependent var		0.1257
S.E. of regression	0.1222	Sum squared resid		10.7127
F-statistic	2.3530	Durbin-Watson stat		1.9003
Prob(F-statistic)	0.0000			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

In the model with such specification, age was not a statistically significant variable, while the return was significant at the 5% level and had a positive coefficient of around 0,008. The positive influence of the ETFs' returns on fund flows was investigated in several other studies (Broman and Shum, 2013; Clifford, Fulkerson and Jordan, 2014). The ESG variable in this model had a smaller coefficient – around 0,032. To test for the justification to use cross-section random effects, the Hausman test was exploited (Table 23). The Chi-squared statistic provided strong evidence against the null hypothesis that there was no misspecification in the model.

Table 23. Output of Hausman test, bond ETF 1-1 panel data sample

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	13.164649	6	0.0405**

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

The addition of more non-ESG funds in the sample did not dramatically change the results, although the same significant variables can be observed (Table 24).

Table 24. Output of the regression model with bond ETF 1-2 panel data sample, pooled OLS method

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 1125				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0325	0.0071	4.5912	0.0000***
ER	-0.3954	1.9772	-0.2000	0.8416
LOG__TURNOVER	0.0046	0.0012	3.6929	0.0002***
PRICE_NAV	3.9370	1.0303	3.8214	0.0001***
SPREAD_PRICE	0.0001	0.0005	0.1388	0.8896
HOLDING	0.0000	0.0000	-0.9239	0.3557
AGE	-0.0001	0.0001	-1.0472	0.2953
RETURN	0.0055	0.0026	2.1299	0.0334**
C	-4.0030	1.0302	-3.8856	0.0001***
R-squared	0.0540	Mean dependent var		0.0185
Adjusted R-squared	0.0472	S.D. dependent var		0.1101
S.E. of regression	0.1074	Akaike info criterion		-1.6159
Sum squared resid	12.8807	Schwarz criterion		-1.5757
Log likelihood	917.9594	Hannan-Quinn criter.		-1.6007
F-statistic	7.9645	Durbin-Watson stat		1.8155
Prob(F-statistic)	0.0000			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

In the pooled OLS specification, the set of significant variables was the same as in the 1-1 sample model with mixed effects. However, some variables had rather different coefficients. For instance, the price-to-NAV ratio had an even higher value – around 3,93. The ESG variable caused a change of the conditional mean of the dependent variable by 3,25%, which did not deviate from previous models. Returns and the logarithm of turnover had slightly lower values of coefficients than in models with the 1-1 sample. The model with mixed results had even more similar outputs compared to models with the 1-1 sample, especially the model with same specification (Table 25).

Table 25. Output of the regression model with bond ETF 1-2 panel data sample, mixed effects model

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 1125				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0337	0.0096	3.5260	0.0004***
ER	0.4578	2.6700	0.1715	0.8639
LOG__TURNOVER_	0.0064	0.0016	3.9486	0.0001***
PRICE_NAV	2.9667	1.0861	2.7316	0.0064***
SPREAD_PRICE	0.0000	0.0005	0.0329	0.9737
HOLDING	0.0000	0.0000	-0.8136	0.4160
AGE	0.0000	0.0001	-0.4436	0.6574
RETURN	0.0098	0.0030	3.3154	0.0009***
C	-3.0678	1.0859	-2.8251	0.0048***
R-squared	0.0822	Mean dependent var		0.0185
Adjusted R-squared	0.0553	S.D. dependent var		0.1072
S.E. of regression	0.1042	Sum squared resid		11.8538
F-statistic	3.0576	Durbin-Watson stat		1.8897
Prob(F-statistic)	0.0000			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

All significant variables in this model were significant at the 1% level and had values of coefficients close to those observed in the 1-1 mixed effects model. The ESG variable had a coefficient of around 0,034, while return and turnover had higher coefficients – around 0,001 and 0,006 respectively. The price-to-NAV implied a change of the conditional mean of the flow-to-TNA ratio by 297%, which was closer to values observed in 1-1 samples. The model itself had a higher R-squared value than previous models, although it was still rather low – less than 9%. The results of the Hausman test showed the existence of misspecification once again and the need for fixed effect modelling, which was not available because of dummy variables (Table 26).

Table 26. Output of Hausman test, bond ETF 1-1 panel data sample

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	13.164649	6	0.0405**

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

The Sample of equity ETFs was divided not just on sub-samples with 1-1 and 1-2 matched ETFs and two applied methods, but also according to the time periods covered. The first portion of the models related to a 2-year period (2018.03-2020.03), the same as the period covered by the bond ETFs. The second portion of the models extends this period to 3 years (2017.03-2020.03). Interestingly enough, this kind of subsampling has led to different regression outputs. The first model dealt with the 1-1 sample of funds covering 2 years (Table 27).

Table 27. Output of the regression model with equity ETF 1-1 panel data sample, pooled OLS method

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 2100				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0297	0.0074	4.0191	0.0001***
ER	-10.7778	2.0696	-5.2076	0.0000***
LOG__TURNOVER_	0.0023	0.0022	1.0414	0.2978
PRICE_NAV	2.6599	1.0514	2.5299	0.0115**
SPREAD_PRICE	0.0061	0.0034	1.8310	0.0672*
HOLDING	0.0000	0.0000	0.8677	0.3857
AGE	0.0001	0.0001	0.7019	0.4828
RETURN	0.0041	0.0007	5.5148	0.0000***
C	-2.6731	1.0544	-2.5352	0.0113**
R-squared	0.0502	Mean dependent var		0.0028
Adjusted R-squared	0.0465	S.D. dependent var		0.1639
S.E. of regression	0.1601	Akaike info criterion		-0.8221
Sum squared resid	53.5809	Schwarz criterion		-0.7978
Log likelihood	872.1545	Hannan-Quinn criter.		-0.8132
F-statistic	13.8059	Durbin-Watson stat		1.9336
Prob(F-statistic)	0.0000			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

The most influential variable in this model was the expense ratio. The higher management fee reduces the conditional mean of the flow-to-TNA ratio by 1100%. This was intuitively obvious, and it complied with other studies of the topic of ETFs' flows (Broman and Shum, 2013; Clifford, Fulkerson and Jordan, 2014). The price-to-NAV ratio had a high value of the coefficient. It was close to most bond ETF samples at around 2,66. On the contrary, unlike in previous models, the logarithm of turnover was not significant, while the return variable had a relatively low value of coefficient – 0,004. What was noteworthy, the spread-to-price ratio was significant in models with equity ETFs, in current specification. A 1% higher spread-to-price was associated with approximately 0,6% larger flow-to-TNA ratio. Clifford, Fulkerson and Jordan (2014) achieved a positive value of influence on the average daily price on sector net flow as well. Possible implications of such a result are discussed in the next section. ESG variable has a close, but a slightly lower value of the coefficient, compared to bond ETFs – 0,0297. The model itself had an R-squared value of about 5%, which once again denoted the low explanatory power of the model.

In the model with mixed effects, most variables maintained their significance levels and similar values of coefficients, however, the price-to-NAV ratio becomes not statistically significant (Table 28).

Table 28. Output of the regression model with equity ETF 1-1 panel data sample, mixed effects model

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 2100				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0306	0.0087	3.5056	0.0005***
ER	-10.6475	2.4273	-4.3866	0.0000***
LOG__TURNOVER	0.0033	0.0026	1.2908	0.1969
PRICE_NAV	1.4044	1.0987	1.2783	0.2013
SPREAD_PRICE	0.0062	0.0034	1.8228	0.0685*
HOLDING	0.0000	0.0000	0.8399	0.4011
AGE	0.0001	0.0001	0.5256	0.5992
RETURN	0.0065	0.0014	4.7341	0.0000***
C	-1.4352	1.1008	-1.3038	0.1925

R-squared	0.0663	Mean dependent var	0.0028
Adjusted R-squared	0.0518	S.D. dependent var	0.1617
S.E. of regression	0.1575	Sum squared resid	51.2626
F-statistic	4.5867	Durbin-Watson stat	1.9347
Prob(F-statistic)	0.0000		

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

In such specification, the ESG variable had a value around 0,031, while the model itself did not dramatically differ in terms of explanatory power. It was unexpected that the variable of age was not significant in models with equity ETFs. However other studies also received heterogeneous results, including non-significance, in specifications with various dependent flow variables (Clifford, Fulkerson and Jordan, 2014; Białkowski and Starks, 2016). The important nuance is that in this particular specification with the 1-1 equity ETF sample and two years covered, the Hausman test results denoted no misspecification. The statistics provide strong evidence against the null hypothesis (Table 29). Such results leave room for discussions of the appropriate econometric methods for investigating the relationships between ETF flows and their determinants.

Table 29. Output of Hausman test, equity ETF 1-1 panel data sample

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	9.392676	6	0.1527

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

Adding more funds to the equity ETFs sample did not seriously change the overall result (Table 30).

Table 30. Output of the regression model with equity ETF 1-2 panel data sample, pooled OLS method

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 3150				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0222	0.0061	3.6401	0.0003***
ER	-9.4493	1.5879	-5.9510	0.0000***
LOG__TURNOVER	0.0020	0.0017	1.1439	0.2528
PRICE_NAV	2.8820	0.7960	3.6205	0.0003***
SPREAD_PRICE	0.0048	0.0024	2.0293	0.0425**

HOLDING	0.0000	0.0000	-0.0736	0.9413
AGE	0.0000	0.0001	-0.2742	0.7839
RETURN	0.0039	0.0005	7.3749	0.0000***
C	-2.8784	0.7982	-3.6060	0.0003***
R-squared	0.047488	Mean dependent var		0.001758
Adjusted R-squared	0.045062	S.D. dependent var		0.149159
S.E. of regression	0.145759	Akaike info criterion		-1.01087
Sum squared resid	66.7329	Schwarz criterion		-0.99357
Log likelihood	1601.118	Hannan-Quinn criter.		-1.00466
F-statistic	19.57456	Durbin-Watson stat		1.920342
Prob(F-statistic)	0			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

In the model with the pooled OLS method, all significant variables had coefficients that were the same coefficients or a bit lower. The exception was the price-to-NAV ratio, which was meaningfully higher, compared to the same specification with the 1-1 sample: 2,88 against 2,66, and the expense ratio was significantly lower: -9,45 against -1,078. Compliance with ESG criteria in such specification implies approximately 2,2% of the shift of the conditional mean of flow-to-TNA ratio. The model itself had even less explanatory power than the model with the 1-1 sample., whose derivations were relevant for the model with mixed effects as well (Table 31).

Table 31. Output of the regression model with equity ETF 1-2 panel data sample, mixed effects model

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 3150				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0233	0.0073	3.1806	0.0015***
ER	-9.3855	1.9012	-4.9366	0.0000***
LOG__TURNOVER	0.0027	0.0020	1.3552	0.1755
PRICE_NAV	1.7455	0.8273	2.1099	0.0349**
SPREAD_PRICE	0.0045	0.0024	1.8738	0.0611*
HOLDING	0.0000	0.0000	0.0595	0.9526
AGE	0.0000	0.0001	-0.2735	0.7845
RETURN	0.0067	0.0010	6.8537	0.0000***
C	-1.7560	0.8288	-2.1187	0.0342**
R-squared	0.0626	Mean dependent var		0.0018
Adjusted R-squared	0.0530	S.D. dependent var		0.1470
S.E. of regression	0.1430	Sum squared resid		63.7515

F-statistic	6.5054	Durbin-Watson stat	1.9341
Prob(F-statistic)	0.0000		

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

In this specification, the price-to-NAV ratio coefficient was much lower (1.74), while other variables had results similar to the model with the pooled OLS method. The coefficient of the ESG was somewhat higher – 2,3 compared to 2,2 in the previous model. Using mixed effects did not dramatically increase the quality of the model; R-squared was just slightly higher than in the comparable model with a pooled OLS method. Results of the Hausman test once again denoted the existence of misspecification and the need for cross-section fixed effects (Table 32).

Table 32. Output of Hausman test, equity ETF 1-2 panel data sample

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	14.179275	6	0.0277**

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

Serious differences in results were observed when the sample was extended in the time-series dimension to cover three years. Compared to the two-year sample model, age and the logarithm of turnover became statistically significant, while the spread-to-price ratio became insignificant (Table 33).

Table 33. Output of the regression model with equity ETF 1-1 3-year panel data sample, pooled OLS method

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 3108				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0261	0.0057	4.5981	0.0000***
ER	-3.7342	1.5621	-2.3905	0.0169**
LOG__TURNOVER	0.0071	0.0017	4.0849	0.0000***
PRICE_NAV	2.4031	0.7589	3.1666	0.0016***
SPREAD_PRICE	0.0032	0.0028	1.1530	0.2490
HOLDING	0.0000	0.0000	1.2656	0.2058
AGE	-0.0002	0.0001	-3.3771	0.0007***
RETURN	0.0046	0.0006	7.3246	0.0000***
C	-2.4958	0.7619	-3.2756	0.0011***
R-squared	0.0469	Mean dependent var	0.0106	

Adjusted R-squared	0.0445	S.D. dependent var	0.1518
S.E. of regression	0.1484	Akaike info criterion	-0.9753
Sum squared resid	68.2241	Schwarz criterion	-0.9578
Log likelihood	1524.5660	Hannan-Quinn criter.	-0.9690
F-statistic	19.0813	Durbin-Watson stat	1.9062
Prob(F-statistic)	0		

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

Age and the logarithm of turnover had very low coefficients – around 0,0002 and -0,007. The negative coefficient of the age variable was in line with the results of models with samples comprising bond ETFs. The expense ratio coefficient was dramatically lower than in previous models – around -3,73 – while the logarithm of turnover showed a small but positive coefficient – about 0,07. The coefficient of the return variable was not different from those in models with other specifications – approximately 0,0047. The price-to-NAV ratio had a comparable coefficient of influence – about 2,4. Being an ESG ETF according to current specifications caused a shift in the conditional mean of the flow-to-TNA ratio by 2,6%. Although all variables except spread-to-price ratio and the number of holdings were significant, the model itself did not have greater explanatory power. Almost the same results were observed in the model with mixed effects (Table 34).

Table 34. Output of the regression model with equity ETF 1-1 3-year panel data sample, mixed effects model

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 3108				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0282	0.0071	3.9598	0.0001***
ER	-3.6497	1.9528	-1.8689	0.0617*
LOG__TURNOVER_	0.0087	0.0020	4.2305	0.0000***
PRICE_NAV	1.3157	0.7941	1.6569	0.0976*
SPREAD_PRICE	0.0030	0.0028	1.0596	0.2894
HOLDING	0.0000	0.0000	1.1007	0.2711
AGE	-0.0002	0.0001	-2.7183	0.0066***
RETURN	0.0067	0.0011	6.0832	0.0000***
C	-1.4377	0.7965	-1.8051	0.0712*
R-squared	0.0633	Mean dependent var	0.0106	
Adjusted R-squared	0.0498	S.D. dependent var	0.1497	
S.E. of regression	0.1460	Sum squared resid	65.2553	
F-statistic	4.7020	Durbin-Watson stat	1.9158	

Prob(F-statistic)	0.0000			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

All significant variables had similar coefficients compared to a previous model, except the price-to-NAV ratio, which had a coefficient of 1,32 against 2,4 in a previous specification. The value of the coefficient for the ESG variable was around 0,028, which might be interpreted as a 2,8% shift of the conditional mean of flow-to-TNA ratio caused by the compliance of the ETFs with ESG criteria. Results of the Hausman test showed once again the existence of misspecification in the model (Table 35).

Table 35. Output of Hausman test, equity ETF 1-1 3-year panel data sample

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	27.023901	6	0.0001***

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.
Source: computed by author in Eviews.

Finally, the last specification, which comprises the biggest number of observations, was the model with the sample of 1-2 equity funds covering a 3-year period. However, as in previous cases, the addition of more funds to the sample did not meaningfully change the outputs of regression (Table 36).

Table 36. Output of the regression model with equity ETF 1-2 3-year panel data sample, pooled OLS method

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 4662				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0213	0.0047	4.5617	0.0000***
ER	-3.1600	1.1987	-2.6363	0.0084***
LOG__TURNOVER	0.0062	0.0013	4.6711	0.0000***
PRICE_NAV	2.7082	0.5989	4.5217	0.0000***
SPREAD_PRICE	0.0029	0.0021	1.4052	0.1600
HOLDING	0.0000	0.0000	1.2210	0.2221
AGE	-0.0002	0.0000	-4.8267	0.0000***
RETURN	0.0044	0.0005	9.6012	0.0000***
C	-2.7835	0.6014	-4.6283	0.0000***
R-squared	0.0468	Mean dependent var		0.0090
Adjusted R-squared	0.0451	S.D. dependent var		0.1388
S.E. of regression	0.1356	Akaike info criterion		-1.1560

Sum squared resid	85.5831	Schwarz criterion	-1.1435
Log likelihood	2703.5740	Hannan-Quinn criter.	-1.1516
F-statistic	28.5433	Durbin-Watson stat	1.9079
Prob(F-statistic)	0.0000		

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

All significant variables were significant at the 1% level, and the values of coefficients were rather close to those of the model with pooled OLS 1-1 sample for the 3-year period. However, the price-to-NAV ratio and expense ratio coefficients fluctuated a lot across models. The ESG variable had the lowest value of the coefficient in such specification – 0,021. Applying the mixed effects approach reduced the coefficient of price-to-NAV ratio similar to models with 2-year samples (Table 37).

Table 37. Output of the regression model with equity ETF 1-2 3-year panel data sample, mixed effects model

Dependent Variable: FLOW_TNA				
Total panel (balanced) observations: 4662				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ESG	0.0241	0.0060	3.9911	0.0001***
ER	-3.0522	1.5439	-1.9769	0.0481**
LOG__TURNOVER	0.0078	0.0016	4.8564	0.0000***
PRICE_NAV	1.6105	0.6237	2.5821	0.0099***
SPREAD_PRICE	0.0025	0.0021	1.2011	0.2298
HOLDING	0.0000	0.0000	1.0195	0.3080
AGE	-0.0002	0.0001	-3.8955	0.0001***
RETURN	0.0069	0.0008	8.7122	0.0000***
C	-1.7154	0.6257	-2.7418	0.0061***
R-squared	0.0627	Mean dependent var		0.0090
Adjusted R-squared	0.0538	S.D. dependent var		0.1367
S.E. of regression	0.1330	Sum squared resid		81.6360
F-statistic	7.0223	Durbin-Watson stat		1.9286
Prob(F-statistic)	0.0000			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

Overall, the output of this model was rather similar to the output of the model with a 1-1 sample, except for the expense ratio, which had a lower coefficient: -3,05 against -3,65 in the model with mixed effects and lower sample. According to this specification, compliance with ESG criteria caused the shift of the conditional mean of the dependent variable by 2,4%. Results of the Hausman test suggested the existence of misspecification in the model (Table 38).

Table 38. Output of Hausman test, equity ETF 1-2 3-year panel data sample

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	34.893747	6	0.0000***

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

It might be seen that coefficients of the ESG variable were all statistically significant and fluctuated between 0,0213 and 0,0345. Such results give strong evidence regarding the relationship between the compliance of ETFs with ESG criteria and their flow-to-TNA ratio. When an ETF is labelled as ESG, it can cause a shift of the conditional mean of the flow-to-TNA ratio by 2,1-3,5%. This can be regarded in the following way: an average increase in ETF inflows by 2,1-3,5% is caused by the compliance of the fund with ESG criteria (Table 39).

Table 39. Values of regression coefficients for ESG variable in different specifications

	Bond ETFs		Equity ETFs			
	1-1	1-2	1-1	1-2	1-1 (3-year)	1-2 (3-year)
Pooled OLS	0.0345	0.0325	0.0297	0.0222	0.0261	0.0213
Mixed effects	0.0318	0.0337	0.0306	0.0233	0.0282	0.0241

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

These results, on the one hand, add to similar studies regarding ESG funds. On the other hand, they open a new discussion about the pros and cons of labelling ETFs as complying with ESG criteria. These results will be further discussed in the next chapter.

7. Discussion and Conclusion

This study was focused on examining two hypotheses. The first one argued that the higher ESG score of an ETF is associated with more cash flows available for that ETF. We conducted a regression analysis with two samples comprising bond and equity ETFs, and we partially proved this hypothesis. The coefficient of the ESG score was statistically significant and positive in the model with the sample of equity ETFs. However, the value of the coefficient was very low. In the case of the bond ETFs, we could not find any strong evidence for proving the hypothesis. Despite many methodological issues observed during this analysis, we might derive some implications from these results and refer to some problems, which were discussed in different strands of the literature.

First, the ambiguity of ESG criteria for determining better financial performance was complemented by the results of our study. Although, there are studies that report a strong and positive relationship between ESG practices and financial performance (Andersson, Bolton and Samama, 2016; Tarmuji, Maelah and Tarmuji, 2016), the vast majority of the literature has not come to any conclusion about whether ESG investing adds to financial measures. Most of the studies (Humphrey and Tan, 2014; Meziani, 2016; van Duuren, Plantinga and Scholtens, 2016) found mixed evidence regarding the relationship between different measures of ESG criteria and better performance. The significance of the ESG score in one sample in parallel with insignificance in another sample once again leads to the discussion about the contradictive nature of integrating ESG criteria into the investing process. This issue may be further explored using ESG ETFs as the studying object.

Second, using the ESG score as the measure of compliance with ESG criteria by investing funds or any other entities with ESG criteria creates some space for various arguments. As this study showed, ESG criteria can be methodologically measured and represented in models in different ways. Using ESG scores is one way to mirror the compliance of a company with the concept of sustainable development. Producers of ESG scores, such as

Thomson Reuters ASSET4, argue that such a score represents the adequate measure of a company's business practices and may have significant value as stock selecting factor (Ribando and Bonne, 2010), some scholars challenge such statements. Tarmuji, Maelah and Tarmuji (2016) argued that ASSET4 data included only publicly listed companies. Nevertheless, greater applicability of results may be achieved if public companies could be opposed to exclusive ones. Siew, Balatbat and Carmichael (2013) came to several conclusions around using ESG as a proxy of companies' business practices. Non-financial reporting may have low power in comprehending such practices and objectively score them. Nevertheless, the ESG score could not reflect those practices fully. Moreover, the scoring mechanism was subjective, and it might omit the specificities of different industries. In this study, the MSCI ESG score was used. We could not find any obvious drawbacks to its methodology. However, scoring non-financial activities of companies is an ambiguous process.

In addition, there is a separate issue here, which should be broadly discussed. Since ESG scores, and the ESG labels discussed later, cover only a small number of ETFs, the problem of bias connected with competition might occur. That is, it may be hypothesised that the influence of ESG metrics has been overestimated and, if all companies and funds were embraced by such metrics, the power of ESG criteria would be reduced. Actually, although ESG experts consider ESG movement not as a trend, but as a new overwhelming global paradigm (Investors, 2020), it is obvious that compliance with ESG criteria has become a popular selling point, driven by recent global concerns around ecological problems. In this sense, investors' preferences for ESG assets might not last in the long-term perspective. So, any company that has an ESG score or an ESG label will be in focus not because its high ESG score reflects its efforts to mitigate ecological and social risks compared to other market players, but because it has an ESG score per se, regardless of that score's actual value. In that case, the correlation between ESG scores and labels and an ETF's flows investigated in these models will not be fully diminished, but they might be temporary. Unfortunately, such an issue is not easy to address. It may be seen from the dynamics of the ESG ETF market and the overall pace of ESG popularisation, that the number of ESG instruments grows rapidly and ESG investing has a chance to become a truly new paradigm in the global financial industry. However, ESG instruments occupy only a modest share of global finance. Likewise, ESG metrics provided by special companies cover only part of the global market. For example, MSCI ESG metrics embrace corporate data on 13 years of shareholders' meetings and 65 thousand individual directors, and MSCI ESG fund ratings cover 13,000 issuers with 36,000 mutual funds and ETFs globally (MSCI, 2019b). Sustainalytics ESG risk ratings encompass more than 12,000 companies globally and most ESG indexes (Sustainalytics, 2020). Such coverage is extensive enough to provide high-quality scores. Nevertheless, these companies do not embrace the whole universe of listed companies (around 41,000 globally according to OECD, 2019) and all funds (over 122,000 globally as was noted before). That is why problems of competition skew the results of any study devoted to ESG issues today. So, markets need more time to incorporate ESG criteria fully and provide more robust data for research. As for our study, only 1605 ETFs from 2290 funds traded in the U.S. market (for which data were gathered from ETFdb.com) had ESG scores. This is substantial, but not comprehensive. Furthermore, the number of ETFs that bear the ESG label in the U.S., according to Morningstar, is even smaller. There are only 111 such funds, which of course leaves room for discussion around the problem of competition. There is no simple way to deal with this problem, unless ESG investing is promoted more and the entire financial industry incorporates ESG criteria. A study like this one is believed to foster such a process so that future studies will be able to access more robust data. Third, it is important to discuss the results from observing the control variables in the cross-sectional models. Most variables follow the financial logic in their regression coefficients rather closely.

(This is described in the preliminary analysis in Chapter 5.) However, the point of particular interest is the difference between the two samples in the signs of coefficients related to variables reflecting volatility – 200-day volatility and the average standard deviation of return. In the model with equity ETFs, both variables had positive signs, while in the model with bond ETFs the signs were negative. This refers to the distinction between these two types of funds, based on two kinds of underlying holdings. Investors do not seek risky options on the fixed asset market. On the contrary, they tend to hedge equity market risks while investing in bond ETFs. IShares reports that bond ETFs are an appropriate way to enter the bond markets in periods of volatility. Core bond ETFs may offer protection when stocks sell off, while short duration bond ETFs can ensure stability and income (IShares, 2020). In this sense, we may conclude that bond and equity ETFs are oriented to oppositely motivated investors. This creates another direction for further analysis, especially with regard to ESG investing.

Finally, the methodological drawbacks of the exploited models should be highlighted and discussed. Using cross-sectional data for any analysis of fund performance was seen to be inconsistent and problematic. Although we owned a large dataset with huge amounts of variables and a wide range of ETFs, the aggregated character of data seriously limits the possibilities for creating valuable models. There is no chance to lag any variables, which makes characteristics like return inappropriate for analysis. The 1-year level of aggregation itself is too compressing, and it decreases the influence of independent variables even in samples with many cross-sectional observations. It is even more problematic, taking into account this year's data, which are affected by shocks caused by the COVID-19 crisis. Even though we have reached the result, which at least partially allowed us to determine a relationship between ESG criteria and ETF flows, the level of aggregation is so high that we cannot refer to any coefficients and draw any numerical conclusions. That is why, we proved the first hypothesis, only partially then paid more attention to the second hypothesis and the implications derived during that analysis.

The second hypothesis we investigated was whether an EFT's compliance with ESG criteria significantly and positively affected that ETF's inflows. This statement was thoroughly checked using panel data regression analysis with various specifications, including different methods, different types of ETFs, different sample sizes and two time periods. The hypothesis was proved in all kinds of models. That is, the regression coefficients of the dummy variable, responsible for capturing compliance of the fund with ESG criteria, fluctuated between approximately 0,0021 and 0,0035. We regard this result as robust, so we may conclude that being labelled an ESG ETFs leads to an increase of fund flows by 2,1%-3,5% on average. This sheds light on the relationship between ESG investing and financial flows as applied to exchange-traded funds, while opening a new direction in ETF-related literature and adding to many studies that have investigated such relationships in mutual funds (Białkowski and Starks, 2016; Hartzmark and Sussman, 2019). In fact, this study presents a strong argument in favour of papers that have reported a positive relationship between integrating ESG criteria and better financial performance (Friede, Busch and Bassen, 2015; Andersson, Bolton and Samama, 2016), and it challenges papers which could not find that relationship (Humphrey and Tan, 2014; Meziani, 2016). Moreover, it gives arguments to stakeholder-agency approach (Freeman, 2016) and natural-resource-based views (Hart, 1995). Thus, the dilemma of whether markets need to sacrifice financial benefits to become more responsible is complemented with another argument based on the results of this study.

ESG ETFs enjoy more inflows and may be in greater demand than conventional funds. That opens up current preferences of investors, who choose ESG funds for financial and non-financial motives. These motivations might be further analysed in other articles. The results of this study mean that compliance with sustainability criteria and labelling an

ETF as ESG may be beneficial for various kinds of stakeholders. However, the main implications are for ETF providers. This study gives a strong motivation for them to create funds that comply with ESG criteria. Doing this, ETF providers are likely to attract additional inflows, which can be transcribed into additional profits. However, such a process should be shown in detail.

The total revenue of a fund can be found by multiplying total assets by the expense ratio. However, total assets themselves might be found by multiplying the number of shares outstanding by the market price per share (Cussen, 2016). Thus, assets of the fund fluctuate because of two main components, the way that the underlying securities affect the market price and the creation and redemption of shares by authorized participants. APs are driven by two motives. The first one is linked to their response to the demand for shares and their consequent duty to conduct market-making. The second one is connected with the trading activity of APs for their own arbitrage profits and in anticipation of upcoming news (Wang and Xu, 2019). In any case, regardless of the motive, any creation and redemption process (i.e. any change in the number of shares outstanding – one of two components in the total assets formula) is itself the ETF flow. That is why ETF inflows are the main source of change in total assets and so, a change in revenue for ETF providers derived from running the funds. It is obvious that since APs are responsible for providing ETF flows, they also can benefit from working with ESG ETFs specifically. This is mirrored in higher flows associated with such funds. However, since APs may have different reasons for conducting the creation and redemption process, including the ordinary role of market-makers, their precise motives are another topic for further research.

Another important point here is that ETFs usually track market indexes, which implies the need for more market indexes that address ESG issues. This is a signal to index providers to incorporate ESG criteria whenever they are when creating indexes more widely. According to this study, compliance with ESG criteria is profitable for such entities. This is the ground-breaking insight for the whole financial industry. It should be noted that the costs of this labelling should not exceed the possible profits from additional inflows. This creates possibilities for further studies that conduct a detailed cost-profit analysis of the creation of ESG ETFs.

There are other participants in financial markets who can benefit from more labelled ESG ETFs in emerging countries. They include the market agencies responsible for ESG labelling, market makers and investors. These entities are indirectly affected by the integration of ESG criteria. For market agencies and market makers, the creation of more ESG funds would open new market opportunities, and investors, who usually look for the returns from a fund, may use information about higher inflows to ESG ETFs as broad representations of market trends. They can see these inflows as ta market signal that ESG funds are currently promoted and can soon be major investment vehicles, which may result in higher profitability in the future.

In addition, these results provide a basis for discussions by policy makers about the global trends towards sustainability that are already affected society, a fact that is mirrored in the profitability of integrating ESG criteria. This does not merely justify regulations approved by Europe and other countries described previously, but it also creates demands for further national laws and various international agreements concerning ESG investments, such as the requirements for integrating ESG factors and market infrastructure around ESG labelling. Government entities like The United States Securities and Exchange Commission (SEC) should promote clearer labelling of ESG securities, and institutional investors like pension funds should rely on evidence like the results of this paper to include ESG ETFs in their portfolios for the profitability they offer. Overall, national and supranational authorities should reflect on further promotion of ESG criteria and sustainability in general, since such measures may receive a good response from markets in current circumstances, according to the results of this study.

Finally, the whole area of green finance benefits from this study. These results may imply a huge shift in market perceptions regarding the profitability of ESG investing. The possibility of higher inflows to ESG funds may lead to massive trends towards complying with ESG criteria and following the concept of sustainable development when constructing fund portfolios. This predetermines further increases in the number of ESG ETFs, and it may lead to the reorientation of the whole market to ESG criteria. Such processes provide a strong rationale for green finance to develop further, and they might enrich the sustainable development movement with large amounts of money if this result is proved in further studies. With an overall trend towards the prevalence of passive investing, it is even more important to conduct similar studies into passive investment instruments like ETFs. Such results might provide strong justifications for global trends of sustainability to emerge, and they might draw more attention from practitioners in both financial markets and other industries to achieve sustainable development goals.

In parallel to the main result of the study, let us observe the findings from the preliminary analysis and the other variables in the regression models, which are relevant for investing literature as well. For instance, several implications come from descriptive statistics. Both bond and equity ESG ETFs had better returns than their conventional counterparts. Once again, this is especially relevant for investors who are looking for profits on their investments. They do not have to sacrifice returns when adding ESG securities into their portfolios. Moreover, they can enjoy even higher returns when investing in ESG ETFs. Such a result gives important insight for institutional investors, looking for responsible investments with sufficient levels of returns. The result is in line with other studies (Mallett and Michelson, 2010; Reiser and Tucker, 2015; Tularam and Reza, 2016). However, the literature includes many papers that contend that responsible investments do not persistently outperform conventional funds (Sabbaghi, 2011; Revelli and Viviani, 2015; Meziani, 2016). Moreover, Sabbaghi observed that green ETFs are much more volatile and vulnerable to market shocks and crises. We have found the same evidence for the sample of equity ETFs, observing standard deviations of returns and spread-to-price ratio. However, we could not determine such an effect on bond ETFs. It might be hypothesised that, as was shown above, bond ETFs are not suitable for risky investments and demonstrate flatter trading. Lower age of ESG ETFs is to be expected since most of them emerged in the last three years, and if the sample had been constructed randomly without the matching procedure to adjust for age, the gap would be even larger, since ETFs, in general, have existed since the 1990s. We did not find any substantial proof of higher expense ratios for our cases of ESG and non-ESG ETFs, as Winegarden,(2019) found.

The results from econometric models with panel data also create a space for further some discussion. First, the positive influence of lagged returns on fund flows addresses the literature on the flow-performance relationship. This is consistent with other studies of the same issue (Oztekin, 2018; Yousefi, Najand and Sun, 2020). Moreover, Clifford, Fulkerson and Jordan (2014) argued that ETF investors chase past returns to the same extent as mutual funds investors, but they do this because of naïve extrapolation bias. Madhavan and Sobczyk (2018) found the same evidence for both equity and bond ETFs. They stated that for cases of funds when past returns are chased, a greater return gap exists between what an investor experiences and what is reported.

Second, the unexpected price-to-NAV ratio had a very high influence on the dependent variable, hundreds of percent. This is unusual, especially taking into account the creation/redemption mechanisms of ETFs, which should eliminate any gaps between market price and NAV. Positive influence is even more surprising, since a price-to-NAV ratio above 1 denotes that the security is traded with the premium, while normally investors seek undervalued options. This result is consistent with Clifford, Fulkerson and Jordan (2014), whom we followed in choosing our control variables. Moreover, Broman and Shum (2018) came to the huge positive regression coefficient as well in the model with an average premium, represented as the subtraction of NAV from price, not the ratio. It might be hypothesised that investors seek for securities with no ‘problems’ reflected in undervaluation. More studies are needed to investigate that issue.

Another possible direction for elaboration is the strong and significant negative influence of expense ratio in equity ETFs sample and insignificant coefficient in bond ETFs sample. This refers to the current contradictive trends around funds fees in the market. On the one hand, investors use costs as one of the main performance metrics (MacBride, 2018), so they look for the lowest fees in the market. On the other hand, many fees have reached the level where they do not have room to fall further. Hence investors are recommended to look beyond expense ratios and be prepared for hidden fees (Vlastelica, 2017). This is reflected in the ambiguity in the coefficients of expense ratio variable in models with bond ETFs and equity ETFs. Different results may once again distinguish investors who are willing to buy equity and fixed asset ETFs.

It is also represented by a significant and positive value of the coefficient of spread-to-price ratio variable. Normally, wider spreads mirror the illiquidity of the underlying securities or the ETF itself. However, they can also occur because of some trading effects such as spreads on the underlying securities, costs of trading, market impact costs and market risks in periods of volatility (RBC, 2017). This effect and other unexpected results observed in the models might be further studied in research into the market specificities of ETFs.

To conclude, this study has investigated the financial flows of ESG ETFs in comparison with their conventional counterparts. First, using cross-sectional data for 163 bond and 863 equity ETFs it discovered that an ESG score can have a significant influence on flows of the fund. However, this result is relevant only for equity ETFs. Both models suffer from various methodological drawbacks, related mostly to the use of cross-sectional data. Second, having exploited panel data for samples with bond and equity ETFs for two- and three-year time period we concluded that compliance with ESG criteria can add 2,1-3,5% to ETFs inflows on average. The result is robust for different types of funds, different time-periods, sizes of samples and different model specifications.

These results are of the highest importance for ETF providers, who should create more ESG ETFs and incorporate sustainability strategies more broadly to attract more investors and have higher profits from running funds. Authorized Participants also are important beneficiaries of investors' preferences for ESG ETFs. Other market participants and policy makers regulating the financial industry should also pay attention to this result and adjust their actions to foster ESG investing and get benefits from more ESG ETFs. Furthermore, the result gives another rationale behind the prosperity of the green economy, green finance and sustainable development concept. For academia, this study contributes to the literature regarding financial flows of ESG investment funds, and it opens a new direction for scientific research drawing such conclusions from the ETFs. In addition, several implications have been identified which address the literature around the flow-performance relationship as it applies to ETFs and other issues related to trading peculiarities of exchange-traded funds.

Obviously, the paper suffers from several limitations. Cross-sectional models involve aggregated data and a modest number of observations. This reduces the quality of models, and it skews the values of coefficients. In addition, using ESG scores as the measure of compliance funds to ESG criteria is not obvious. Panel data models use dummy variables to denote ESG funds. This prevents them from applying cross-section time-effects model and creates ambiguity around the applicability of results. Finally – the number of existing ESG ETFs, especially bond ETFs, is yet pretty modest. Further results might use historical data on ESG score for ESG funds to combine two approaches and find more adequate measures of the influence of ESG investing on fund flows. Moreover, ESG ETFs are being created rapidly and later studies will have the possibility of involving bigger samples in their analyses and find more robust results. Finally, various sub-directions are opened by this study: ESG ETFs can be divided into passively and actively managed funds to further delineate two types of investing. Data on funds listed in various countries and in different currencies might be added, and there are large portions of inverse, leveraged, multi-asset and other kinds of funds that were removed from this research. These funds may not just increase the samples for analysis, they might also gather new insights into the relationship between ESG criteria and the financial flows of ETFs.

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Appendix A

List of Bond ESG ETFs

Table A.1. Full names and tickers of bond ESG ETFs

Ticker	**Name of the fund**
IBD	Inspire Corporate Bond Impact ETF
SUSC	iShares ESG USD Corporate Bond ETF
GUDB	Sage ESG Intermediate Credit ETF
JPHY	JPMorgan High Yield Research Enhanced ETF
NUBD	Nuveen ESG U.S. Aggregate Bond ETF
HTRB	Hartford Total Return Bond ETF
JPGB	JPMorgan Global Bond Opportunities ETF
SUSB	iShares ESG 1-5 Year USD Corporate Bond ETF
JPST	JPMorgan Ultra-Short Income ETF
GRNB	VanEck Vectors Green Bond ETF
PWZ	Invesco California AMT-Free Municipal Bond ETF
HMOP	Hartford Municipal Opportunities ETF
PZA	Invesco National AMT-Free Municipal Bond ETF
RVNU	Xtrackers Municipal Infrastructure Revenue Bond ETF
PZT	Invesco New York AMT-Free Municipal Bond ETF

Source: devised by the author based on Yahoo!Finance service.

Appendix B

Industrial breakdown for ETFs in equity ESG and 1-1 non-ESG samples

Up-to-date data are gathered on precise weightings for 11 industries inside the portfolio of each fund. After that, by multiplying money values of total assets of each fund on the weightings, actual investments in a particular industry of each fund and consequently all funds in the sample are found (Figure B.1).

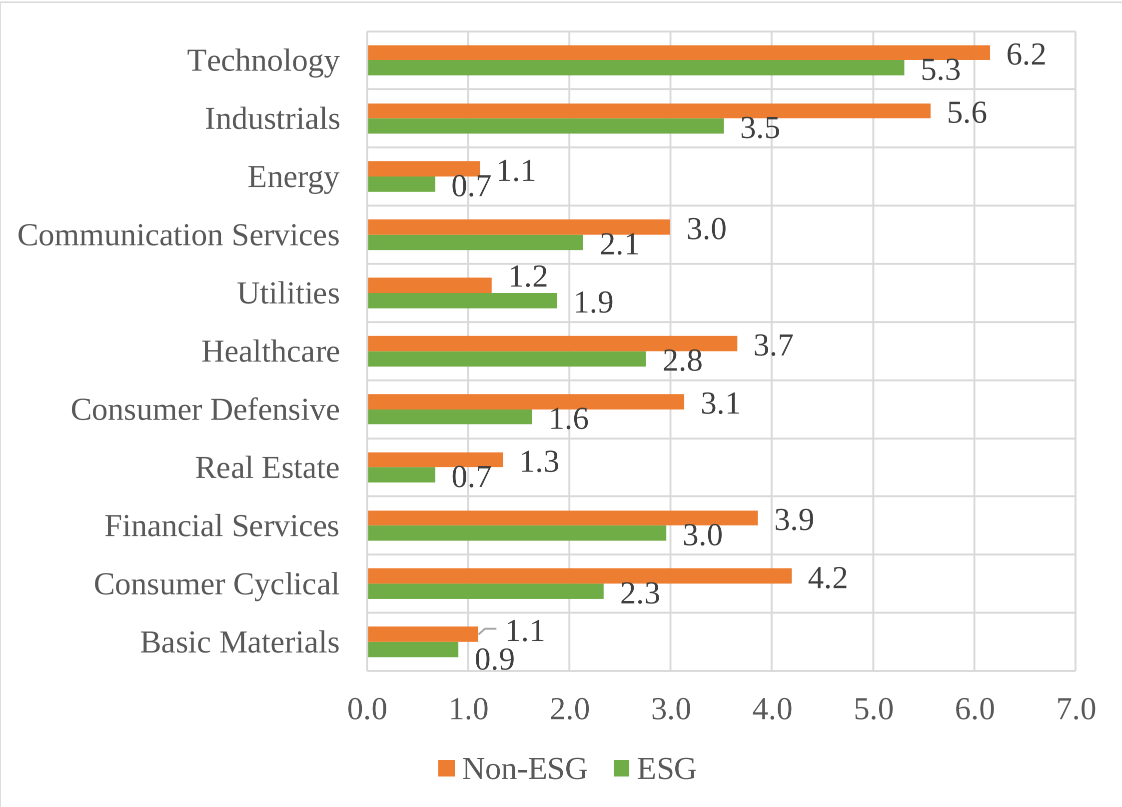

Figure B.1. Investments of equity ESG and non-ESG ETFs in particular industries, $ billion

Source: devised by the author based on Yahoo!Finance service.

Appendix C

Model with bond and equity ETFs combined

Table C.1. Output of cross-sectional model with bond and equity ETFs

Dependent Variable: FUND_FLOW_ASSETS				
Included observations: 1059				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LOG__VOLUME_	0.0146	0.0245	0.598360	0.5497
ESG_SCORE	0.0636	0.0244	2.605194	0.0093***
ER	-29.9	26.7	-1.121605	0.2623
AGE _	-0.000669	0.000908	-0.736840	0.4614
RETURN	0.0181	0.0376	0.482002	0.6299
STANDARD_DEVIATION	0.592	0.905	0.653819	0.5134
BOND	0.4	0.168	2.377138	0.0176**
VOLATILITY	0.674	0.454	1.486059	0.1376
C	-0.785	0.243	-3.225218	0.0013
R-squared	0.016382	Mean dependent var		-1.01E-07
Adjusted R-squared	0.008888	S.D. dependent var		1.37E-06
S.E. of regression	1.37E-06	Akaike info criterion		-24.16143
Sum squared resid	1.96E-09	Schwarz criterion		-24.11923
Log likelihood	12802.48	Hannan-Quinn criter.		-24.14544
F-statistic	2.185947	Durbin-Watson stat		2.000615
Prob(F-statistic)	0.026267	Wald F-statistic		9.477385
Prob(Wald F-statistic)	0.000000			

Notes: *,**,*** denote significance at 10%, 5% and 1% levels respectively.

Source: computed by author in Eviews.

초 록

ESG 요소의 투자 프로세스 통합은 지속가능한 발전 전략 및 환경 문제와 관한 전세계적 관심의 증대와 함께 관심을 받고 있다. 그러나, ESG 투자와 금융 수익의 관계 및 금융 기업의 성과 영향 등에 대해서는 합의된 결론이 존재하지 않는다. ESG 투자는 다양한 금융 상품을 통해 수행될 수 있으나, 본 연구에서는 상장지수펀드(ETF)를 중점적으로 살펴본다. 상장지수펀드는 고유의 특성으로 인해 가장 유망한 투자 수단 중 하나로 주목받고 있다. ESG ETF 는 대중화되고 있으며 실무자 및 학계의 높은 관심을 얻고 있으나, 관련 기존 연구는 대부분 위험-수익 특성에 의해 추정된 상품의 성과에 초점을 맞추고 있다.

본 연구는 ESG ETF 와 관련하여 기존에 발견되지 않았던 특별한 금융 이슈를 제시하여 기존 연구의 한계를 보완한다. 이는 ESG ETF 에 대한 투자자들의 수요를 표현하여 다른 전통적인 투자 수단에 대비하여 더 많은 금융 흐름을 유도하는 ESG ETF 의 특성에 기반한다. 구체적으로, 본 연구는 두 가지 유형의 회귀분석을 사용하여 ESG 기준에 따른 자금의 조달과 유입 간의 관계를 확인한다. 먼저, 미국에서 거래되는 채권 및 주가 ETF 의 자료를 조사하여 높은 ESG 점수와 ETF 관련 현금 흐름 간의 관계를 조사한다. 이어, 미국의 채권 및 주가 ETF 에 관한 2~3 년의 과거 데이터를 활용하여 ESG 와 비-ESG 간 효과의 차이를 최소자승법(OLS) 및 혼합 효과 모형으로 추정한다.

분석 결과, 금융 흐름과 ESG 점수 사이에는 양의 관계가 부분적으로 존재하는 것으로 나타났으나 강한 상관관계를 증명하기에는 부족하였다. 결합 ETF 가 있는 모형에서는 샘플 수의 부족 및 방법론적 한계로 인해 유의한 관계가 나타나지 않았다. 반면, ESG 라벨링을 나타내는 더미 변수를 사용한 분석에서는 통계적으로

유의한 양의 관계가 나타났다. 구체적으로는, ESG 기준에 따른 ETF 의 평균 자금 조갈은 추가 유입의 2.1 ~3.5%를 차지하는 것으로 나타났는데, 이는 뮤추얼 펀드와 관련한 기존 연구의 결론과 일치한다.

본 연구의 결과는 정책 입안자 뿐 아니라 ETF 의 제공 업체 및 기타 시장 참여자에게 시사점을 제공한다. 구체적으로 ESG 요소의 재정적 영향에 대한 딜레마를 표현하고, ESG ETF 의 재무 특성 및 기타 특성과 관련한 방향성을 확인할 수 있다. 상장지수펀드와 관련한 다양한 문헌에서 언급된 결론 역시 본 연구의 결과를 통해 해석될 수 있다. 현재 ESG ETF 와 관련한 많은 제한이 있지만, 더 많은 상품의 등장을 통해 해결할 수 있을 것으로 기대된다. 본 논문은 관련 분야의 후속 연구에 있어서 연구 배경과 향후 연구를 통한 개선점을 제시하는 의미가 있다.

주요어: 상장지수 펀드, ESG, 금융 흐름, 회귀 분석

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