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MEASURING THEMATIC INVESTOR APPETITE AND ITS EFFECTS ON ASSET PRICING

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Abstract

This thesis investigates changes in investor demand for particular investment themes, which we term "thematic investor appetite". We develop novel measures of thematic investor appetite, analyze what determines shifts in appetite, and how it affects investment theme performance. We construct thematic appetite measure based on ETF fund flows, using US-listed ETFs from January 2004 to December 2019. We find that variation in thematic appetite is mainly negatively driven by past performance of investment themes, supporting negative feedback-trading. Then, we present empirical evidence that a positive shift in thematic investor appetite causes a long-term structural positive change in the performance of thematic funds - on average, the returns increase by 1pp, maintaining the cumulative effect for more than 12 months. Altogether, our research makes a substantial contribution to a growing, yet puzzling topic of thematic fund flows that has been overlooked in research.

Keywords: Thematic appetite, exchange traded funds (ETFs), fund flows, thematic investing, Google Trends.

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Table of Contents

1. Introduction

More and more people depart from the market portfolio and traditional investing strategies such as adhering to indexes. Instead, investors tilt to investment themes. Thematic investing has taken off in the past 10 years. It is rapidly developing and has already become massive: in the last three years, total funds under management of thematic investment vehicles have tripled from 75 to 195 billion dollars (Johnson, 2020).

Thematic investing can be likened to fashion trends. Like fashion, specific investment themes go through waves of popularity among investors while others become outdated over investment-fashion cycles. Currently popular investment themes include, for example, technology, climate, ESG, but, in general, investors can invest in any theme from cannabis to AI, which they think will grow in the future (Johnson, 2020). According to Bérubé, Ghai & Tétrault (2014), the main idea of a thematic investment is to catch the long-term trends rather than success of single company. Thematic investing is based on perceptions of investors about the prospects of investment themes; it is a way for investors to express and support their values and beliefs via directing funds to the preferred themes (Eckett, 2019).

The supply of thematic investing vehicles "has mushroomed" in the past years (Johnson, 2020). In 2018, a record high number of 169 new thematic funds were launched, followed by 154 new thematic funds worldwide in 2019. A contributor to the boom in thematic investing is the rapid proliferation of exchange traded funds (ETFs), which have made thematic investing cheaper and more accessible to investors. Currently, the global thematic investing universe amounts to 923 thematic funds that attract substantial investments (Johnson, 2020). The enormous money flows raise questions among researchers and call for clarity among investors. Recently, researchers have found that most of the fluctuations in asset prices and risk premia are caused by the fund flows due to the aggregate stock market being price-inelastic (Gabaix & Koijen, 2020). What causes the money flows between thematic funds? How do these flows affect assets? What consequences might that bring? To the best of our knowledge, there has not been done any research on thematic fund flows answering these questions.

Firstly, general mood among investors can be analyzed through preferences for themes, which we call *thematic appetite*. Being the pioneers in this field, we first determine the approach of measuring thematic appetite. However, the real puzzle is the causes of shifting from one theme to another. Therefore, we research the drivers of variation in thematic appetite. Finally, just like in the world of fashion, when some trends become so popular that the clothing supply is unable to meet the growing demand, the pricing is prone to be affected. In a case of thematic investing, the impact on stock prices is going to be reflected through returns. So, we explore the effect of shifts in thematic investor appetite on the performance of investment themes.

Our tool to analyze thematic appetite is fund flows of exchange traded funds (ETFs), which, as far as we know, has not been previously used in academic research. ETFs are the ones that have made thematic investing more accessible due to a large number of niche instruments: they provide exposure to any possible theme one can imagine (Easley, Michayluk, O'Hara, Putnins, 2020). Furthermore, the fact that ETFs are low-cost investment vehicles, they are traded intra-day and they are easily understandable by retail investors gives us an exclusive chance to capture thematic appetite. The research questions we aim to answer are formulated as follows:

1. *How to measure thematic appetite?*
2. *What drives the variation in thematic appetite?*
3. *How do the shifts in thematic investor appetite affect the performance of investment themes?*

This paper is structured as follows: Section 2 presents an overview of available academic literature and proposes hypotheses that will be tested in our research. Section 3 provides the description of the data used in the thesis and sources from which it was obtained. The following three sections present methodology, results and discussion answering a particular research question: Section 4 – measurement of thematic appetite, Section 5 – determinants of thematic appetite, Section 6 – effects on asset pricing. Section 7 analyzes the robustness of the obtained results to alternative thematic measures. Section 8 provides conclusion, implications and recommendations for future research.

2. Literature Review and Hypotheses

The literature review starts with the description of the concept of thematic investing and investment themes. We then consider the preferences for certain themes as thematic appetite and look further into possible determinants of shifts in the thematic appetite. Finally, we describe the effect of shifts in thematic appetite on the performance of investment themes. At the end of the section, we establish hypotheses guiding our further research.

2.1. Thematic investing and the identification of investment themes

To analyze the shifts in thematic appetite and their impact on asset pricing, we start with the definition of thematic investing. Thematic or style investing is defined as grouping assets into broad categories referred to as themes or styles based on long-term macro level trends and directing funds into and out of these themes (Teo & Woo, 2004). Parallels could be drawn with sector investing; however, thematic investing covers broader scope, meaning that a theme can include numerous sectors. For example, health care fund can invest in high-tech, health insurance and medical equipment, etc. (Blackrock, n.d.). Most importantly, thematic-investment attempts to catch the long-term trends and cyclicalities in different asset classes worldwide (Bérubé, Ghai & Tétrault, 2014). Johnson (2020) adds that the identified themes might refer to macroeconomic or systemic trends, which are transforming the conventional economic cycle, for example, technological development or growing attention to sustainability.

Johnson (2020) defines "universe of thematic funds" as investment vehicles whose assets under management provide exposure to single or multiple themes not limiting the meaning of a *theme*. The niche investment vehicles that provide this possibility are exchange traded funds. ETFs provide access to any possible theme from artificial intelligence to religious values (Easley, Michayluk, O'Hara, Putnins, 2020). If previously thematic investing was only accessible to institutional investors who had to perform extensive analysis and manually pick stocks for a specific theme, nowadays ETFs provide access to already pooled stocks with exposure to a specific theme with one trade (Lettau & Madhavan, 2018).

Barberis and Shleifer (2003); Teo and Woo (2004) identify two reasons why thematic investing is favored by investors: simple and efficient framework for organizing investment strategies and easy performance evaluation of money managers. Also, thematic investing is a way for investors to express and support their values and beliefs via directing funds to the preferred themes, meaning that it is based on perceptions of investors about the prospects of investment themes, and on personal preferences (Eckett, 2019). We call the preferences for certain themes *thematic appetite*.

Barberis and Shleifer (2003) have found that investors are reluctant to change their overall investment theme preferences, rather they transfer funds between extremes of a theme or so-called *twin* stocks. Authors define them as "stocks with a high value of some characteristic and stocks with a low value of the same characteristic", meaning opposing thematic ends (p.

167). For example, value and growth stocks. Similarly, using fund flows of investors with AUM of $9 trillion, Froot and Teo (2008) prove the existence of theme-level trading by institutional investors across all three thematic dimensions they identified for stocks: small vs. large capitalization, value vs. growth, and company sector. Then, Teo and Woo (2004) mention such themes as technology vs. non-technology stocks, value vs. growth stocks, and small vs. large stocks. The authors support finding of Barberis and Shleifer (2003) and state that investors move resources across every thematic dimension more actively than they do over random groups of stocks. Furthermore, Froot and Teo (2008) document a negative relationship between the net flows into opposing theme ends (for example, extreme value vs. growth), which supports the reallocation of resources from one end of the spectrum towards a contrasting extreme of a theme.

2.2. Shifts in thematic appetite and their determinants

After we have examined literature on investment themes and fund flow patterns, we turn to justification of the relationship of fund flows to thematic appetite. We begin with the concept of fund flow measures and then turn to possible determinants of shifts in thematic appetite.

2.2.1. Thematic appetite and flow measures

Brown et al. (2002) prove that mutual fund flows are a valid measure of investor sentiment, highlighting “money-flow” investor sentiment instrument importance because they do not confuse measurement of sentiment with the measurement of asset returns. Moreover, they clarify the distinction between other investor sentiment measures, such as Baker and Wurgler (2006) composite sentiment index that allows only for two states of sentiment - either bearish or bullish, and money-flow measures that cannot be characterized as only optimistic or pessimistic. Frazzini and Lamont (2006) also present justification with the help of mutual fund flows as a sentiment instrument for individual stocks. Therefore, money-flow measures enable us to capture many more dimensions than bearish-bullish. For instance, the market is characterized as bearish, but at the same time, cannabis and AI themes thrive; therefore, money-flow measures allow us to distinguish between the overall situation in financial markets and separate sub-segments of them, which makes studying thematic investor appetite feasible.

We build on investor sentiment proxied by mutual fund flows to introduce our original thematic appetite measure based on thematic ETF fund flows – so far, there is no research available on ETF fund flows as a proxy for thematic appetite. Sentiment usually reveals overall attitude of investors. However, thematic appetite allows us to capture investor preferences across different investment themes.

2.2.2. Past performance of thematic funds

As thematic funds continued to grow, researchers began to question the drivers behind shifts in thematic fund flows. Barberis and Shleifer (2003) were among the first ones to study thematic investing and establish several explanations. As the first determinant of shift in thematic preferences, authors identify relative past performance of thematic funds. They find that fund flows follow relative thematic returns, implying positive feedback trading at the theme level, which means that higher returns of a certain theme result in higher fund inflows and vice versa. In simple words - investors do chase returns (Karceski, 2002). Further, Teo and Woo (2004) support results of Barberis and Shleifer (2003): thematic fund flows move towards well-performing funds complying with positive feedback trading. Moreover, Teo and Woo (2004) suggest that noise traders or uninformed retail investors are the ones pursuing positive feedback trading. According to Warther (1995), mutual funds are very likely to attract uninformed investors, such as retail investors. Furthermore, Ben-Rephael et al. (2012) support the previous statement because "the assumption that investors are uninformed is reasonable, since investors who perceive themselves as "informed" presumably invest directly in the market" (p.365). Chau, Deesomsak and Lau (2011) discover significant positive feedback trading in the US market, which intensifies when investors are optimistic. Authors also support the belief that feedback trading is mainly influenced by sentiment-driven noise trading.

Researchers also document negative feedback trading. Bohl and Siklos (2004) support existence of both positive and negative feedback trading. Furthermore, Frijns, Gilbert, and Zwinkels (2016) reveal that more than a half of investors following feedback trading strategy is pursuing negative feedback trading, increasing exposure to recent losers. The authors find that momentum trading in the short run and opposite trading in the long run increases performance. Interestingly, Hirshleifer, Subrahmanyam and Titman (2006) find that irrational investors that act against the market can earn positive profits. Additionally, the authors state that feedback is a form of second order private information that is perceived similarly by investors with similar psychological biases resulting in a bigger volume of trading in the same way. The phenomenon possibly relates to disposition effect that we discuss in the next section. Wan, Liu, Wang and Yang (2016) argue that negative feedback traders are rational contrarian traders who correct the market and prevent from the formation of bubbles. To sum up, both positive and negative feedback trading are coexisting in the market.

2.2.3. Psychological biases of investors

Further, researchers have tried to explain fund flows by psychological biases of investors. Researchers as Shiller (2003) and Thaler (2016) strongly believe in irrationality of investors turning attention to behavioral economics. Thaler (2016) states that actual choices of people are explained by prospect theory proposed by Kahneman and Tversky (1979) together with expected utility theory. Shiller (2003) then reveals that feedback trading is driven by systemic biases (representativeness heuristic) and biased self-attribution.

Bailey, Kumar and Ng (2011) say that the trend chasing is connected to behavioral biases, rather than to rationality, meaning that behaviorally biased investors are the ones contributing to trend chasing money flows. Also, Vayanos and Woolley (2013) suggest that both momentum and reversals are the result of investor inertia. What is more, Fong, Sze and Ho (2018) present evidence that the return-chasing behavior amplifies fund flows' volatility in times of market downturn. Wahal and Yavuz (2013) find that theme chasing behavior also magnifies asset return waves. Finally, Froot and Teo (2008) conclude that results in their study about shifts in fund flows are mainly characterized by behavioral models, stating that thematic flow represents investor sentiment that relate to thematic appetite.

2.2.4. News and events

Then, thematic appetite can be influenced by news and events. To begin with, Barberis and Shleifer (2003) predict that creation of an investment theme is stimulated by positive fundamental news about the securities in a certain dimension. Similarly, themes break down or go out of favor because of bad fundamental news about themselves or good news about another theme, which pulls funds away. According to Froot and Teo (2004), thematic fund flows reflect investor reaction to certain information and fundamental news temporarily. Vayanos and Woolley (2013) study the effect of asymmetric information: fundamental shocks provoke fund flows that intensify the effects of these shocks on stock returns. Researching mutual fund flow response to sustainability rating news, Guercio and Tkac (2008) find significant inflows due to positive information regarding respective funds. Teo and Woo (2004) argue that it is very unlikely that investors overreact or underreact at the theme level. However, Chou, Ko and Yang

(2019) discover that limited attention makes investors miss crucial information which leads to underreaction. This phenomenon links together with the disposition effect, implying that investors sell stocks when prices go up, but they hold "losers" when prices go down, because it is painful to admit that they have made a poor decision. Therefore, there are delays and underreaction (Barberis and Thaler, 2003).

Benson and Humphrey (2008) add that investors do not only use long term information on performance, but also recent information that is readily available on such websites as Morningstar. Drake, Roulstone and Thornock (2012) uncover using Google Search that investor demand for information climbs significantly in the periods surrounding announcements and has a positive relationship with news and media attention. It leads to availability bias, which makes investors think that readily available information on the websites and news highlights are the most representative facts.

2.2.5. Economic and financial conditions

Finally, researchers have found that overall economic conditions and the financial situation have an impact on fund flows. Jank (2012) has concluded that economic conditions explain the shifts in mutual fund flows. Furthermore, he points out that the fund flows are better explained by changes in the economic conditions rather than the returns of mutual funds. In his paper, Jank (2012) also finds that both mutual fund flows and returns respond to the changes in the real economy; he explains that the changes in the economic conditions are accountable for the co-movement of the fund flows and returns. Jank (2012) uses market, dividend-price ratio, default spread, term spread, relative T-Bill rate as predictive variables for economic activity. So, a positive relationship between market return and fund flows is expected, supporting feedback-trader and price pressure hypothesis (Warther, 1995; Jank 2012). Then, a positive relationship is expected between dividend-price ratio and fund flows, meaning that a higher dividend yield attracts investors, which leads to inflows. Considering information response hypothesis, a negative relationship is implied between an increase in default spread and fund flows, and an increase in term spread and fund flows. The relationship between relative T-bill rate and fund flows is expected to be positive, meaning that lower equity premium attracts funds (Jank, 2012).

Further, examining mutual fund flows, Kopsch, Song and Wilhelmsson (2015) find that not only financial variables explain shifts in fund flows, supporting results of both Warther (1995) and Jank (2012), but fund flows are also predicted by market volatility proxied by VIX.

Moreover, Ben-Rephael et al. (2012) document a negative relationship between shifts between funds and VIX, meaning that higher VIX implies risk, which leads to outflows from ETFs. As discussed in the methodological section below, regarding the volatility variable, we draw inspiration from the authors that propose VIX index; nevertheless, to account for the fundamental variable in finance – risk, instead of using VIX index, we construct theme-based volatility variable due to the specificity of our research as investment themes differ in volatility.

2.3. Effect of thematic appetite shifts on asset pricing

Recently, Gabaix and Koijen (2020) have presented evidence that aggregate fund flows drive almost half of the market fluctuations. To be more specific, the authors state that fund flows on macro level substantially affect prices and risk premium, implying that capital market is price-inelastic. They explain it by the fact that households instead of directly investing into the market, direct funds to institutional investors such as mutual funds and ETFs first, and institutional investors are reasonably restricted in their investment choices; thus, it contributes to price-inelasticity. Warther (1995) explains the correlation between fund flows and returns stating that fund inflows are positively related to asset returns given that investor sentiment is powerful market force and fund flows are a fair indicator of it. In his paper, Warther (1995) finds that aggregate mutual fund flows are positively-correlated with the returns; so, inflows are associated with positive returns, but outflows – with negative returns. This phenomenon has been proved by several other authors.

The literature presents three hypotheses why fund flows should be positively correlated with returns: price-pressure hypothesis, feedback-trader hypothesis, information-response hypothesis. Price pressure hypothesis says that "flows cause returns" (Jank, 2012, p.3060). Ben-Rephael et al. (2012) explain that uninformed investors driven by the sentiment induce asset price fluctuations that push market prices away from asset fundamental values. Frazzini and Lamont (2008) point out that price increases are a result of high investor demand realized through fund inflows. Warther (1995) finds no evidence for the price-pressure hypothesis; however, he admits that the tests performed were not powerful enough. Ben-Rephael et al. (2012) discover that fund flows and subsequent returns are negatively-correlated.

Feedback-trader hypothesis claims that "market returns cause fund flows", meaning that investors respond to growing prices and purchase assets, and sell when prices decline, implying positive relationship (Jank, 2012, p.3060). Warther (1995) contradicts the belief that fund flows follow high past returns, and he rejects the feedback-trader hypothesis. Jank (2012) doubts both price-pressure and feedback-trader hypotheses because he proves that changes in the real economy have more explanatory power of mutual fund flows rather than market returns.

Along with feedback trading, Teo and Woo (2004) observe reversals at the theme level, meaning that stocks in themes with worst past performance and net inflows deliver abnormal returns in future. Shiller (2003) suggests that if the feedback process is not interrupted, expectations about the future price create unsustainably high current price, which results in a bubble that will eventually burst responding to or independent from news about fundamentals. Moreover, authors find that effect is more pronounced for themes that appear to investors as substitutes (for example, value and growth), consistent with Barberis and Shleifer (2003). Teo and Woo (2004) do not find explanation for findings as they do not relate to any theme-level learning or psychological framework. Recently, Pastor, Stambaugh and Taylor (2020) have discovered that a popular theme is performing very well, attracting fund inflows. Subsequently, the theme is expected to have low returns because investors have driven up the prices. Referring to De Bondt and Thaler (1985), Shiller (2003) points out that stocks maintain momentum for a period up to six months to a year, which is then followed by a reversal over a longer time frame.

Jank (2012) interprets the information-response hypothesis as simultaneous reaction of stock market returns and fund flows to news. He finds that market returns and mutual fund flows respond to new information at the same time, concluding that mutual funds and returns incorporate overlapping information. Jank argues that other authors have researched the information-response hypothesis, but the prior research does not lead to unambiguous conclusions.

Analyzing thematic flows, Teo and Woo (2004) find proof that theme returns have an effect on stock returns because of the positive feedback trading of style switchers. Their findings support the ones proposed by Kumar (2002) and Barberis and Shleifer (2003). When popularity of themes changes, for example, one becomes more favored than the other, prices differ substantially from fundamental values. However, in the long-term prices are likely to approach fundamentals (Barberis and Shleifer, 2003).

Then, Froot and Teo (2008) discover that fund flows have substantial effect on future returns. Authors identify two possible explanations of the effect: anticipated fundamentals and investor sentiment, meaning that either investors expect positive fundamental information or investors are driven by sentiment. In both explanations, buying increases prices which leads to rationally expected return increase. Moreover, as stated previously, Froot and Teo (2008) have found a negative relationship between the net flows into opposing thematic extremes. Building up on this, the authors present evidence that the opposite extreme of a theme flows and returns negatively forecast stock returns, while similar end flows are related positively. Broman (2016) also states that abnormal co-movements are positive for ETFs in the same theme and prices of ETFs are the ones causing deviations from fundamentals, not NAVs themselves.

Based on the reviewed academic research, we formulate the following hypotheses:

Hypothesis 1: Flows in and out of thematic vehicles reveal thematic appetite for an investment theme.

Hypothesis 2: Variation in the thematic appetite is driven by past performance of the investment themes and news/events. Strong past performance leads to high thematic appetite; trend popularity is positively associated with thematic appetite.

Hypothesis 3: Very strong thematic appetite drives the returns up, which then leads to overreaction and the theme being overpriced in the short run.

Hypothesis 4: In the long run, thematic appetite decreases, which leads to subsequently relatively poor performance of a theme, and the price returns to the fundamental value.

3. Data and Classification of ETFs

3.1. Data description

In this research, as the main data sources we use Thomson Reuters Datastream, the Center for Research in Security Prices (CRSP) and ETF Global data on ETFs listed in the US market. Our reason for using the US setting is that the US has bar far the most ETFs of any country, which is crucial for us to be able to develop our measures of thematic appetite and then examine the impacts on asset prices. The vast majority of the sample of ETFs used in this research consists of US-listed equity ETFs; however, we consider a few US-listed commodity, fixed income, multi-asset and real estate ETFs as well, and we exclude all US-listed short ETFs due to their feature to replicate an underlying index inversely.

We obtain detailed data from ETF Global about the universe of ETFs such as primary benchmark, asset class, category, focus, geographic exposure, sector exposure, industry exposure, ETF name and ticker so that we have all the necessary characteristics of ETFs to classify them to themes. Additionally, for the classification of ETFs, we obtain data from popular investor websites such as ETFdb.com, ETF.com and Bloomberg.com. As we specify below, the main principle of classification is searching for keywords in ETF names, we acknowledge that we will not be able to pick up all the thematic ETFs in this way. Therefore, we obtain revenue exposure in percentage terms to a specific theme of each ETF from ETFdb.com.

The return variable, price per share and the number of shares outstanding is obtained from CRSP for each ETF in the time period between January 1, 2004 and December 31, 2019. The data of the following US real economy variables: Moody's BAA and AAA seasoned corporate bond yield, 10-year, 1-year and 3-month maturity treasury rates, come from FRED, the S&P 500 composite value comes from Thomson Reuters Datastream, and the data for S&P 500 dividend yield come from Robert Shiller's homepage. We align the time frame of real economy variables with the time period of ETF data: from January 1, 2004 to December 31, 2019.

The data for trend popularity measures is taken from Google Trends, where we search for representative keywords, and extract the relative search frequency of those keywords. As the earliest date when Google search history and frequency was recorded is January 2004, we obtain data starting from this point in time.

All the variables used in the research are of monthly frequency to enable us to capture the most significant trends, and even more importantly, their evolution, which would not be possible if we used weekly or daily data as fluctuations on a daily basis would blur the actual growth of trends.

Lastly, we acknowledge that our data sources contain some imperfections. In March 2014, several ETFs seem to have increased the number of shares outstanding from 100 to a substantially larger number (e.g., hundreds of thousands). This is a flaw of our data source because it seems that for several ETFs the number of shares outstanding was not documented prior to March 2014; therefore, our data source assumes the number of shares outstanding to be exactly 100 before March 2014. It directly affects the quality of our research and calculations - if the number of shares outstanding increases by 1,000-100,000 times just in one month, it affects the market capitalization and creates deceitfully high percentage inflow in the ETF market and several thematic portfolios. Thus, we treat March 2014 as an exception, and assume that the ETF market stayed neutral, meaning that the percentage flow equals 0.

3.2. Classification of ETFs

In this research, we analyze five investment themes where each theme has two opposing dimensions – in total, 10 thematic dimensions. The investment themes are chosen so as to represent the major global and investment trends. Also, we draw inspiration from existing thematic classification in popular investor websites. Consequently, we combine countless small investment themes into broader categories and make a distinction between two opposing thematic dimensions. The themes and dimensions are as follows:

1) ESG: socially-responsible investing and sin
2) Technology: high-tech and low-tech
3) Strategy: value and growth
4) Climate: climate change and heavy manufacturing
5) Size: large-cap and small-cap

Next, we describe the allocation procedure of ETFs to a particular portfolio of each thematic dimension. We select specific ETFs that represent the two opposing ends of each theme, and exclude those ones which lay in the middle of each theme. In this way, we filter out such ETFs that do not possess strong thematic characteristics, and that are not likely to reflect thematic appetite of investors.

The main 2 principles according to which we classify ETFs are specific words that the name of an ETF contains and classification in websites that are popular among retail investors like ETFdb.com. Although we could allocate ETFs to thematic portfolios based on formal academic principles, for instance, calculate the revenue exposure of an ETF to certain themes, we insist that, in this case, what truly matters is the investors' perception about which theme an ETF belongs to. We argue that popular websites, their classification and the name of an ETF itself are critical factors in shaping retail investors' views about thematic ETFs.

In the literature, several authors support this classification method. For example, Brown et al. (2002) classify funds based on specific words in the fund names, for instance, forming bull fund portfolios that involve words "bull", "double" and exclude "bear" and "reverse" (p.9). Teo and Woo (2004) bring up a crucial idea that although "while it is possible to classify funds based on their loadings on the Fama and French (1993) factors or on stock market indexes like the Russell indexes, these loadings are latent variables and not directly observed by investors. Hence, these investors are less likely to rely on these loadings when determining their style allocation strategies" (p.369). They imply that the majority of retail investors do not classify funds based on specific metrics like market-to-book ratio or revenue exposure to some themes. Rather they are guided about fund investment policies relying on what they read in the fund's name, or in a popular website. Furthermore, oftentimes the fund's name suggests what style or theme it follows and in which assets the fund invests in (Teo & Woo, 2004).

Besides, several authors point out that the majority of mutual fund investors are uninformed retail investors, such as households, who would not participate in the financial markets if mutual fund costs would not be so low and who simply are not so sophisticated as informed or institutional investors (Warther, 1995, Ben-Rephael et al., 2012, Jank, 2012). Above-mentioned facts might be even more plausible in the case of ETFs as there are even less restrictions and difficulties to get involved in the financial markets.

Therefore, we develop a general approach of classifying thematic ETFs that consists of 5 steps:

1. Filter ETFs whose names contain specific keywords, and exclude the keywords of the opposite side of a thematic dimension. For example, the portfolio of value ETFs would be formed of those ETFs that contain "value" and simultaneously exclude "growth". The keywords are chosen based on the most frequently used words in the names of ETFs in popular investor websites. To avoid a survivorship bias, we must take into account dead ETFs as well. As our dataset contains all ETFs that have ever existed, we are able to pick up dead ETFs as well by filtering ETF names by keywords.
2. If the name of an ETF does not contain representative keywords, then we add such ETFs to portfolios based on the revenue exposure to a particular theme, taken from popular investor websites such as ETFdb.com and ETF.com. For example, alcohol ETFs do not have the word "alcohol" in their name. Instead, the majority of ETFs with revenue exposure to alcohol are named as "consumer staples" ETFs. In such cases, we rely on the classification performed by websites that explicitly and unambiguously indicate that those ETFs can be considered as "alcohol ETFs".

The first 2 steps allow us to gather the maximum amount of ETFs that would be included in each portfolio, and for exactly this reason our portfolios are rather "noisy" because some ETFs might not have a strong thematic investment objective. Therefore, we have developed 3 more steps, where steps 4 and 5 are reiterated until the conditions are satisfied:

3. As we intend to calculate correlations of returns in the following steps, we exclude those ETFs that are less than 4 months old on December 31, 2019 or that died being less than 4 months old at any other point in time because such ETFs may demonstrate atypical returns in the first months of their life, and such ETFs simply do not have enough observations to draw meaningful conclusions about the correlation of returns with other ETFs
4. Next, we calculate the correlations of returns between all ETFs in the portfolio as well as of each ETF with the weighted average returns of the portfolio. If a particular ETF shows a negative correlation with the majority of other ETFs in the portfolio or the weighted average returns of the portfolio, then this ETF would be the first one to be examined in detail in step 5. If step 5 does not give us a strong reason to keep the ETF, then it is excluded from the portfolio.
5. Once we have performed the above-mentioned 2 steps, we search for qualitative descriptions of each ETF's investment objective in ETF.com and Bloomberg.com in order to validate our previous steps and crosscheck if ETFs indeed are put into appropriate portfolios. If it turns out that an ETFs investment objective is not aligned with the theme of that portfolio, then it is excluded.

In our portfolios, there are a few ETFs that deliberately target two themes; therefore, these ETFs can be found in two portfolios, meaning that themes are not mutually exclusive. For example, there are ETFs that are both exposed to technology and ESG like ROBO Global Healthcare Technology and Innovation ETF (HTEC). Similarly, iShares S&P Small-Cap 600 Growth ETF (IJT), for instance, combines both small cap and growth theme. The same ETF, however, is not included in the opposing dimensions of investment themes. Overlap is justified by the nature of ETFs, which includes combinations of themes or trends. Exclusion of ETFs from certain themes in this case would be unjustified as these ETFs possess strong thematic characteristics, and only 8% of all ETFs are present in two portfolios of different investment themes. Also, some of our portfolios of ETFs consist of other asset classes than equity. However, only 6% of all ETFs in this research are non-equity ETFs; thus, the possible effect of asset classes is insignificant, yet these ETFs possess strong thematic characteristics.

The total number of ETFs used in the research is 799. The keywords that we look for to form each of the portfolios and number of ETFs in each portfolio are presented in Table 1.

Table 1. Classification of ETFs

The table reports the main chosen investment themes, two opposing dimensions of each investment theme, the keywords used in filtering the names of ETFs, and the final number of ETFs within each dimension.

Investment theme	Dimension	Keywords	#ETFs
ESG	Socially responsible investing	*Biotechnology, biotech, biopharma, healthcare, health, health care, medical, immunotherapy, immunology, pharmaceutical, impact, ESG, longevity, equality, sustainable*	*94*
	Sin	*Military, gaming, video games, igaming, betting, cannabis*	*47*
Technology	High-tech	*Robotics, robo, tech, innovation, innovative, internet, AI, artificial intelligence, automation, information technology, electric vehicles, digital, data, mobile, connectivity, fintech, 3D, analytics, nextgen, next generation, machine, quantum, computing, cloud, disruptive, semiconductor, software, cyber, space*	*118*
	Low tech	*Bank, financial, real estate, consumer goods, consumer services, construction, homebuilders, housing, infrastructure, insurance, mortgage, retail, shipping, transportation*	*115*
Strategy	Value	*Value*	*92*
	Growth	*Growth*	*86*
Climate	Climate change	*Energy, power, clean, renewable, wind, solar, green, environment, cleantech, low carbon, water*	*39*
	Heavy manufacturing	*Timber & forestry, oil, gas, coal, steel, uranium, mining, miners, explorer, brent*	*66*
Size	Large-cap	*Large cap*	*61*
	Small-cap	*Small cap*	*81*

4. Measuring Thematic Appetite

We start this section by defining the fundamental variables of our research - the thematic appetite measures. As noted above, the rapid evolution of ETF market and ETF investment strategies has created unique circumstances to reflect the thematic inclination of investors. Additionally, in case there is a shift in the thematic investor appetite, ETFs allow them to change their preferences in a fast and accessible way. Therefore, we construct the measures of thematic appetite based on the thematic ETF fund flows. Below we present 2 versions of our thematic measures. The first one is an *abnormal thematic appetite* for specific themes reflected by the abnormal thematic fund flow benchmarked against the total flow within the whole ETF market. The second version is *directional thematic appetite,* which can be interpreted as the relative flow across one theme and is used in the robustness tests in Section 7.

Firstly, based on the monthly log-returns of each ETF, we calculate the weighted average return ($Return_{j,t}$) of the thematic portfolio of ETFs:

$$Return_{j,t} = \sum_{l=1}^{l} \frac{TNA_{l,t}}{TNA_{j,t}} \cdot R_{l,t} \tag{1}$$

$TNA_{l,t}$ represents total net assets of each ETF within the corresponding portfolio and is proxied by the market capitalization, which is the product of price per share and the number of shares outstanding. l represents each ETF, and j represents each investment theme. $TNA_{j,t}$ shows the total net assets of the whole portfolio. t stands for month. The monthly log-return of each ETF is denoted by $R_{l,t}$.

Secondly, absolute fund flows can be expressed as a difference between TNA over time taking into account the appreciation or depreciation of an asset as well; therefore, we calculate monthly fund flows ($F_{l,t}$) based on monthly total net assets of each ETF and the log-return of the same month:

$$F_{l,t} = TNA_{l,t} - TNA_{l,t-1}(1 + R_{l,t}) \tag{2}$$

Thirdly, we normalize the fund flows of each ETF ($F_{l,t}$) by the total net assets of a corresponding ETF on the previous month ($TNA_{l,t-1}$) in order to obtain the fund flows in percentage terms for each ETF. We account for the fact that smaller ETFs tend to have higher fund flow fluctuations in percentage terms, but larger ETFs – lower fluctuations, so a simple average of individual percentage flows would artificially increase or decrease the percentage fund flow for the whole portfolio due to different sizes of ETFs. Thus, we compute the weighted average percentage flow of all ETFs within a portfolio ($APF_{j,t}$), where the weight, similar to the weighted average return of a portfolio, is the share of an ETFs total net assets to the whole portfolio's total net assets:

$$APF_{j,t} = \sum_{l=1}^{l} \frac{TNA_{l,t}}{TNA_{j,t}} \cdot \frac{F_{l,t}}{TNA_{l,t-1}} \tag{3}$$

Finally, following the same logic, we calculate the average percentage flow for the whole ETF market over time by treating the market as one large portfolio:

$$APF_{ETF\ market,t} = \sum_{l=1}^{l} \frac{TNA_{l,t}}{TNA_{ETF\ market,t}} \cdot \frac{F_{l,t}}{TNA_{l,t-1}} \tag{4}$$

Now, we have all the necessary inputs to define our thematic appetite measures. The first way to estimate the thematic appetite is to investigate which themes have higher percentage inflows than the percentage inflows of the whole ETF market, and which ones have smaller inflows of funds or even outflows. In this research, we do not measure the plain percentage flows of investment themes because the growth of the ETF market itself has catalyzed the growth of thematic investing. What we are truly interested in is to find investment themes that managed to grow, on one hand, faster than the market, and on the other hand, slower than the market because it would reflect an enhanced or weakened demand for particular investment themes. Thus, we call the first measure *abnormal thematic appetite*, which, in simple words, shows whether the demand for an investment theme has been stronger or weaker than the demand for ETFs in general:

$$Abnormal\ appetite_{j,t} = APF_{j,t} - APF_{ETF\ market,t} \tag{5}$$

The second way how we measure the thematic investor appetite is to compare two opposing ends of each theme. In this case, we are interested to which side (dimension) an investment theme has tilted and how the inclination toward one or another end of the spectrum changes over time. A simple analogy would be to imagine a weighing scale. As soon as one side of the theme becomes more popular than the other, it receives relatively higher fund inflow. Consequently, it grows, becomes heavier and the weighing scale leans to that direction. So, we call this measure *directional thematic appetite* as investors can direct their investment into either side of the theme, where superscripts *1* and *2* indicate the two opposing sides of the spectrum:

$$Directional\ appetite_{j,t} = APF_{j,t}^{1} - APF_{j,t}^{2} \tag{6}$$

Conceptually, we define the directional appetite as follows: for ESG – SRI minus sin, technology – high-tech minus low-tech, strategy – value minus growth, climate – climate change minus heavy manufacturing, size – large-cap minus small-cap.

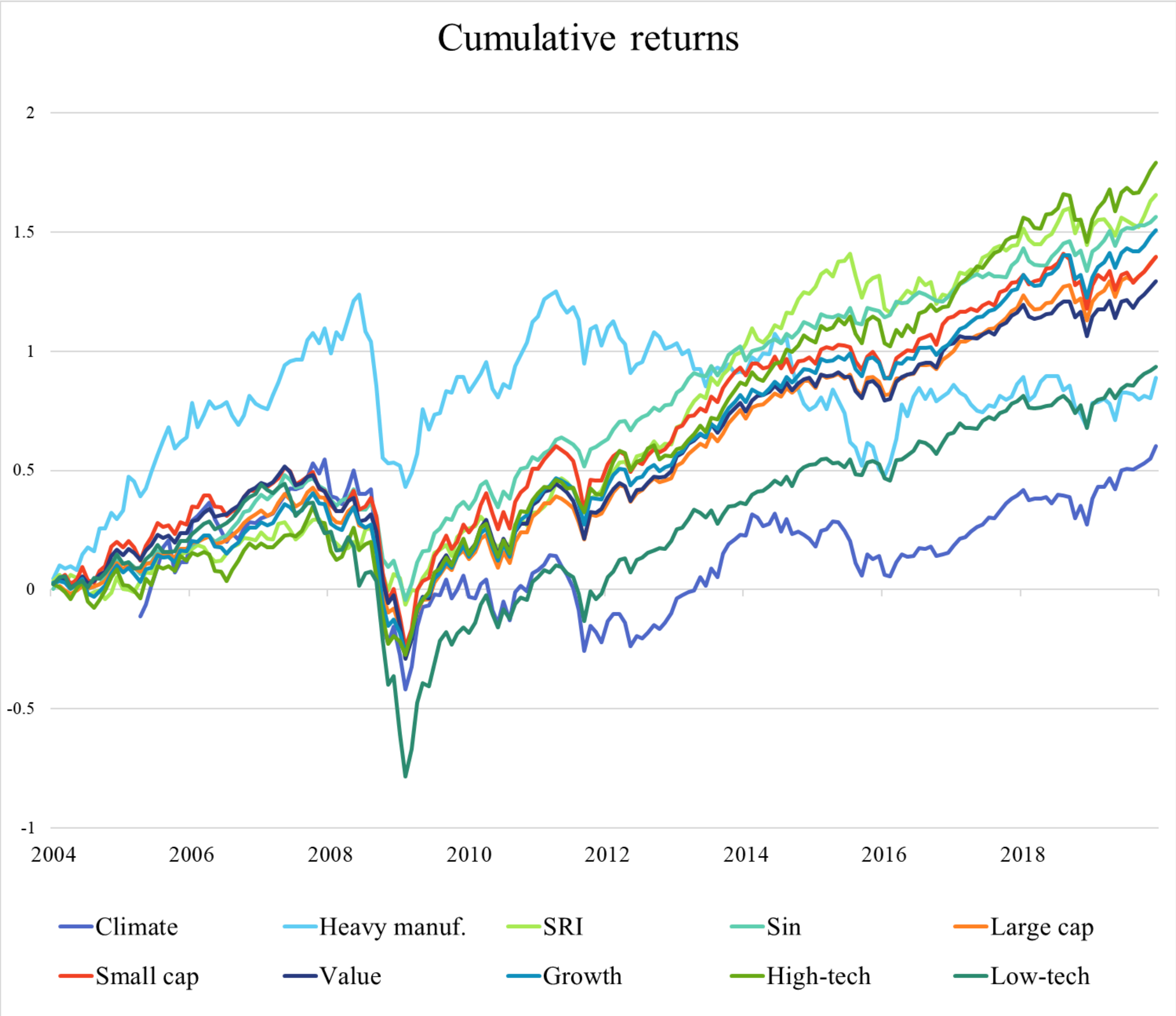
Below, in Table 2, we present the summary statistics of our thematic measures of monthly data. Considering that ETFs of climate change and large-cap investment themes emerged later than January of 2004, they have less observations as for them we take the earliest data available.

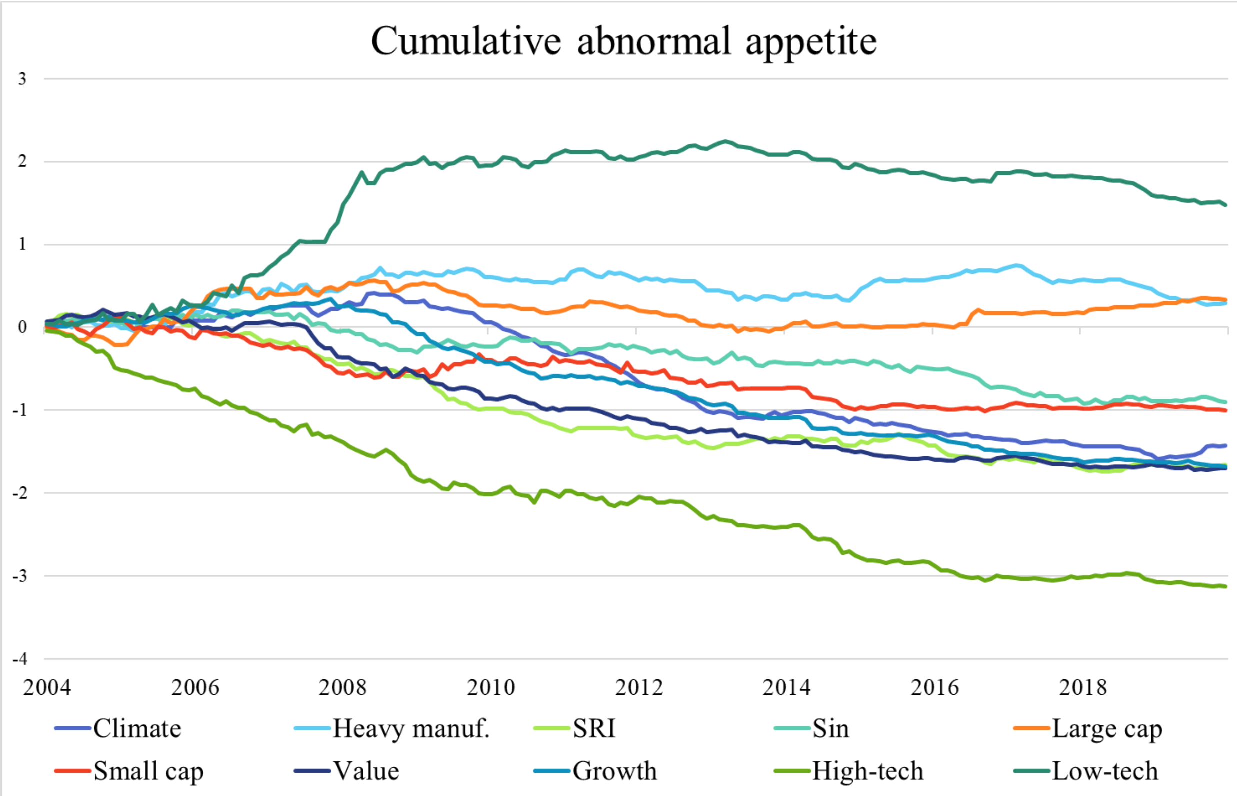
Table 2. Summary statistics

The table reports weighted average returns defined in (1), abnormal appetite defined in (5) and directional appetite defined in (6) between January, 2004 and December, 2019 of monthly frequency.

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: Returns across thematic dimensions					
RetSRI	192	0.0086	0.0424	-0.1366	0.0905
RetSin	192	0.0082	0.0358	-0.1797	0.0895
RetHighTech	192	0.0093	0.0480	-0.1647	0.1194
RetLowTech	192	0.0049	0.0529	-0.2473	0.1949
RetValue	192	0.0067	0.0438	-0.2096	0.1262
RetGrowth	192	0.0079	0.0428	-0.2096	0.1140
RetClimate	177	0.0034	0.0647	-0.3459	0.1719
RetHeavyManuf	192	0.0046	0.0655	-0.2991	0.1863
RetLargeCap	191	0.0073	0.0393	-0.1889	0.1057
RetSmallCap	192	0.0073	0.0503	-0.2346	0.1651
Panel B: Abnormal appetite across thematic dimensions					
AbnSRI	192	-0.0086	0.0290	-0.0850	0.0575
AbnSin	192	-0.0047	0.0310	-0.0815	0.0676
AbnHighTech	192	-0.0163	0.0349	-0.1362	0.1409
AbnLowTech	192	0.0077	0.0494	-0.1306	0.2233
AbnValue	192	-0.0089	0.0267	-0.1011	0.0728
AbnGrowth	192	-0.0087	0.0238	-0.0925	0.0443
AbnClimate	177	-0.0080	0.0290	-0.0722	0.1171
AbnHeavyManuf	192	0.0015	0.0382	-0.0896	0.1243
AbnLargeCap	191	0.0018	0.0326	-0.1057	0.1212
AbnSmallCap	192	-0.0052	0.0363	-0.0985	0.1217
Panel C: Directional appetite across thematic dimensions					
DirectESG	192	-0.0054	0.0458	-0.1434	0.1475
DirectTechnology	192	-0.0215	0.0597	-0.2537	0.1363
DirectStrategy	192	-0.0005	0.0250	-0.0981	0.0928
DirectClimate	177	-0.0067	0.0411	-0.1127	0.1439
DirectSize	191	0.0071	0.0426	-0.1481	0.1604

Figure 1 depicts the evolution of the weighted average returns of each portfolio, abnormal appetite and directional appetite between January, 2004 and December, 2019 in cumulative terms. As we can see from the cumulative returns graph, the top 3 performers are high-tech, SRI, and sin themes. At the same time, cumulative abnormal appetite graph shows that over time, investors have had the greatest appetite for low-tech, heavy manufacturing and large-cap themes. For other themes, the abnormal appetite measure cumulated into negative zone meaning that they experienced smaller percentage fund flows benchmarked against the market. Cumulative directional appetite graph shows that the largest differences between two dimensions of a theme have been for size and technology themes. The evolution of the market capitalization of investment themes is presented in Appendix A.





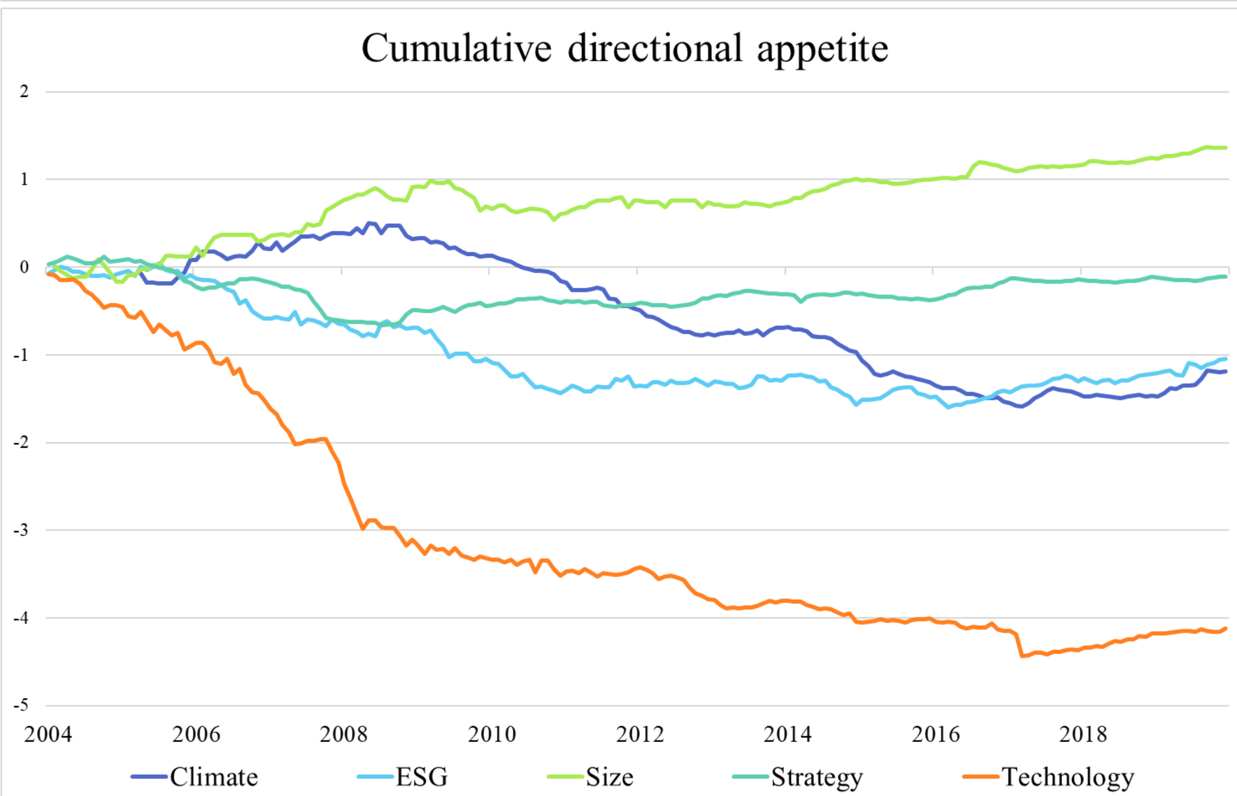


Figure 1. Cumulative returns, abnormal appetite and directional appetite by investment themes from January 1, 2004 to December 31, 2019.

5. Determinants of Thematic Appetite

5.1. Past performance of investment themes

The first factor that impacts thematic investor appetite is the past performance of investment themes. As a proxy for past performance, we use the weighted average return of portfolio of investment themes, which is defined in the equation (1). Although we could use other more complex measures of past performance, we will favor the returns. First of all, the returns are the single most important indicator of past performance in the eyes of retail investors. Second, returns are easily observable. Third, returns are perhaps the most understandable measure of performance. The beauty of returns is that they are able to capture nearly any changes in the subjective value of assets.

5.2. Global trends and their popularity

Apart from the past performance of the investment themes, we account for the possibility that reversals of thematic fund flows might come not only from the observed past returns, but also due to the release of some other significant information or events that reflect ongoing trends. In this paper, we use the frequency of specific word searches on the web through Google Search engine as a measure of trend popularity across time, which is compiled in Google Trends website. Typically, if newly released information is significant enough, people will look it up on the web, they will talk about it, and spread it. Therefore, there must be a link between search frequency of theme-specific terms on Google and our thematic appetite measures.

In Appendix B, we present the names of topics that correspond to each of our investment themes. Google Trends uses a measure called *interest over time*, which is defined as the "search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term" (Google Trends, 2020). In order to calculate the combined interest over time for the whole thematic portfolio, we take the simple average of all the values of interest over time for different topics within each portfolio for every month. In this way, we get an analogical measure of interest over time that includes many search topics. Further, we define the GT variable as a percentage change in the average interest over time:

$$GT_{j,t} = \frac{Interest\ over\ time_{j,t}}{Interest\ over\ time_{j,t-1}} - 1 \tag{7}$$

5.3. Real economy

Thirdly, we bring up the fact that the real economy and financial markets are interlinked, so the changes in the real economy are a crucial determinant of changes in the financial markets. This has been proven by the very recent Covid-19 outbreak when the development of the real economy stopped, and the financial markets plummeted almost immediately. However, causality can go the other way around. For example, the financial crisis of 2008 when the crisis stemmed from the financial markets and spilled over to the real economy. Thus, the relationship between the real economy and financial markets is of enormous importance. In this paper, we use real economy variables as control variables in addition to theme-specific variables. Following Jank (2012, p.3062), we define the predictive real economy variables because they contain forward-looking information about the real economy and equity premium:

1. Market Return - S&P 500 return
2. Dividend-price ratio – “dividend yield of the S&P 500”
3. Default spread – “the end-of-period difference between Moody’s BAA and AAA Seasoned Corporate Bond Yield”
4. Term spread – “the difference between the 10-year and 1-year maturity Treasury rates”
5. Relative T-Bill rate – “the 3-month T-Bill rate minus its 12-month moving average”

Additionally, to account for the fundamental variable in finance – risk, we construct theme-based volatility variable:

6. Volatility – standard deviation of returns of the past 6 months for each thematic dimension

Besides, we use Augmented Dickey-Fuller tests to test if any of our variables contain a unit root. By this approach, we ensure that we use stationary data in our research. If we arrive at a conclusion that a variable indeed has a unit root, then we use first differences of a corresponding variable in following models. In our case, the thematic appetite measures, weighted average returns, the GT and $Volatility$ variables are stationary by construction; however, real economy variables - $Dividend\ yield_t$, $Default\ spread_t$, $Term\ spread_t$, $Relative\ T - Bill_t$ - are used in differences rather than in levels.

5.4. Structural Vector Autoregression Model (SVAR)

Considering economic theory and previous literature, we follow the assumption that fund flows can cause returns contemporaneously but not the other way around: flows respond to returns more slowly than returns respond to flows. Therefore, we start our analysis using a contemporaneous model - SVAR, where the order of variables does matter and is chosen accordingly.

For each investment theme we perform 3 separate SVAR models due to the fact that we have proposed 2 investor appetite measures: abnormal appetite and directional appetite, where abnormal appetite is applied to 2 opposing ends separately, but the directional appetite captures both ends of the spectrum. The SVAR model contains the following equations:

$$\begin{aligned} Appetite_t = \ & \beta_0 + \sum_{i=0}^{6} \beta_i^a \, Appetite_{t-i} + \sum_{i=0}^{6} \beta_i^b \, Return_{t-i} + \sum_{i=0}^{6} \beta_i^b \, GT_{t-i} + \sum_{i=0}^{6} \beta_i^d \, S\&P_{t-i} \\ & + \sum_{i=0}^{6} \beta_i^e \, \Delta Dividend\ yield_{t-i} + \sum_{i=0}^{6} \beta_i^f \, \Delta Default\ spread_{t-i} + \sum_{i=0}^{6} \beta_i^g \, \Delta Term\ spread_{t-i} \\ & + \sum_{i=0}^{6} \beta_i^h \, \Delta Relative\ T - bill_{t-i} + \sum_{i=0}^{6} \beta_i^i \, Volatility_{t-i} + u_t^a \end{aligned} \tag{9}$$

$$\begin{aligned} Return_t = \ & \beta_0 + \sum_{i=0}^{6} \beta_i^a \, Appetite_{t-i} + \sum_{i=0}^{6} \beta_i^b \, Return_{t-i} + \sum_{i=0}^{6} \beta_i^b \, GT_{t-i} + \sum_{i=0}^{6} \beta_i^d \, S\&P_{t-i} \\ & + \sum_{i=0}^{6} \beta_i^e \, \Delta Dividend\ yield_{t-i} + \sum_{i=0}^{6} \beta_i^f \, \Delta Default\ spread_{t-i} + \sum_{i=0}^{6} \beta_i^g \, \Delta Term\ spread_{t-i} \\ & + \sum_{i=0}^{6} \beta_i^h \, \Delta Relative\ T - bill_{t-i} + \sum_{i=0}^{6} \beta_i^i \, Volatility_{t-i} + u_t^r \end{aligned} \tag{10}$$

$$\begin{aligned} GT_t = \ & \beta_0 + \sum_{i=0}^{6} \beta_i^a \, Appetite_{t-i} + \sum_{i=0}^{6} \beta_i^b \, Return_{t-i} + \sum_{i=0}^{6} \beta_i^b \, GT_{t-i} + \sum_{i=0}^{6} \beta_i^d \, S\&P_{t-i} + \sum_{i=0}^{6} \beta_i^e \, \Delta Dividend\ yield_{t-i} \\ & + \sum_{i=0}^{6} \beta_i^f \, \Delta Default\ spread_{t-i} + \sum_{i=0}^{6} \beta_i^g \, \Delta Term\ spread_{t-i} + \sum_{i=0}^{6} \beta_i^h \, \Delta Relative\ T - bill_{t-i} \\ & + \sum_{i=0}^{6} \beta_i^i \, Volatility_{t-i} + u_t^t \end{aligned} \tag{11}$$

Appetite$_t$ represents our thematic appetite measures. *Return*$_t$ stands for the weighted average returns. *GT*$_t$ includes the relative interest over time measure from Google Trends.

All other variables are control variables. S&P$_t$ represents S&P 500 market returns. Dividend yield t is the dividend-price ratio of the S&P 500. Defaul*t spread*$_t$ is the end-of-period difference between Moody's BAA and AAA Seasoned Corporate Bond Yield. *Term spread*$_t$ is the difference between the 10-year and

1-year maturity Treasury rates. *Relative T-Bill* $_t$ is the difference between 3-month T-Bill rate and its 12-month moving average. *Volatility* $_t$ represents the 6-month standard deviation of returns. Δ stands for change in the variable.

In the models where we use *abnormal appetite* measures for either of the opposing ends of a theme, the $Return$ and GT variables correspond to that particular portfolio. For instance, when testing the socially responsible side of the ESG theme, we include in our model *abnormal appetite* measure for the socially responsible side, the weighted average returns for the socially responsible side, and the GT variable for the socially-responsible side. The same logic applies when testing the other end of the theme with *abnormal appetite* measure.

The number of lags in the SVAR models is primarily determined by BIC information criteria, which suggests that we use 1 lag. However, we consider including more lags in the models - up to 6 lags - firstly, to test for the effects that stem deeper in the past as suggested in the reviewed literature, and secondly because the BIC information criteria are satisfied in any case.

5.5. Determinants of the abnormal appetite

To graphically represent the results and interpret our SVAR models, we employ orthogonalized cumulative impulse response functions 12 months ahead to satisfy assumptions about contemporaneous causality and long-term horizon of thematic investing. Impulse response functions show what is the impact on an endogenous variable from an external shock. The shocks are commonly defined as one standard deviation change in the only exogenous variables in the system of SVAR equations - namely the residuals.

We start with portraying the average results across all investment themes. In general, our findings regarding the determinants of the shifts in the thematic appetite support the negative feedback-trader hypothesis proposed by Bohl and Siklos (2004), Frijns, Gilbert, and Zwinkels (2016), and Wan, Liu, Wang and Yang (2016). As soon as investment themes encounter with an average positive shock in the returns of 4.86pp, investors seem to pursue negative feedback-trading strategies and short their ETF shares within a month; therefore, on average, there is a fund flow of 0.6pp out of thematic funds (Figure 2). Analogically, when there is a negative shock in returns of investment themes, investors tend to enter long positions. The cumulative average effect across all investment themes levels out and disappears after one month at 10% significance level.

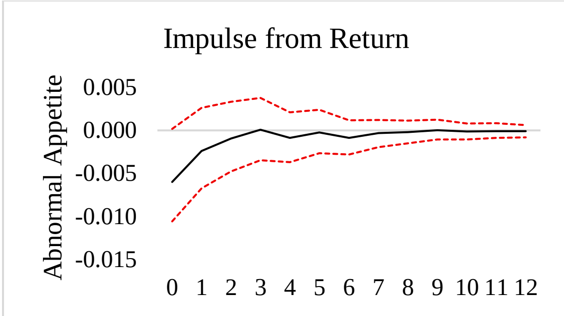


Figure 2. Cumulative impulse-response function: average response of *Abnormal appetite* across all investment themes featured in the reserach to an average shock in *Return*. The dashed lines are 90% confidence interval, and the solid line is the impulse response.

As our average result tilts towards negative feedback-trading, our findings support the conclusion of Frijns, Gilbert, and Zwinkels (2016) that more than 50% of feedback-traders pursue negative feedback-trading strategy. As discussed below, both positive and negative feedback-traders are coexisting on the market; however, negative feedback-traders pursue momentum strategies to exploit the positive feedback-traders. While positive feedback-traders buy expensive and sell cheap, negative feedback-traders take the opposite position – buy cheap and sell expensive, and thus, according to Hirshleifer, Subrahmanyam and Titman (2006) earn profits. From a practical point of view, retail investors such as households would rather invest in ETFs when they become cheap, and benefit from the long-term appreciation of the assets.

With regard to search frequency on Google, on average, we find no statistically significant effect on abnormal appetite at 10% significance level (Figure 3).

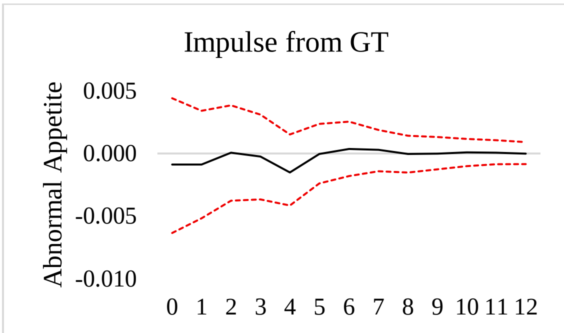


Figure 3. Cumulative impulse-response function: average response of *Abnormal appetite* across all investment themes featured in the reserach to an average shock in *GT*. The dashed lines are 90% confidence interval, and the solid line is the impulse response.

Importantly, in this case, average impulse response functions do not consider individual characteristics of investment themes because trend popularity on Google can have either negative or positive underlying message, which would cause fund outflows or inflows respectively. Therefore, we turn to individual investment themes. We find a positive effect of a shock in GT on abnormal appetite for low-tech, value, large-cap, small-cap, and SRI investment themes of 6.37pp, 14.25pp, 17.15pp, 15.98pp, 8.89pp with the percentage increase in abnormal appetite of 1.22pp, 0.5pp, 0.27pp, 0.46pp, 0.25pp respectively at its highest. A common pattern across these investment themes is that the cumulative effect becomes statistically significant at 10% significance, and does not last longer for one month.

Interestingly, we document a negative response from a shock in the trend variable of 10.73pp for heavy manufacturing theme (Figure 4), which can be explained by the fact that this specific investment theme might have rather negative than positive associations in our minds. If heavy manufacturing theme suddenly becomes popular and people start discussing it a lot, chances are that the reason why it became popular in the first place is its adverse impact on the environment and climate; hence, negative fund flows compared to the market.

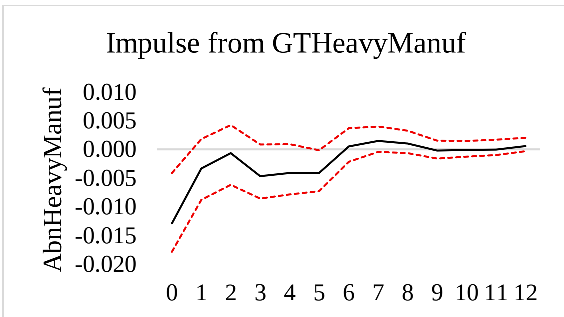


Figure 4. Cumulative impulse-response function: response of *Abnormal appetite* of the respective thematic dimension to a shock in *GT* of the same dimension. The dashed lines are 90% confidence interval, and the solid line is the impulse response.

The results demonstrate that on a theme level, prior to choosing a sound investment theme for a long-term investment, investors do look up information about business and investment processes of that theme, and the more people get interested, the greater is a prompt to make an investment decision. Bailey, Kumar and Ng (2011) make a hypothesis that biased investors are the main body of trend-chasers, and based on our results, we cannot exclude an option that the availability bias and herding behavior are present on internet platforms which have an impact on thematic investing. In contrast, an increased activity on the web can be attributed to news releases about the fundamental value and future prospects of investment themes, which is identified by Froot and Teo (2004).

Depending on the nature of the investment theme, it is likely that the relation between fund flows and search frequency on Google for the corresponding theme is either positive or negative; nevertheless, our tests do not provide us with a unifying logic that would clearly explain the causality of GT on abnormal appetite as our results are quite disperse.

We conclude that observable characteristics of investment themes play a greater role in investment decisions than plain popularity of investment themes on the web. This can be explained by a theory that investors are cautious about the available information on the web even if the discussions on the web point out long-term structural trends, and rather prefer observable characteristics of investment themes.

We accept the first part of our second hypothesis that the variation in the thematic appetite is driven by past performance of the investment themes and news or global events. However, we reject the second part of the hypothesis that strong past performance leads to high thematic appetite and trend popularity is positively associated with thematic appetite because our results favor negative feedback-trading, and depending on the nature of investment themes, high popularity not always is equal to positive attention.

6. Effect on Asset Pricing

Finally, we examine how the shifts in thematic investor appetite affect the performance of investment themes. Here, we also run the SVAR model defined in Section 5.4., and perform impulse-response functions based on equation (10), where abnormal appetite measure acts as shock and returns respond to it. We would expect the returns to react to high abnormal fund flows contemporaneously as high fund inflows drive the price up; therefore, there must be a positive immediate impact on returns. We discover that on average, across all investment themes, a positive shock in abnormal appetite of 3.31pp causes the returns of investment themes to increase by approximately 1pp (Figure 5).

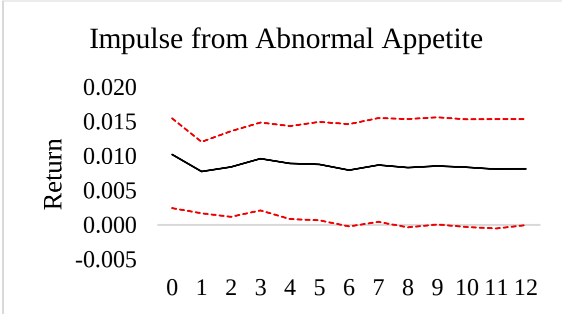


Figure 5. Cumulative impulse-response function: average response of *Return* across all investment themes featured in the reserach to an average shock in *Abnormal appetite*. The dashed lines are 90% confidence interval, and the solid line is the impulse response.

The most striking part of the results obtained is that high abnormal appetite does have a long-term cumulative positive impact on the returns of investment themes. On average, investment themes maintain the cumulative effect of 1pp increase in returns for more than 12 months. We illustrate that high thematic investor appetite leads to remarkable structural changes in the performance of investment themes that persist over the long-term.

The findings of this paper are aligned with Gabaix and Koijen (2020), who recently have found that fund flows on macro level have a significant impact on asset pricing due to aggregate stock market being price-inelastic, and as they propose, institutional investors like ETFs are subject to constraints in investment decisions; therefore, they are likely to be price-inelastic. In our case, if investment themes experience high fund flow fluctuations meaning that there are fluctuations in aggregate demand, the supply curve is unable to adjust so quickly; therefore, there must be a high volatility in asset prices. Gabaix and Koijen (2020) lay out "inelastic market hypothesis" (p.7), and we observe a similar phenomenon in thematic investing. Also, our results contribute to Frazzini and Lamont (2008), who demonstrate that price-pressure hypothesis holds on stock level; however, we illustrate that price-pressure hypothesis holds on a whole aggregate investment theme level, regardless of asset class or geographical exposure.

On individual theme level, we find that the largest impact on performance in terms of percentage points is for climate change and SRI investment themes meaning that if there is an unexpected shift thematic investor appetite, climate change and SRI themes are likely to be the most profitable. A shift in the abnormal appetite of climate change and SRI themes of 2.9pp causes the cumulative returns of climate change theme rise by 2.5pp in the long-term, and the returns of SRI investment theme rise by 1.4pp in the long-term (Figure 6).

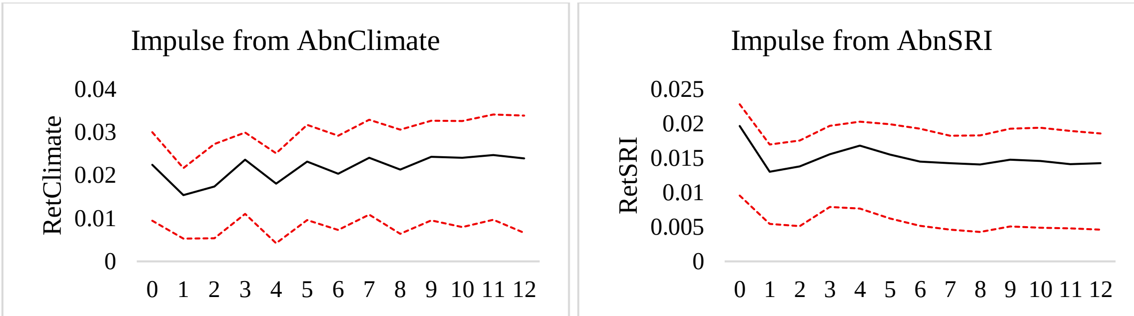


Figure 6. Cumulative impulse-response function: response of *Return* of the respective thematic dimension to a shock in *Abnormal appetite* of the same dimension. The dashed lines are 90% confidence interval, and the solid line is the impulse response.

Our results are in line with Froot and Teo (2008), who discovered that fund flows have substantial effect on future returns due to investor appetite. Furthermore, our results challenge Barberis and Shleifer (2003), and Pastor, Stambaugh and Taylor (2020), who find that successful investment themes attract fund inflows, but later experience low returns due to the overpricing correction. Even though at some point in time the returns might be negative, the overpricing correction effect is not large enough to net out the cumulative long-term improved performance.

To conclude, results obtained from SVAR model reveal that returns react to high thematic appetite instantly, and the cumulative effect of 1pp increase in returns stays positive for more than 12 months. Thus, we accept our third hypothesis that very strong thematic appetite drives the returns up, which then leads to overreaction and the theme being overpriced in the short run. However, we reject the fourth hypothesis that subsequently there is a relatively poor performance of an investment theme because the price does not seem to rebound to the fundamental value – our main finding is that the cumulative effect persists in the long-term.

7. Robustness Tests

7.1. Results based on directional appetite

We start assessing the robustness of our tests by expressing our main variables – fund flows, returns, and trend – as directional measures across two dimensions of each theme. In this way, we examine the dynamics of fund allocations between two opposing ends of themes. Here, we perform SVAR regressions based on equations (9), (10), and (11).

In the models where we use the *directional appetite* measure, we include the directional weighted average returns and directional GT measure, which are defined based on the same logic as the *directional appetite*:

$$Directional\ Return_{j,t} = Return_{j,t}^{1} - Return_{j,t}^{2} \tag{12}$$

$$Directional\ GT_{j,t} = GT_{j,t}^{1} - GT_{j,t}^{2} \tag{13}$$

$Return_{j,t}$ represents the weighted average return of a portfolio defined in equation (1). $GT_{j,t}$ represents percentage change in the average interest over time defined in equation (7). j stands for each investment theme, and t stands for month. Superscripts 1 and 2 indicate the two opposing dimensions of each theme.

The average results across all investment themes suggest that neither past directional returns, nor directional GT have a statistically significant effect on directional appetite. It means that investors' preferences for one dimension of an investment theme rather than the other is not influenced by the return or GT differential between two dimensions of an investment theme. On average, the two opposing ends of each investment theme are viewed as independent themes. If one side of a theme has relatively higher returns or gains relatively higher popularity on the web than the other one, there is no long-term significant reallocation of fund flows.

However, both *factor* investment themes – strategy and size themes – do experience relocation of funds by 0.6pp and 0.9pp as a response to a shock in GT of 27.01pp and 21.08pp respectively. Noteworthy, we observe positive feedback-trading for technology and strategy investment themes 5-6 months after a shock.

Continuing with the effect on asset pricing from a shift in the directional appetite, based on our results, we observe two distinct categories of investment themes. Firstly, is an investment theme for which the cumulative effect maintains momentum for three months (technology) - on average, the return differential due to an unexpected shift of 5.97pp in directional appetite is 1pp (Figure 7, Panel A). Secondly, there are investment theme for which the cumulative effect becomes statistically significant at 10% significance level in the long-term (strategy and ESG), and the return differential is 1pp as a response to a shock on directional appetite of 3.54pp (Figure 7, Panel B).

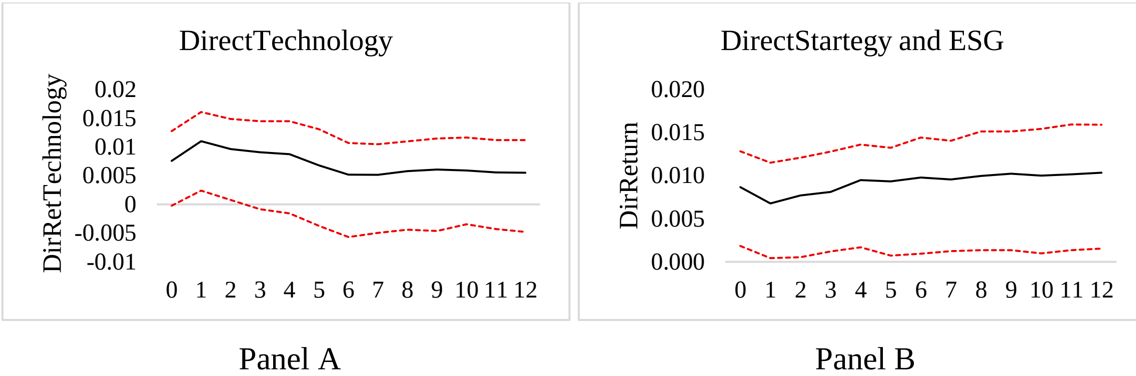


Figure 7. Cumulative impulse-response function: response of *Directional Return* of the respective thematic dimensions to a shock in *Directional Appetite* of the same dimension. The dashed lines are 90% confidence interval, and the solid line is the impulse response.

Thus, if investors guide the funds into one thematic dimension more than in the other one, short-to-medium-term advantages or, in specific cases – long-term advantages, in performance of one dimension across the other dimension are possible.

7.2. Results based on data starting from 2010

Another approach to assessing the robustness of the main results is to divide the sample period of 15 years into smaller sub-samples. Specifically, we explore the time period starting from 2010 because of two main reasons: first, interest over time via Google Trends is likely to have anomalous values at the beginning of its launch in 2004, and second, the number of ETFs and their popularity steadily increased after 2010 when the total assets under management surpassed $1 trillion (Cummans, 2013). We employ identical SVAR models to the main results of full sample period.

We obtain results very similar to the main results of a full sample period. There are no major changes in conclusions about how to measure the thematic investor appetite, what drives the variance in thematic investor appetite, and how the shifts in thematic investor appetite impact the performance of investment themes, because based on the sub-sample tests, the significance of results, and direction, size and timing of an effect closely track the main results.

8. Conclusion

The purpose of this research is to analyze the thematic investing, the determinants of investor choices behind thematic investing, and its implications on asset pricing. Our paper unveils a new area of research that investigates thematic investor appetite based on thematic ETF fund flows. Given that the thematic investing seeks to capture long-term structural trends or medium-term cyclical trends with a hope that the trends will materialize and overperform passive index funds in the long-term, and the overwhelming importance of ETFs during the recent years, thematic ETFs give us a unique opportunity to study incentives and effects of thematic investing as opposed to traditional passive investing.

Answering the first research question of how to measure the thematic investor appetite, we have developed two novel measures based on thematic ETF fund flows – abnormal appetite and directional appetite. Abnormal appetite encompasses percentage fund flows of individual investment themes benchmarked to the percentage fund flows of the whole ETF market. Directional appetite measures the percentage fund flow differential between two opposing dimensions of each investment theme. Just like with fashion trends when people purchase clothing that they find appealing, investors express their appetite towards an investment theme by buying or selling thematic assets; therefore, fund flows must reveal thematic investor appetite.

The second research question is "what drives the variation in thematic appetite?", and our results show that the past performance of investment themes is an essential aspect. Although the popularity of investment themes on the web and news about the fundamental value might induce fund inflows, especially on individual theme level, investors rather look for the changes in the performance of thematic funds. Our results are in favor of negative feedback-trading in the first month after a shock in the returns.

The answer to the third research question "how do the shifts in thematic investor appetite affect the performance of investment themes?" is that a positive shift in the thematic appetite has a positive effect on the performance of investment themes where the cumulative increase in returns persists for more than 12 months. Analogous to fashion industry, as clothing trends gain popularity through increase in the demand, the supply is unable to adjust so quickly; therefore, trendy clothing becomes more expensive. We draw a conclusion that a sudden shift in thematic investor appetite causes a long-term structural positive change in the performance of thematic funds, where on average, the returns rise by 1pp in the long-term.

Our research demonstrates that it is crucial to correctly identify long-term structurally-changing trends that will impact the economy and how the businesses within the theme work. By thematic investing, not only investors support the development of certain industries that will change the way we live in the future, but also thematic investing strategies are profitable in the long-term. Even though ETFs have been considered as low-cost passive investment vehicles that pool together various stocks, with the arrival of niche ETFs that provide exposure to specific investment themes, in fact, investors engage in a light form of active investing by picking favorable thematic ETFs. In our opinion, valuable areas for further research would be alternative crowd-sentiment platforms other than Google and their impact on thematic investing; other determinants of thematic appetite like corporate policies of companies, advertising impact of institutional investors, changes in household wealth, and government role in capital markets; and how high or low thematic appetite affects the emergence of new businesses, investment vehicles, and the competition within the themes.

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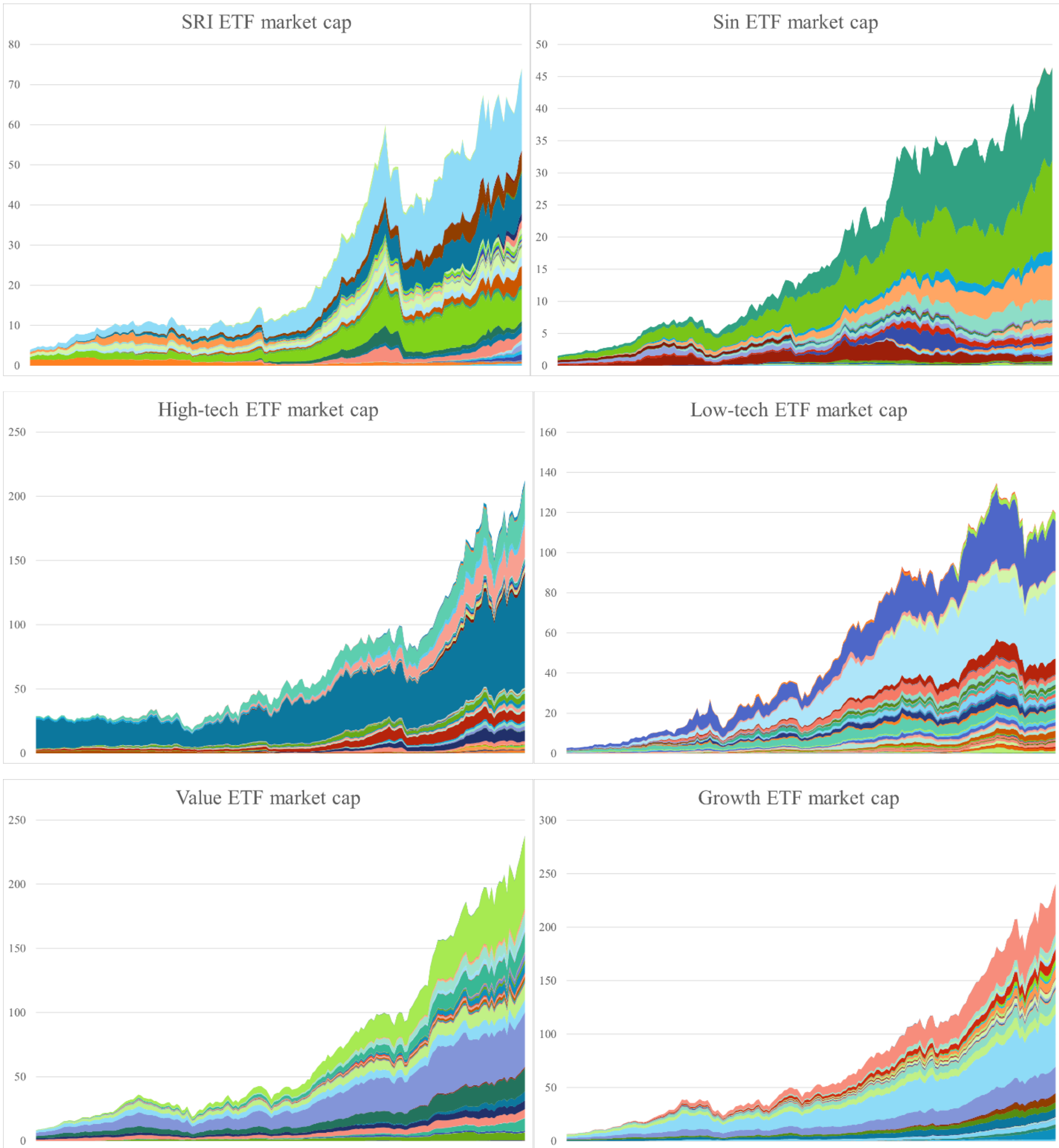
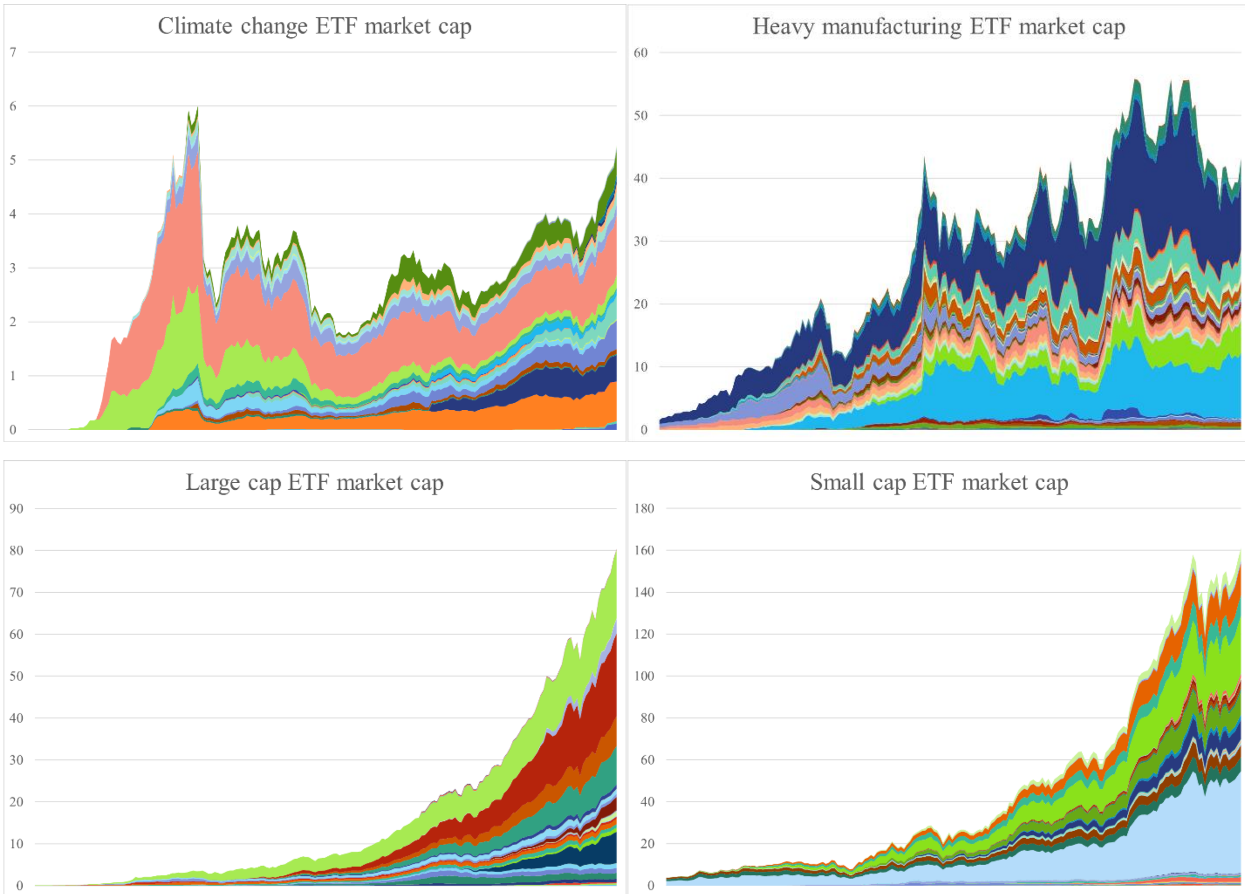
10.Appendices

Appendix A. Market capitalization of investment themes in millions of USD from January, 2004 to December, 2019.





Market capitalization of thematic portfolios of ETFs by investment themes from January 1, 2004 to December 31, 2019. The different colors represent a share of individual ETFs that constitute to the total market capitalization of investment themes.

Appendix B. Topics corresponding to investment themes used for Google Trends.

Investment theme	Dimension	Topic
ESG	Socially responsible investing	*Biotechnology, ESG, gender equality, health care, impact investing, medicine, pharmacy, socially responsible investing, sustainable investing*
	Sin	*Cannabis, gambling, gaming, sin, sports betting, tobacco*
Technology	High-tech	*Artificial intelligence, big data, computer, digitalization, high tech, information technology, robotics, technology*
	Low-tech	*Infrastructure, investment banking, low technology, real estate, retail*
Strategy	Value	*Value investing, value stocks*
	Growth	*Growth investing, growth stocks*
Climate	Climate change	*Climate change, green climate fund, green energy, green stocks, renewable energy*
	Heavy manufacturing	*Oil, oil investing, petroleum*
Size	Large-cap	*Large cap*
	Small-cap	*Small cap*