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Efficient Scholars: Academic Attention and the Disappearance of Anomalies

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Abstract

This study examines the dynamics of ten most notable stock market anomalies through 1926-2018 and assesses the joint impact of academic attention, post-publication decay, data-snooping bias, institutional trading, and time trend on their disappearance. It proposes new and simple measures of academic attention attracted by stock market anomalies using the number of articles published on the relevant topic available via Google Scholar or respective citation counts. The study finds that academic attention is the most dominant factor explaining the diminishing abnormal returns of anomaly-exploiting strategies. The approach developed by this study can also be useful in determining whether a stock return regularity is a behavioural anomaly or a systematic risk factor.

Keywords: stock market anomaly, market efficiency, publication impact, Google Scholar

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1. Introduction

Immediately since the elaboration of the efficient market hypothesis (EMH) in its modern conceptual form (Fama, 1970), many enthusiastic scholars have been thoroughly examining the stock market data in search for decisive counterexamples. A wide range of literature has been established identifying some key stock market anomalies, i.e., predictable stock return patterns violating the EMH (Thaler, 1987a, b).

This study reviews most notable calendar and fundamental anomalies and proposes a simple technique that seeks to solve a nascent debate in academic finance regarding whether these stock return regularities have behavioural foundations or proxy for important systematic risk factors (Cochrane, 1999). More importantly, novel evidence on the relevance of academic research for the disappearance of stock market anomalies and corresponding improvements in market efficiency is presented, utilising original measures of academic attention derived from publication and citation count retrieved via a Google Scholar search algorithm. It is proven that academic research is an important information dissemination channel that contributes to the decay of the anomalies' magnitude and that it is significant for most anomalies even when controlled for other factors, such as data-snooping bias, immediate post-publication decay, institutional trading, and time trend. Research and trading activity corresponding to respective stock market anomalies are shown to be independent of each other, with the effect of trading being insignificant when research is controlled for. The study capitalises on and addresses the limitations of existing literature in the field (Marquering et al., 2006; McLean and Pontiff, 2016), predominantly resolving the endogeneity and heterogeneity biases issues via introducing anomaly-specific time-series regressions, an extensive set of controls, and instrumental variable estimations.

The next section reviews the literature and develops the theoretical basis of the study, mainly concerned with the definition and characteristics of respective anomalies, and possible reasons for their existence and subsequent disappearance. In section 3, the methodology of the study is outlined, discussing the definition of original variables and model specification. Section 4 presents and interprets the findings. The last section concludes.

2. Theoretical basis

2.1. Stock market anomalies in perspective

Stock return regularities that are seemingly inconsistent with the EMH have been prominent in academic research at least since Merrill's (1966) seminal work on the weekend effect. Ten most notable stock market anomalies that are still dominating the hearts and minds of investors and academics alike are outlined below in Table 1 while also referring to the first relevant publication on the topic. Next, various anomalies considered by the study are briefly discussed.

Table 1. Notable anomalies in academic research

Stock market anomaly	Sample	First publication	Original sample of first publication
Monday effect	1926-2018	Merrill (1966)	1952-1965
Friday effect	1926-2018	Merrill (1966)	1952-1965
Turn-of-the-month effect	1926-2018	Ariel (1987)	1963-1981
Holiday effect	1926-2018	Thaler (1987b)*	1963-1982
January effect	1927-2018	Keim (1983)	1963-1979
Size effect	1927-2018	Banz (1981)	1936-1975
Value effect	1927-2018	Basu (1983)**	1962-1978
Momentum	1927-2018	Grinblatt et al. (1995)	1974-1984

Operational profitability anomaly	1964-2018	Novy-Marx (2013)	1963-2010
Investment anomaly	1964-2018	Titman et al. (2004)	1973-1996

*the first thorough empirical study of the holiday effect is in fact Ariel (1990), which has been referenced in Thaler (1987b) as the 1985 working paper. However, Ariel's work has not been published until 1990, therefore the study considers Thaler (1987b) as the earliest academic source for the holiday effect.

**book and market values of companies in relation to their cross-sectional stock return patterns have been first examined in Stattman (1980). Nevertheless, this early paper utilises not the book-to-market ratio common in more contemporary sources but the difference between book and market values of companies, which Stattman (1980) considers to be another measure of size effect rather than of a separate value anomaly. Furthermore, the text of Stattman's (1980) article is not available online which is crucial for the focus of this study. Therefore, the second oldest paper on the value effect (Basu, 1983) is referred to instead.

The first two anomalies studied by this paper – Monday and Friday effects – have the longest history in the academic discussion (Merrill, 1966) and are perhaps the most famous with specialists and laypeople alike. Sometimes, they are referred to jointly as the "weekend effect" (Thaler, 1987b; Marquering et al., 2006) and they signify relative stock market underperformance on Mondays (when the trading opens after the weekend) and outperformance on Fridays (before the trading closes for the weekend), respectively. This study, however, treats Monday and Friday effects separately for more clarity and to avoid possible heterogeneity biases. Moreover, unlike Marquering et al. (2006), this study tracks the research of the Monday and Friday effects to an earlier initial academic source (Merill, 1966 instead of Cross, 1973).

Turn-of-the-month effect (Ariel, 1987; Lakonishok and Smidt, 1988) is specified as stock return regularities on particular days of the month. The exact approach to the measurement of turn-of-the-month effect in the literature varies from article to article: in some, it is defined as the abnormal return on the four last trading days of the month and three first trading days of the following month (Lakonishok and Smidt, 1988), and in others it is understood as the relative outperformance of the stock market on the last trading day of the month and on the first two weeks of the following month (Ariel, 1987). This study measures two separate turn-of-the-month effects using both methodologies outlined above.

Holiday effect (Thaler, 1987b; Ariel, 1990) is defined as the abnormal returns of the stock market on the single trading day immediately preceding public holidays. This study considers three major American festive events celebrated both nowadays and historically throughout the country – New Year, Christmas, and Independence Day – to calculate its estimation of the holiday effect. Existing literature reviews in the studies of the disappearance of anomalies widely credit Lakonishok and Smidt (1988) as the first academic publication on the topic, however perhaps they were unaware of Ariel's 1985 working paper that has been referenced in Thaler (1987b), but published much later in 1990 (Ariel, 1990). This study corrects for that inaccuracy in the methodology of the preceding research and thus accounts for the transmission of information among academicians and professionals with greater precision.

January effect (Keim, 1983; Thaler, 1987a) is the widely documented outperformance of the stock market in January relative to other months. This study measures it directly according to this definition.

Two fundamental anomalies that has been discovered early (simultaneously with some calendar anomalies) are size effect (or small-firm effect, Banz, 1981) – the outperformance of stocks of companies with low market capitalisation (small stocks) relative to the stocks of companies with high market capitalisation (large stocks) – and value effect (Stattman, 1980; Basu, 1983) – the outperformance of stocks of companies with high book-to-market ratio (value stocks) relative to the stocks of companies with low book-to-market ratio (growth stocks). They have remained perhaps the most prominent anomalies among all and have been integrated into the CAPM framework to establish the famous Fama-French three-factor model (Fama and French, 1992, 1993). The abnormal returns of size and value effects have been intensely reviewed in the literature and several of them have attempted to explain on the possible linkages although there is no unanimity among studies. For example, Ferguson and Shockley (2003) related the SMB and HML anomalies with leverage and distress risk but their findings have been refuted on the ground that the risk of failure tends to deliver anomalously low returns (Campbell et al., 2008) and the SMB and HML factors are imperfect proxies for distress risk (Agarwal and Poshakwale, 2010).

Momentum as an anomaly has become a staple in academic research later in the 1990's and have been historically studied on a fund level in the context of performance persistence (Grinblatt et al., 1995; Carhart, 1997), but have been also defined as the outperformance of past year winners relative to past year losers respective to any portfolios or individual stocks.

Finally, most recently, two more fundamental anomalies – operating profitability (firms with robust operating profitability outperform those with weak operating profitability, Novy-Marx, 2013) and investment (firms conservative in their payout policy outperform those reinvesting their profit aggressively, Titman et al., 2004; Cooper et al., 2008) – have gained significant academic attention and have been incorporated into the Fama-French factor model as the fourth and fifth factors (Fama and French, 2015, 2016).

2.2. Why do they appear? Behavioural, data-mining and risk-related explanations

Once a stock market anomaly is discovered, typically, a set of competing theories trying to explain it emerges in the literature.

Most commonly and especially for the calendar anomalies and momentum, the early theories are developed in the behavioural finance framework (Thaler, 1987a, b). For example, weekend effect has been explained in the context of funds and other institutional investors restraining from selling stocks at the end of the week so as not to decrease the aggregate weekly performance indicators (Thaler, 1987b). For Friday and holiday effects specifically, mood-related explanations have been popular as investors could be more optimistic while anticipating a weekend (Thaler, 1987b). Some other notable concepts of universal and predictable behavioural biases, e.g., overreaction bias (Bondt and Thaler, 1985), have also been applied to the studies of calendar anomalies and momentum.

However, in the early 2000s a new paradigm has evolved in the study of anomalies arguing that most of the well-known stock return regularities are in fact data-mining artifacts or results of biased sampling (Sullivan et al., 2001). In case of calendar anomalies, Sullivan et al. (2001) have proposed a bootstrapping technique showing that hardly any abnormal returns generated by anomaly-exploiting strategies are significant. McLean and Pontiff (2016) have also found that data-snooping bias arising from the sample choice by researchers accounts for approximately 10% of the average magnitude of 82 cross-sectional stock return regularities they examined. Most recently, Linnainmaa and Roberts (2018) investigate pre-sample, in-sample, and post-sample abnormal returns of 36 anomalies separately, and find that 17 anomalies have insignificant alphas out-of-sample, potentially evidencing substantial data-snooping in the anomaly literature. Interestingly, the issue with investors and researchers seeing patterns in perfectly random data and thus “discovering” anomalies on an efficient market can be conceptualised as a psychological bias (Clarke and Statman, 1998), thus also giving some behavioural content to the data-snooping explanation of anomalies.

However, the most common contemporary line of reasoning, in application to fundamental anomalies in particular, is that they are risk factors in disguise (Cochrane, 1999). The speculation that size and book-to-market ratio could be proxying for some form of systematic risk have been present in the literature since the initial discoveries of these effects (Banz, 1981; Basu, 1983), however it has been fully formalised only with the introduction of the Fama-French three factor model, where returns of self-financing portfolios formed on size and book-to-market ratio are considered to be systematic risk factors additional to the traditional market risk factor represented by the well-known CAPM beta (Fama and French, 1993). Theoretical arguments emphasising the risk content of size and value indicators have also been developed, for example, Zhang (2005) has derived a mathematical model relating book-to-market ratios of firms to systematic risk of downsizing and costs of shrinkage. Based on this model, the "value premium" can be interpreted as risk premium perfectly compatible with EMH (Zhang, 2005).

The degree to which each of these theories describes the existing stock market anomalies is unclear and extremely hard to assess conceptually. For example, data-snooping bias could be an appealing argument for some of the more dedicated EMH advocates, however US and international replicability of most calendar anomalies evidenced by data from samples succeeding those of initial articles on the topic (Thaler, 1987a; Cadsby and Ratner, 1992; Hensel and Ziemba, 1996; Kunkel et al., 2003) implies that they reveal some deeper internal properties of the stock market. "Rational" theories of the January effect (which are mostly related to tax preferences as the fiscal year in many countries begins in January) also fail to fully explain the anomaly since it is well-documented on the markets where the fiscal year starts in April, most notably, in the UK (Thaler, 1987a). Therefore, this study proposes an ambitious yet simple technique grounded in the weak-form EMH and the existing theories of market learning and information transmission that could reveal valuable insights about the inherent nature of well-known stock return regularities empirically by analysing their dynamics.

2.3. Why do they disappear? Market learning, trading costs, and academic research

The existing body of literature emphasises that the nature of the anomaly (whether it is behavioural or risk-related) should directly influence its long-term behaviour (Fama, 1998; Cochrane, 1999). In line with the market learning theory (List, 2003; Timmermann and Granger, 2004) and the weak-form EMH, true behavioural anomalies might appear on the market for a short period of time, but as investors become aware of them and start exploiting them, they should be slowly arbitraged away (Fama, 1998). This assertion has later been verified on experimental data with regards to endowment effect – a well-known behavioural bias (List, 2003).

In contrast, if a stock return regularity reveals an important systematic risk factor priced on the market, it should not disappear after it is documented (Cochrane, 1999). In the spirit of this argument, "limits to arbitrage" theory has been developed in behavioural finance, linking the relative persistence of behavioural anomalies either with arbitrage costs usually proxied as volume traded, firm size, or stock idiosyncratic volatility (McLean and Pontiff, 2016) or with institutional impediments to arbitrage, such as the design of some performance evaluation techniques that might discourage an investor from efficiency-enhancing arbitrage (Baker et al., 2011). Following this line of reasoning, McLean and Pontiff (2016) argue that the slow disappearance of cross-sectional stock return predictability was attributable to the declining trading costs rather than growing awareness of market participants. The existing studies generally assume that trading costs steadily decrease with time and assess the impact of costly arbitrage on the disappearance of anomalies using a time trend (Marquering et al., 2006). However, there is no consensus in the literature yet whether actual trading and investment inspired by particular anomalies contribute to their disappearance. A large volume of literature on institutional trading and stock return regularities offers at best inconclusive evidence, various sources arguing that institutional investors either arbitrage the anomalies away (Shu, 2013), exacerbate them (Sias and Starks, 1995), or that the effect is conditional on the time horizon (Edelen et al., 2016) or net positions (Ng and Wang, 2004). This study addresses this gap by estimating the joint effect of academic attention and institutional trading, while also considering potential interdependence between academic and practitioner information dissemination channels using a fund-based proxy of anomaly-driven institutional investment.

The findings of McLean and Pontiff (2016) as well as earlier work by Marquering et al. (2006) show that anomalies significantly decrease in magnitude after the first academic article on the relevant topic is published. McLean and Pontiff (2016) estimate the average post-publication anomaly decay at 25% and Marquering et al. (2006) report 77% decrease in the abnormal return of the holiday anomaly after the initial publication. Therefore, academic research might serve as an important information transmission channel for the market participants that could increase their awareness of the anomalies and thus enhance market efficiency. However, no attempts have been made in the existing literature to quantify the academic attention a particular anomaly attracts. Even in the most recent research (McLean and Pontiff, 2016), academic attention is treated as a binary variable (an anomaly is "known" since the article on it is published and available and "unknown" otherwise). Moreover, while theoretically acknowledging the important distinction between behavioural and risk-related anomalies, the existing studies fail to reflect it in their methodology, effectively treating all anomalies homogeneously (McLean and Pontiff, 2016). Therefore, this study improves upon this approach and seeks to develop a method of jointly assessing the impact of academic attention, post-publication decay (announcement effect), data-snooping (sampling bias), and time trend (interpretable either as declining arbitrage costs or as growing general awareness) on the disappearance of individual anomalies that could both assess the relative importance of these factors and, perhaps most interestingly, distinguish between behavioural, data-snooping, and risk-related sources of anomalous stock market movements.

3. Data and Methodology

3.1. Stock return data

It has been widely acknowledged in the existing literature on stock market anomalies that the measurement of various stock return regularities is extremely sensitive to data-snooping and other methodological issues (Sullivan et al., 2001; McLean and Pontiff, 2016). Therefore, this study opts for using the most reliable data source which is also publicly available – the Kenneth French database. As this data is also commonly used by researchers, this will guarantee that the findings of the study are not attributable to sampling and methodology choices of this study. Furthermore, Kenneth French database provides sufficient data to identify both calendar and fundamental anomalies investigated by the study.

Five calendar anomalies (Monday effect, Friday effect, turn-of-the-month effect, holiday effect, and January effect) are calculated for the 1926-2018 sample period based on the daily US-specific excess market return factor provided by the Kenneth French database according to the methodologies identified in the literature. Monday and Friday effects are measured as the average excess return of the market on Mondays and Fridays, respectively, minus the average excess return of the market in the year (Merrill, 1966; Thaler, 1987b). Turn-of-the-month effect, however, has ambivalent methodological descriptions: it can be defined either as the average excess return of the market on the three last trading days of the month and the four first trading days of the following month (Lakonishok and Smith, 1988) or as the average excess return of the market on the last trading day of the month and on the first two weeks of the following month (Ariel, 1987; Thaler, 1987b), in both cases relative to the average daily excess return of the market in the respective year. Holiday effect is referred to as the average excess return of the market on the trading day preceding public holidays (Thaler, 1987b). The study considers three most significant festive events relevant for the US stock market due to the nature of the data – New Year, Christmas and Independence Day – as they are the only holidays that were celebrated countrywide throughout the whole sample period of this study. Therefore, in this study some less relevant holidays such as Memorial Day and Good Friday have been omitted, in contrast to previous studies (Marquering et al., 2006). Finally, January effect is calculated as the average excess monthly market return in January relative to the average excess monthly market return in the particular year (Keim, 1983).

In contrast, the data on fundamental anomalies (size and value effects, operating profitability and investment anomalies) and momentum is directly obtained from the Kenneth French database for the whole available sample period on an annual frequency.

The graphical representation of the stock market anomalies considered by this study can be consulted in Appendix (Figures A1-A11). The figures show the dynamics of the abnormal returns generated by respective anomaly-exploiting strategies throughout the sample periods with a time trend fitted for illustrative purposes. For most of the anomalies, a clear downward trend is visible. However, to generate causal inferences regarding the factors of anomaly disappearance, the study employs a wide range of estimation techniques discussed further in this section.

3.2. Academic attention data

Existing studies on the disappearance of stock market anomalies in the context of relevant academic research are limited to the measurement of post-publication effect of the first article published on the topic (Marquering, 2006; McLean and Pontiff, 2016). Most recently, data-snooping biases attributable to the sample choice of original pieces of research have also been identified and estimated (McLean and Pontiff, 2016). However, there has been no research quantifying the academic attention received by an anomaly and relating that to the magnitude of its decay. This study aims at filling this gap and suggests an easy yet rigorous method of measuring the academic attention attracted by the anomalies using Google Scholar search algorithms.

Table 2 below presents the list of anomalies considered by this study and respective search requests made in Google Scholar to identify the number of articles published on the topic in a particular year.

Table 2. List of notable anomalies and their Google Scholar search requests

Stock market anomaly	**Google Scholar search request**
Monday effect	(“Monday effect” OR “Friday effect” OR “Weekend effect”) AND “stock market”
Friday effect	(“Monday effect” OR “Friday effect” OR “Weekend effect”) AND “stock market”
Turn-of-the-month effect	“turn-of-the-month” AND “stock market”
Holiday effect	“holiday effect” AND “stock market”
January effect	(“January effect” OR “turn-of-the-year”) AND “stock market”
Size effect	(“small-firm effect” OR “size effect” OR “small-minus-big”) AND “stock market”
Value effect	(“value effect” OR “value premium” OR “high-minus-low”) AND “stock market”
Momentum	(“momentum” OR “winners-minus-losers”) AND “stock market”
Operational profitability anomaly	(“operational profitability anomaly” OR “robust-minus-weak”) AND “stock market”
Investment anomaly	(“investment anomaly” OR “conservative-minus-aggressive”) AND “stock market”

Then, for each anomaly, three data series are constructed. PUB_{it} is the number of published articles found in Google Scholar in year t relevant for the anomaly i. $TPUB_{it}$ is the total number of articles on the anomaly i published by the year t, therefore it can be defined using a recursive relationship $TPUB_{it} = TPUB_{it-1} + PUB_{it}$. Finally, $LTPUB_{it}$ is the natural logarithm of $TPUB_{it}$.

Additionally, this study also uses a second measure of academic attention: the volume of citations the leading articles identifying or studying an anomaly attract over a particular time period as per Google Scholar. Table 3 below presents the articles this study links to each of the anomalies, counting the number of citations in each of the sample years. Analogously to the publication count, citation-related measures $CITE_{it}$, $TCITE_{it}$, and $LTCITE_{it}$ are constructed as alternative academic attention variables to use in the estimations.

Table 3. List of anomalies and relevant articles for the citation count

Stock market anomaly	**Leading articles**
Monday effect	Merrill, 1966; Cross, 1973
Friday effect	Merrill, 1966; Cross, 1973
Turn-of-the-month effect	Ariel, 1987; Lakonishok and Smidt, 1988
Holiday effect	Thaler, 1987b; Ariel, 1990
January effect	Keim, 1983
Size effect	Stattman, 1980; Banz, 1981; Fama and French, 1992, 2015
Value effect	Stattman, 1980; Basu, 1983; Fama and French, 1992, 2015
Momentum	Grinblatt et al., 1995; Carhart, 1997
Operational profitability anomaly	Novy-Marx, 2013; Fama and French, 2015
Investment anomaly	Titman, 2004; Cooper et al., 2008; Fama and French, 2015

Publication and citation counts serve a similar purpose in the estimation strategy of this study, however accounting for both could theoretically reveal the differing impact of the various facets of the academic attention phenomenon. As such, citations can proxy for asymmetric effects (e.g., one well cited study can disseminate more information than multiple uncited papers) as well as measure the general awareness of a particular anomaly in the literature (e.g., when anomaly-related literature is being cited in research that is not focused on anomalies directly).

This study considers annual, cumulative, and the natural logarithm of cumulative citations and publications to model conceptually different information dissemination processes, with relative significance of respective estimators supporting various market learning concepts, such as constant or decreasing marginal informational value of an additional publication and the degree of knowledge retention by market participants. The application of these competing measures is discussed in greater detail later in this section.

The graphical representation of the academic attention data throughout the sample period can be consulted in Appendix (Figures A12, A13). The volume of publications and citations on all anomaly-related topics is steadily accumulating with time. Most interestingly, one can clearly notice how the general interest in size and value effects, particularly, is revitalised after 1993, when Fama-French three-factor model (Fama and French, 1993) has been introduced. Further, this study exploits the dynamics of academic attention variables to potentially explain the process of anomaly disappearance.

3.3. Testing for the disappearance of anomalies

This study is concerned with testing a set of hypotheses typical for disappearing anomalies research with a focus on academic attention, but also considering effects like post-publication decay (Marquering et al., 2006, McLean and Pontiff, 2016), data-snooping bias originating from the sampling procedures used by the first article that has discovered the anomaly (McLean and Pontiff, 2016; Linnainmaa and Roberts, 2018), time trend, and institutional trading (Sias and

Starks, 1995; Shu, 2013). Determining whether anomalies disappear or at least decrease in magnitude once they have attracted significant academic attention is important not only to glorify the role of academic research in enhancing market efficiency but also to thoroughly investigate the very nature of the anomalies considered from an empirical perspective. Cochrane (1999) argues that those stock return regularities that persist despite their wide coverage in academic research manifest not "anomalies" per se, but rather systematic risk factors in disguise. Otherwise, an anomaly which is still present on the market despite already been observed by traders and academicians, would clearly violate the efficient market hypothesis (Fama, 1970). This is also consistent with the theory of market learning as proposed by List (2003) and Timmermann and Granger (2004), which states that as market participants become aware of the anomaly, the abnormal returns related to it should vanish. Therefore, one could distinguish behavioural anomalies (Thaler, 1987a, b) from systematic risk factors proxied by fundamentals (Fama and French, 1992, 1993; Fama and French, 2015, 2016) to the degree that they decrease in magnitude in response to academic attention (measured by the study as the number of relevant articles published in Google Scholar or respective citation counts). However, most recent literature (McLean and Pontiff, 2016), despite acknowledging the anomaly-risk factor dichotomy, considers all cross-sectional stock return regularities homogeneously in a pooled regression model, therefore suffering from heterogeneity bias. Furthermore, as McLean and Pontiff (2016) try to attribute the rate of anomaly decay to costly arbitrage, they suggest a variety of arbitrage costs proxies, including size, liquidity, idiosyncratic risk, and dividend payments. They argue that the idiosyncratic risk proxies arbitrage costs the best, i.e., characteristic portfolios with low idiosyncratic risk exhibit the most post-publication decay (McLean and Pontiff, 2016). However, in the light of the anomaly-risk factor dichotomy (Cochrane, 1999) and the pooled regression approach utilised by McLean and Pontiff (2016), this finding might in fact be a result of an inherent bias of their methodology. As a return regularity can represent a systematic risk factor instead of a true behavioural anomaly, the idiosyncratic risk of the portfolio measured by the model that does not acknowledge it would be higher. Therefore, the differences in post-publication decay between low- and high-idiosyncratic risk characteristic portfolios in the methodology of McLean and Pontiff (2016) might reflect the specifics of the documented return regularity itself and not the costly arbitrage as they claim. An intuitive example might be a portfolio that is concentrated on energy sector stocks heavily exposed to oil returns. In standard CAPM or another factor model that does not specify oil as a systematic risk factor, such a portfolio would show higher levels of idiosyncratic risk. Consequently, failure of the oil effect on stock returns to diminish with time in the methodological framework described above would be attributed to the estimated "high arbitrage costs" and not to the relevance of oil as a systematic risk factor.

This study overcomes the methodological issue of McLean and Pontiff (2016) by simply treating the anomalies heterogeneously and estimating a set of separate time-series models for each of them and comparing them with estimators obtained from a pooled regression. First, to test for the initial relationship of academic attention and anomaly decay, the following simple regression is estimated:

$$R_t = \alpha + \beta_1 LTPUB_{t-1} + \varepsilon_t \tag{1}$$

Where R_t is the abnormal return of an anomaly in year t, α is the magnitude of the anomaly given it attracted no academic attention, β_1 is the impact of academic attention on an anomaly, ε_t is the error term, and $LTPUB_{t-1}$ is the natural logarithm of the total number of relevant publications in the year $t-1$. The lagged value is taken both to preserve exogeneity (theoretically, extremely high abnormal returns generated by an anomaly-exploiting strategy in a particular year could attract some academic attention to the topic immediately) and to remain consistent with the post-publication analysis framework emphasising that a piece of research can influence the stock market anomaly it identifies only after the publication (Marquering et al., 2006; McLean and Pontiff, 2016). Furthermore, the estimation is also made with $TPUB_{t-1}$, PUB_{t-1}, and all three citation-based measures ($CITE_{t-1}$, $TCITE_{t-1}$, and $LTCITE_{t-1}$) to determine which of the variables measures academic attention more accurately in the case of each anomaly. While the differences between $LTPUB_{t-1}$, $LTCITE_{t-1}$, $TPUB_{t-1}$, and $TCITE_{t-1}$ are merely technical and are associated with the functional form of the equation that captures the empirical relationship between academic attention and the disappearance of anomalies the best, the possibility of PUB_{t-1} or $CITE_{t-1}$ being the most significant factor among the three variables could have serious methodological implications: if anomalies respond only to the most recent academic publications (namely, those that mention the anomaly in the previous year), then stock market participants tend to "forget" about the anomalies and need to be constantly "reminded" by the academicians of their existence to preserve market efficiency. Therefore, the significance of PUB_{t-1} or $CITE_{t-1}$ and insignificance of $LTPUB_{t-1}$, $LTCITE_{t-1}$, $TPUB_{t-1}$, or $TCITE_{t-1}$ would signal that the market learning is not like riding a bike: once learnt, the existence of anomalies could be forgotten. Theoretically, this concept could be useful to explain the anomalies that tend to disappear and reappear after a certain period of time, such as the size effect (Horowitz et al., 2000). In line with the hypotheses this study tests and following Cochrane (1999), α is expected to be significant for all the anomalies, while β_1 is expected to be significant and have the sign opposite to α for behavioural anomalies and insignificant for "risk factors in disguise".

To ensure that the effect of academic attention on the disappearance of anomalies is robust, this study also estimates equation (1) using the instrumental variables approach within the two-stage least squares (TSLS) method. As the measure of academic attention applied by this study is the number of articles published in Google Scholar identified using a set of keywords and collocations relevant to the anomaly considered or a number of citations attracted by a set of relevant articles (see Tables 2 and 3), it can be subject to some measurement error. For example, some publications might be unavailable online, while some might appear multiple times under varying names (as working papers, conference proceedings, and published articles). Moreover, despite the effort made by the study to isolate keywords and collocations specific for the anomalies, some articles might appear in the list that use them in a different context, while some relevant articles might be missed by such a search procedure as they might use authentic names for the anomalies that are not commonly accepted or are simply written in a language other than English. On the other hand, an anomaly-related paper might be written in English by a foreign academic, and this piece of research might not be disseminated among US investors or simply contain insights that are not readily applicable for the US market. One might argue that the second source of errors is much more prominent, given the status of English as an international language of science, therefore, the measures would seem to be generally exaggerated. Nevertheless, even studies published in English for non-US markets can yield significant informational value for the US investors as they provide robustness and replicability evidence. Hence, there could be measurement errors in both directions roughly of the same magnitude.

Instrumental variables could be extremely useful in ensuring consistency of the estimations in the presence of measurement error (Sargan, 1958; Angrist and Krueger, 2001). To instrument for the academic attention, this study had to introduce a variable that would be strongly correlated with the number of academic publications and citations on the anomalies but would not theoretically influence the magnitude of the anomalies themselves. Therefore, variables IV_t, TIV_t, and $LTIV_t$ – measures of the number of publications on broad stock market-related topics – were constructed to instrument for PUB_t and $CITE_t$; $TPUB_t$ and $TCITE_t$; and $LTPUB_t$ and $LTCITE_t$, respectively. IV_t is the number of publications in Google Scholar responding to the broad query "finance" AND "stock returns" in year t, TIV_t is the cumulative number of such articles published by year t, and $LTIV_t$ is the natural logarithm of TIV_t. Note that the purpose of instrumental variables technique being used for this study is primarily to ensure robustness in the presence of measurement error as it already utilises lagged data and a substantial set of controls to address endogeneity.

Next, a more traditional approach is used to identify whether data-snooping bias and post-publication decay are present:

$$R_t = \alpha + \beta_2 SAMPLE_t + \beta_3 POSTPUB_t + \varepsilon_t \tag{2}$$

Where β_2 is the exaggeration of the anomaly in the sample of the original piece of research, β_3 is the post-publication decay, $SAMPLE_t$ is the binary dummy variable equal to 1 if year t belongs to the original sample period of the first published article on the topic and 0 otherwise, and $POSTPUB_t$ is the binary dummy variable equal to 1 if t is larger than the publication year of the first piece of research on the topic and 0 otherwise. To construct those dummy variables, the data from Tables 2 and 3 is used. The uniqueness of this study's data is that for most of the anomalies, data is available both for the original research sample period as well as for periods preceding and succeeding it (see Table 1), allowing to estimate β_2 with greater precision. For behavioural anomalies β_3 is expected to be significant and with sign opposite of α while the significance and sign of β_2 just reflects the design of the original studies on the topic and allows to derive conclusions about the relative importance of data-snooping bias in comparison with the true magnitude of the anomaly.

$$R_t = \alpha + \beta_1 LTPUB_{t-1} + \beta_2 FUND_{t-1} + \varepsilon_t \tag{3}$$

Equation (3) above tests for the significance of institutional trading as a factor that either contributes to anomaly decay (Shu, 2013) or, on the contrary, to the increase in their magnitude (Sias and Starks, 1995). Institutional trading proxy $FUND_{t-1}$ is estimated using the data on assets under management for funds that claim to pursue a particular anomaly-exploiting strategy at a particular year in per cent of US market capitalisation to account for the growth of the stock market and the mutual fund industry in the sample period. The use of natural logarithm of assets under management instead does not change the results qualitatively or quantitatively.

The funds were screened using content analysis of fund description to match with words and collocations characteristic of a particular anomaly or a group of anomalies. At the end of 2018, there were 31 funds with non-zero assets under management that claimed to follow calendar strategies ($33.8 billion, or 0.11% of US stock market capitalisation), 280 funds pursuing size-related strategies ($499.3 billion, or 1.64%), 1827 value funds ($2.8 trillion, or 9.26%), 148 momentum funds ($70.7 billion, or 0.23%), 34 funds ($51.7 billion, or 0.17%) followed operating profitability strategies, and no funds were associated with the conservative-minus-aggressive anomaly. Calendar funds were grouped together due to the similarity of anomalies they seek to exploit and general sparsity of the data on calendar-driven institutional trading.

$$R_t = \alpha + \beta_1 LTPUB_{t-1} + \beta_2 \log(t - Start) + \varepsilon_t \tag{4}$$

Equation (4) above introduces the time trend factor into the model which controls for the natural disappearance of anomalies unrelated to academic research. t is the year of the observation and $Start$ is the starting year for the study's sample (1926 for Monday, Friday, turn-of-the-month and holiday effects, 1927 for January, size, value and momentum effects and 1964 for operating profitability and investment anomalies). It can be interpreted either as the accumulation of experience by traders identifying the anomaly on their own and starting to exploit it thus contributing to its gradual decay (Fama, 1998; Timmermann and Granger, 2004) or as the impact of non-published or non-academic research, e.g., industry research (Marquering et al., 2006; McLean and Pontiff, 2016). Moreover, time trends are used in empirical models of anomaly disappearance that are based on the "limits to arbitrage" theory as proxies of the steady decline of trading costs with time (McLean and Pontiff, 2016). The logarithm is taken of the $t - Start$ to account for the fact that anomalies should be diminishing at a faster rate during the early years of their existence as well as to avoid some naïve extrapolations from linear trends that could predict anomaly reversals in the long run[2].

After equations (1-4) are estimated for each of the anomalies, a correctly specified model with significant factors is reported to precisely evaluate the contribution of each of the factors (academic attention, post-publication decay, data-snooping bias and time trend) to the disappearance of the anomalies. Standard errors are calculated with the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix (Newey and West, 1987). The assumption violations are identified using the Ljung-Box Q-test (Ljung and Box, 1978) and ARCH heteroskedasticity test (Engle, 1982) and the models are augmented with AR/MA terms where necessary.

[2] The use of the linear time trend instead of the logarithmic time trend does not affect the significance of the academic attention variables while logarithmic trend has also shown more significant explanatory power in case of most of the anomalies

4. Empirical Results and Discussion

4.1. Academic attention and the disappearance of anomalies

First, following McLean and Pontiff (2016), this study estimates the effects of all potential anomaly disappearance factors in a panel regression framework. Table 4 below presents the results of the estimations with two-way clustered standard errors (Petersen, 2009) and different sets of controls. For the panel of 11 stock return regularities, all six academic attention measures show consistent and significant negative effects on the magnitude of anomalies, providing some early evidence in favour of the initial hypothesis. However, when controlled for post-publication decay and sample selection bias, the only measure that retains both sign and significance is the logarithm of the total number of publications ($LTPUB_t$), suggesting that either it is the most robust academic attention measure or that there are significant heterogeneities across anomalies. Post-publication decay is significant and of expected sign in four out of six estimations (notably insignificant in the equation with $LTPUB_t$). There are no signs of sample selection bias on the aggregate panel level in any of the estimations. Time trend is negative and significant in all six equations, and logarithmic attention measures again prove to have the best explanatory power in the panel regression, while institutional trading always demonstrates an increasing effect on the magnitude of anomalies, albeit the significance is inconsistent. Overall, the panel estimations provide inconclusive evidence in favour of the main hypothesis of the study, substantial evidence supporting the post-publication decay theory and disproving the existence of significant data-snooping biases on the level of the whole sample. In terms of the effect of institutional trading on stock return regularities, panel evidence reinforces the assertions of Sias and Starks (1995), showing that trading activity exacerbates the anomalies rather than arbitrages them away.

Table 4. Academic attention and the disappearance of anomalies – panel estimations

Academic attention measure	(1)	(2)			(3)		(4)	
	Academic attention	Academic attention	Post-publication decay	Sample selection bias	Academic attention	Time trend	Academic attention	Institutional trading
	-1.57E-05	**1.05E-05**	**-0.1111**	-0.0244	8.05E-06	**-0.0765**	**-1.63E-05**	0.0008
PUB	**(-4.0840)**	**(1.8068)**	**(-5.3986)**	(-1.2226)	(1.4811)	**(-7.1664)**	**(-3.6781)**	(0.4377)
	0.0000	***0.0711***	***0.0000***	*0.2218*	*0.1389*	***0.0000***	***0.0002***	*0.6617*
	-1.79E-06	8.78E-07	**-0.1093**	-0.0241	7.15E-07	**-0.0760**	**-1.81E-06**	0.0002
$TPUB$	**(-3.882)**	(1.3944)	**(-5.4211)**	(-1.2090)	(1.1721)	**(-7.1873)**	**(-3.5399)**	(0.1096)
	0.0001	*0.1635*	***0.0000***	*0.2270*	*0.2415*	***0.0000***	***0.0004***	*0.9127*
	-0.0160	**-0.0148**	-0.0171	-0.0224	**-0.0063**	**-0.0571**	**-0.0185**	**0.0143**
$LTPUB$	**(-7.0232)**	**(-2.7834)**	(-0.4373)	-1.1291	**(-2.0456)**	**(-4.1365)**	**(-6.9118)**	**(4.8565)**
	0.0000	***0.0055***	*0.6620*	*0.2591*	***0.0410***	***0.0000***	***0.0000***	***0.0000***
	-2.64E-05	**4.13E-05**	**-0.1154**	-0.0224	3.38E-05	**-0.0784**	**-2.89E-05**	0.0011
$CITE$	**(-3.8706)**	**(2.9756)**	**(-5.5140)**	(-1.1282)	(2.8755)	**(-7.2142)**	**(-3.1918)**	(0.5879)
	0.0001	***0.0030***	***0.0000***	*0.2595*	*0.0041*	***0.0000***	***0.0015***	*0.5567*
	-3.01E-06	**3.02E-06**	**-0.1111**	-0.0231	2.92E-06	**-0.0774**	**-3.27E-06**	0.0011
$TCITE$	**(-3.9358)**	**(2.3322)**	**(-5.5189)**	(-1.1624)	(2.3744)	**(-7.2274)**	**(-3.3749)**	(0.5953)
	0.0001	***0.0199***	***0.0000***	*0.2453*	*0.0178*	***0.0000***	***0.0008***	*0.5518*
	-0.0154	-0.0100	-0.0476	-0.0256	**-0.0049**	**-0.0027**	**-0.0185**	**0.0138**
$LTCITE$	**(-6.9414)**	(-1.4280)	(-0.9641)	(-1.2846)	**(-1.7861)**	**(-5.6018)**	**(-6.7879)**	**(4.6763)**
	0.0000	*0.1536*	*0.3352*	*0.1992*	***0.0744***	***0.0000***	***0.0000***	***0.0000***

Notes: panel estimations of disappearance of anomalies with all controls. T-stats are calculated using the two-way clustered covariance matrix (Petersen, 2009) and presented (in parentheses), while the corresponding p-values are reported *in italics*. Significant results (at 10%) are presented **in bold**.

Table 5 below presents the results of the estimations of equation (1) for each of the anomalies using standard OLS. For seven out of 11 stock return regularities investigated by the study, academic attention is a significant factor that explains their slow disappearance with time. For size effect, January effect, and momentum the result is of expected sign albeit marginally insignificant, while for profitability anomaly the effect is very small and even turns positive in some estimations. It might either reflect the fact that the profitability anomaly is very recent and sufficient amount of academic research has not yet been accumulated on the topic or signal that profitability is a systematic risk factor that has not been previously paid much attention to, which is slowly changing as operating profitability anomaly gains appreciation, mostly in the context of the Fama-French five-factor model (Fama and French, 2015, 2016). The second explanation is arguably more plausible as investment is almost as recent of an anomaly as profitability, however it behaves in a way consistent with the "old" calendar anomalies.

Regarding the academic attention measure most suitable for each particular anomaly, the majority (six out of 11) of the stock return regularities are most closely related to the total number of relevant academic publications (in case of size effect and both versions of the turn-of-the-month effect) or the natural logarithm of total citations (in case of Monday effect as well as profitability and investment anomalies). These findings can be fruitfully interpreted in the context of relative conceptual complexity of the anomalies: Monday effect is perhaps the easiest to identify and attracts the least controversies related to its definition and measurement. For example, even turn-of-the-month effect and January effect (seemingly simple calendar anomalies) have competing definitions and measurement techniques (Ariel, 1987; Thaler 1987a; Lakonishok and Smidt, 1988). Therefore, for the "easiest" anomalies each new publication might reveal less new information relevant for the market (interpretable as a sort of "diminishing returns to scale"), whereas for the more conceptually complex anomalies the research can maintain "constant returns to scale", investigating the subject from various perspectives. This can be illustrated, for example, with the relatively long debate in the 1980's about whether value anomaly is autonomous or just another manifestation of size effect (Stattman, 1980) as well as about most suitable fundamental proxies of value effect (Basu, 1983; Fama and French, 1992). For investment and profitability anomalies, in turn, the logarithm of citations has the best fit, potentially as the academic research on these anomalies is mostly focusing on applying the respective factors in the context of Fama-French five-factor model (Fama and French, 2015, 2016), rather than on investigating the causes of these stock return regularities per se.

January effect, value effect, and momentum respond to the number of most recent publications, while Friday effect is the only anomaly responding to the most recent citations on the topic, implying that the market slowly forgets about these four anomalies if it is not constantly reminded by the academics. This is indeed puzzling as in the research Friday and Monday effects are often treated homogeneously as the single "weekend effect" (Marquering et al., 2006). Nevertheless, even the initial estimation results show that Monday and Friday effects are heterogeneous and may require different theoretical explanations.

Overall, the estimation results of individual time-series equations for each of the anomalies imply the existence of heterogeneity among observed stock return regularities and can be used to strongly argue against pooled estimations.

Table 5. Academic attention and stock market anomalies – individual regressions

Anomaly	Monday	Friday	Turn-of-the-month (a)	Turn-of-the-month (b)	Holiday	January	Size	Value	Momentum	Profitability	Investment
	-0.0018	-0.0003	-0.0004	-0.0003	-0.0050	***-0.0002***	-7.17E-06	**-9.55E-06**	**-6.62E-06**	2.08E-05	-0.0002
PUB	(-3.8498)	(-2.5631)	(-2.3178)	(-2.1547)	(-3.5958)	***(-1.4150)***	(-1.0165)	**(-1.8260)**	**(-1.3224)**	(0.2915)	(-1.6533)
	0.0002	*0.0120*	*0.0227*	*0.0338*	*0.0005*	***0.1605***	*0.3121*	***0.0712***	***0.1894***	*0.7718*	*0.1042*
	-0.0001	-2.18E-05	**-3.84E-05**	**-4.01E-05**	-0.0005	-1.44E-05	**-7.87E-07**	-1.13E-06	-5.84E-07	-2.22E-06	-6.58E-05
$TPUB$	(-4.3203)	(-2.3230)	**(-2.5942)**	**(-2.5340)**	(-4.0660)	(-1.1366)	**(-1.2850)**	(-1.7853)	(-1.2723)	(-0.0800)	(-1.5701)
	0.0000	*0.0224*	***0.0110***	***0.0130***	*0.0001*	*0.2587*	***0.2021***	*0.0776*	*0.2065*	*0.9365*	*0.1223*
	-0.0800	-0.0106	-0.0043	-0.0056	-0.0660	-0.0061	-0.0017	-0.0017	-0.0017	-0.0001	-0.0032
$LTPUB$	(-5.1740)	(-2.4122)	(-1.3175)	(-2.3012)	(-3.5716)	(-0.9645)	(-1.2467)	(-1.1434)	(-0.6973)	(-0.2653)	(-1.4567)
	0.0000	*0.0179*	*0.1910*	*0.0237*	*0.0006*	*0.3374*	*0.2158*	*0.2559*	*0.4874*	*0.7918*	*0.1511*
	-0.0092	**-0.0015**	-0.0008	-0.0008	**-0.0107**	-0.0001	-5.62E-06	-1.58E-05	-2.79E-05	-6.61E-07	-3.33E-05
$CITE$	(-3.8794)	**(-2.5913)**	(-2.1616)	(-2.1070)	**(-4.3700)**	(-1.3000)	(-1.0564)	(-1.7020)	(-1.3029)	(-0.0511)	(-1.5634)
	0.0002	***0.0111***	*0.0333*	*0.0379*	***0.0000***	*0.1969*	*0.2936*	*0.0922*	*0.1959*	*0.9595*	*0.1239*
	-0.0007	-0.0001	-6.59E-05	-7.01E-05	-0.0009	-4.54E-05	-6.29E-07	-1.74E-06	-2.71E-06	-7.79E-07	-9.09E-06
$TCITE$	(-4.4026)	(-2.3596)	(-2.4266)	(-2.5326)	(-3.8635)	(-1.2508)	(-1.2821)	(-1.7891)	(-1.2787)	(-0.1495)	(-1.5441)
	0.0000	*0.0204*	*0.0172*	*0.0130*	*0.0002*	*0.2142*	*0.2031*	*0.0770*	*0.2043*	*0.8817*	*0.1285*
	-0.0998	-0.0124	-0.0039	-0.0054	-0.0702	-0.0055	-0.0015	-0.0016	-0.0034	**-0.0001**	**-0.0028**
$LTCITE$	**(-5.2318)**	(-2.2789)	(-1.1415)	(-2.1454)	(-3.5189)	(-0.7803)	(-1.2551)	(-1.0692)	(-1.1059)	**(-0.4461)**	**(-1.8156)**
	0.0000	*0.0250*	*0.2566*	*0.0346*	*0.0007*	*0.4373*	*0.2127*	*0.2878*	*0.2717*	***0.6573***	***0.0751***

Notes: estimates of equation (1) via standard OLS. Standard errors are calculated using the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix and presented (in parentheses), while the corresponding p-values are reported *in italics*. The estimation with the most significant academic attention measure is **in bold**.

4.2. Robustness check

Table 6 below presents the results of the estimation of equation (1) again for each of the anomalies via a TSLS procedure with publications on a broad scope of finance topics instrumenting for academic attention. This serves as a robustness check of the relationship between academic attention and the disappearance of anomalies in the presence of measurement error and potential endogeneity. The findings accentuate the significance of the impact of academic attention for six out of 11 estimations. However, the TSLS estimates mostly do not differ considerably from the OLS results, suggesting that the impact of measurement error and endogeneity is modest. Nevertheless, the insignificance of the TSLS estimation for the investment anomaly implies the inconsistency of the initial result and evidences that academic attention does not influence the magnitude of the conservative-minus-aggressive factor, supporting the hypothesis that investment is a systematic risk factor. In terms of measurement error, this result can be analysed considering the popularity the investment factor has gained in academic research since the development of Fama-French five-factor model (Fama and French, 2015, 2016). However, such popularity does not necessarily contribute to the overall understanding of the anomaly by the market participants. Size effect, momentum, and profitability anomalies seem to be generally unaffected by academic research, stressing the risk content of these factors, while January effect and investment are either marginally insignificant or have inconsistent results in OLS and TSLS estimations. All other anomalies decrease significantly with growing academic appreciation. Therefore, it can be stated with certainty that 5 out of 10 anomalies (Monday, Friday, turn-of-the-month, holiday, and value effects) are indeed behavioural, 3 out of 10 (size, momentum, and operating profitability) represent systematic risk factors while investment anomaly and January effect remain unclear cases.

Table 6. Academic attention and stock market anomalies – robustness check

Anomaly	Monday	Friday	Turn-of-the-month (a)	Turn-of-the-month (b)	Holiday	January	Size	Value	Momentum	Profitability	Investment
	-0.0018	-0.0003	-0.0005	-0.0005	-0.0054	-0.0002	-5.23E-06	**-9.14E-06**	**-7.83E-06**	6.41E-05	-0.0002
PUB	(-3.3288)	(-2.3326)	(-2.0963)	(-2.1070)	(-2.9092)	(-1.4363)	(-0.6629)	**(-1.7652)**	**(-1.1236)**	(0.2736)	(-1.0171)
	0.0013	*0.0219*	*0.0388*	*0.0379*	*0.0046*	*0.1544*	*0.5091*	***0.0809***	***0.2642***	*0.7854*	*0.3137*
	-0.0002	-2.24E-05	-4.23E-05	-4.41E-05	-0.0001	-1.48E-05	-8.03E-07	-1.11E-06	-6.42E-07	5.01E-06	-7.62E-05
$TPUB$	(-4.2996)	(-2.2739)	(-2.3529)	(-2.4821)	(-3.9823)	(-1.1764)	(-1.1574)	(-1.6589)	(-1.1187)	(0.0954)	(-1.3729)
	0.0000	*0.0253*	*0.0208*	*0.0149*	*0.0001*	*0.2425*	*0.2502*	*0.1006*	*0.2662*	*0.9243*	*0.1756*
	-0.0975	-0.0082	-0.0060	-0.0061	**-0.1020**	-0.0091	-0.0009	-0.0007	-0.0014	**0.0054**	-0.0015
$LTPUB$	(-4.7446)	(-1.5562)	(-1.4841)	(-2.1878)	**(-4.2562)**	(-1.3271)	(-0.5298)	(-0.3854)	(-0.4603)	**(1.0670)**	(-0.4249)
	0.0000	*0.1231*	*0.1412*	*0.0312*	***0.0001***	*0.1878*	*0.5976*	*0.7008*	*0.6464*	***0.2908***	*0.6726*
	-0.0094	**-0.0015**	-0.0009	-0.0009	-0.0110	**-0.0010**	-4.09E-06	-1.56E-05	-3.60E-05	1.14E-05	-3.33E-05
$CITE$	(-3.2850)	**(-2.3578)**	(-2.1015)	(-2.1130)	(-2.9482)	**(-1.4421)**	(-0.6647)	(-1.7580)	(-1.1152)	(0.2710)	(-1.0139)
	0.0014	***0.0205***	*0.0384*	*0.0373*	*0.0041*	***0.1527***	*0.5080*	*0.0821*	*0.2677*	*0.7875*	*0.3152*
	-0.0008	-0.0001	**-7.03E-05**	**-7.31E-05**	-0.0001	-4.33E-05	**-6.57E-07**	-1.66E-06	-3.28E-06	1.07E-06	**-1.04E-05**
$TCITE$	(-4.3289)	(-2.2766)	**(-2.3725)**	**(-2.5157)**	(-3.9976)	(-1.1897)	**(-1.1585)**	(-1.6563)	(-1.1114)	(0.0953)	**(-1.3738)**
	0.0000	*0.0252*	***0.0198***	***0.0136***	*0.0001*	*0.2373*	***0.2497***	*0.1012*	*0.2693*	*0.9245*	***0.1753***
	-0.1200	-0.0101	-0.0065	-0.0065	-0.1104	-0.0101	-0.0009	-0.0007	-0.0020	0.0063	-0.0011
$LTCITE$	**(-4.7646)**	(-1.5551)	(-1.4829)	(-2.1852)	(-4.2502)	(-1.3264)	(-0.5302)	(-0.3852)	(-0.4617)	(1.0049)	(-0.4255)
	0.0000	*0.1234*	*0.1416*	*0.0314*	*0.0001*	*0.1881*	*0.5973*	*0.7010*	*0.6454*	*0.3195*	*0.6722*

Notes: estimates of equation (1) via TSLS. Standard errors are calculated using the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix and presented (in parentheses), while the corresponding p-values are reported *in italics*. The estimation with the most significant academic attention measure is **in bold**.

4.3. Post-publication decay and data-snooping bias

Table 7 below presents the data-snooping biases and post-publication decay of the individual anomalies estimated via equation (2). Only two out of 11 cases (Monday and holiday effects) show significant post-publication decrease in the magnitude of abnormal returns, unlike academic attention, which was a significant factor in seven out of 11 estimations. However, it is substantially higher

(69.2% and 93.7%, respectively) than the average 25% reported by McLean and Pontiff (2016), signifying both the heterogeneity bias the pooled regression methodology suffers from in case of the studies of anomalies and the relatively high explanatory power of the academic attention variable. Data-snooping bias attributable to sampling is positive and significant only in the case of Friday effect (where the sample choice of the original study explains 89.8% of the reported anomaly magnitude). None of the other coefficients for either of the two effects are significant.

Table 7. Data-snooping bias and post-publication decay in anomalies

Anomaly	Monday	Friday	Turn-of-the-month (a)	Turn-of-the-month (b)	Holiday	January	Size	Value	Momentum	Profitability	Investment
Constant	**0.7076**	0.0138	**0.0753**	**0.0313**	**0.4067**	0.0522	**0.0308**	0.0151	**0.0290**	0.0043	0.0146
	(7.1862)	(0.4323)	**(5.4545)**	**(3.7309)**	**(6.9365)**	(1.6159)	**(1.8260)**	(1.5838)	**(3.1791)**	(0.2383)	(1.2313)
	0.0000	*0.6665*	***0.0000***	***0.0003***	***0.0000***	*0.1097*	***0.0712***	*0.1168*	***0.0020***	*0.8126*	*0.2238*
Post-publication decay	**-0.4897**	0.0144	-0.0258	-0.0228	**-0.3812**	-0.0156	-0.0303	-0.0062	-0.0203	0.0043	-0.0143
	(-4.0878)	(0.3980)	(-1.2200)	(-1.5494)	**(-3.7307)**	(-0.3171)	(-1.6603)	(-0.4679)	(-0.8782)	(0.2244)	(-1.0219)
	0.0001	*0.6915*	*0.2257*	*0.1248*	***0.0003***	*0.7519*	*0.1004*	*0.6410*	*0.3822*	*0.8233*	*0.3116*
Sample selection bias	-0.1733	**0.1217**	-0.0394	0.0039	-0.0888	0.0226	-0.0227	0.0107	0.0030	0.0065	0.0037
	(-1.4765)	**(3.1491)**	(-1.5999)	(0.2497)	(-0.9047)	(0.3058)	(-1.2061)	(0.7795)	(0.1589)	(0.3415)	(0.2701)
	0.1433	***0.0022***	*0.1131*	*0.8034*	*0.3680*	*0.7605*	*0.2310*	*0.4378*	*0.8741*	*0.7341*	*0.7882*

Notes: estimates of equation (2) via standard OLS. T-stats are calculated using the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix and presented (in parentheses), while the corresponding p-values are reported *in italics*. Significant results (at 10%) are reported **in bold**.

Table 8 below reports the impact of institutional trading on the magnitude of anomalies assessed via equation (3). The results are negative and significant for Monday, Friday, turn-of-the-month, holiday, and value effects, highlighting the importance of institutional investors for the dynamics of calendar anomalies discovered in the early studies in the field (Sias and Starks, 1995; Ng and Wang, 2004). However, the signs of the coefficients seemingly imply that institutional trading does arbitrage the anomalies away rather than exacerbates them, supporting Shu (2013) and contradicting earlier research (Sias and Starks, 1995). Nevertheless, to form a decisive conclusion on the effect of institutional investors on the magnitude of anomalies, it needs to be controlled for other factors.

Table 8. Institutional trading and the disappearance of anomalies.

Anomaly	Monday	Friday	Turn-of-the-month (a)	Turn-of-the-month (b)	Holiday	January	Size	Value	Momentum	Profitability
Constant	**0.4569**	**0.0484**	**0.0629**	**0.0290**	**0.3051**	**0.0578**	0.0100	**0.0187**	**0.0274**	0.0104
	(8.5838)	**(3.1826)**	**(6.1955)**	**(4.5588)**	**(6.9898)**	**(2.3596)**	(1.5950)	**(2.8407)**	**(3.4352)**	(1.6322)
	0.0000	***0.0020***	***0.0000***	***0.0000***	***0.0000***	***0.0205***	*0.1142*	***0.0056***	***0.0009***	*0.1086*
Institutional trading	**-4.6123**	**-0.7711**	**-0.4024**	**-0.4188**	**-4.1636**	-0.6867	-0.0060	**-0.0020**	-0.1396	-0.0052
	(-2.7995)	**(-1.9710)**	**(-2.0464)**	**(-2.2473)**	**(-2.4888)**	(-0.8778)	(-0.8377)	**(-1.7373)**	(-1.1247)	(-0.0736)
	0.0062	***0.0518***	***0.0436***	***0.0270***	***0.0146***	*0.3824*	*0.4044*	***0.0858***	*0.2637*	*0.9416*

Notes: estimates of equation (3) via standard OLS. T-stats are calculated using the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix and presented (in parentheses), while the corresponding p-values are reported *in italics*. Significant results (at 10%) are reported **in bold**.

To understand the relationship between two main dissemination channels of anomaly-related information (academic and practitioner) this study executes Granger causality tests using first differences in institutional trading ($FUND_t$) and academic attention ($LTPUB_t$ and $LTCITE_t$). The results can be extremely important for the efficiency implications of research and trading activity. If trading Granger-causes research and not vice versa, then it means academics just follow the overall trend and do not add much value to information transmission. If, on the other hand, academic attention Granger-causes institutional trading activity, then research is more beneficial in promoting market efficiency. Finally, if there is no Granger-causality or the relationship is bi-directional, it is possible to conclude that both dissemination channels are potentially impactful.

Table 9 below presents the Granger causality test for two lags (selected via the Schwartz criterion minimisation) and nine lags (selected using Akaike information criterion) for additional robustness. The results show that while citations and publications do Granger-cause each other, academic attention and trading activity are independent, implying that both can meaningfully contribute to information dissemination.

Table 9. The independence of academic attention and institutional trading

Number of lags	Two lags (Schwartz)			Nine lags (Akaike)		
Variable	Institutional trading	Publications	Citations	Institutional trading	Publications	Citations
Institutional trading		1.3852 *0.5003*	0.4765 *0.788*		1.2031 *0.9988*	3.2239 *0.9548*
Publications	1.7667 *0.4134*		**24.7544** ***0.0000***	4.1575 *0.9007*		**218.1081** ***0.0000***
Citations	0.3541 *0.8377*	**16.4962** ***0.0003***		1.6882 *0.9955*	**32.6061** ***0.0002***	
All	1.8221 *0.7684*	**17.2487** ***0.0017***	**24.8393** ***0.0001***	6.5650 *0.9933*	**33.6752** ***0.0138***	**218.3823** ***0.0000***

Notes: Granger causality test for first differences in institutional trading and academic attention measures. Corresponding p-values are reported *in italics*. Significant results (at 10%) are reported **in bold**.

Table 10 below addresses the time trend in anomaly decay. Among the 11 time series, only two (Monday and Holiday effects) are shown to significantly diminish with the passage of time, implying that they might be the least sophisticated anomalies to identify and arbitrage away for retail investors without the assistance from academic or institutional dissemination channels.

Table 10. Time trend and the disappearance of anomalies.

Anomaly	Monday	Friday	Turn-of-the-month (a)	Turn-of-the-month (b)	Holiday	January	Size	Value	Momentum	Profitability	Investment
Constant	**1.4319**	0.0890	**0.0985**	**0.0654**	**1.0606**	**0.1492**	0.0175	0.0087	0.0290	-0.0607	0.0470
	(4.8409)	(1.3873)	**(2.4342)**	**(2.5891)**	**(4.9318)**	**(1.6924)**	(0.5851)	(0.3216)	(0.5563)	(-0.8791)	(0.5330)
	0.0000	*0.1687*	***0.0169***	***0.0112***	***0.0000***	***0.0940***	*0.5599*	*0.7485*	*0.5794*	*0.3833*	*0.5962*
Time trend	**-0.2871**	-0.0137	-0.0112	-0.0115	**-0.2242**	-0.0274	-0.0024	0.0016	-0.0013	0.0171	-0.0083
	(-3.6195)	(-0.8243)	(-1.0515)	(-1.6458)	**(-3.7994)**	(-1.1264)	(-0.3135)	(0.2268)	(-0.0953)	(1.0044)	(-0.3945)
	0.0005	*0.4119*	*0.2958*	*0.1033*	***0.0003***	*0.2630*	*0.7546*	*0.8211*	*0.9243*	*0.3197*	*0.6948*

Notes: estimates of equation (4) via standard OLS. T-stats are calculated using the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix and presented (in parentheses), while the corresponding p-values are reported *in italics*. Significant results (at 10%) are reported **in bold**.

4.4. Factor analysis of the disappearance of anomalies

Table 11 below reports the results of the factor analysis of the disappearance of anomalies. TSLS models with respective covariates have been estimated for each of the anomalies, with insignificant factors being eliminated from the model to correctly attribute anomaly decay. Four of the ten anomalies studied (size, investment, momentum, and January effect) are proven to be systematic risk factors and thus persist despite growing public awareness, academic attention, institutional trading, or the passage of time and the accompanying decrease of trading costs. Five anomalies (Monday effect, Friday effect, turn-of-the-month effect, holiday effect, and value effect) show signs of disappearance, thus emphasising their initial behavioural nature. Two of them (Friday and turn-of-the-month effect) respond solely to the academic attention factor, while Monday effect also shows a negative time trend. It highlights the importance of separate treatment of Monday and Friday effects. Interestingly, holiday effect is the only anomaly that seem to have been figured out independently by the market and have been steadily decreasing with time regardless of academic attention. This finding can be interpreted in the context of relative simplicity of the holiday effect and the trading strategies exploiting it. Value effect diminishes in response to academic attention or trading activity separately, but not when both measures are accounted for in the equation, therefore it is challenging to accurately determine the most important factor contributing to the reduction of this anomaly.

Overall, the results emphasise that academic research is most relevant for the disappearance of more technically sophisticated anomalies which are comparatively difficult to identify and measure. Furthermore, turn-of-the-month effect diminishes in response to increasing academic attention in both forms (Lakonishok and Smidt, 1988; Ariel, 1987), evidencing the fact that the market participants can assess the conclusions of the academic research creatively and generalise from them, applying anomaly-exploiting investment strategies to arbitrage away all multiple variants of behavioural stock return regularities.

Table 11. Factors of the disappearance of anomalies

Anomaly	Monday	Friday	Turn-of-the-month (a)	Turn-of-the-month (b)	Holiday	January	Size	Value	Momentum	Profitability	Investment
Constant	**1.2310**	**0.5661**	**0.0682**	**0.0344**	**0.9325**	**0.0745**	**0.0106**	**0.0186**	**0.0310**	0.0062	**0.0151**
	(3.1604)	**(7.4659)**	**(6.1593)**	**(5.0070)**	**(3.8696)**	**(2.5948)**	**(1.6774)**	**(2.7528)**	**(3.9319)**	(1.1545)	**(2.6508)**
	0.0022	***0.0000***	***0.0000***	***0.0000***	***0.0002***	***0.0111***	***0.0969***	***0.0072***	***0.0002***	*0.2535*	***0.0106***
Academic attention	**-0.0859**	**-0.0193**	-0.0002	**-0.0002**	-0.0622	-0.0010	-6.57E-07	-5.55E-06	-7.83E-06	0.0054	-1.04E-05
	(-1.8043)	**(-2.3571)**	(-1.2349)	**(-1.7264)**	(-0.6533)	(-1.4421)	(-1.1585)	(-0.2317)	(-1.1236)	(1.0670)	(-1.3738)
	0.0746	***0.0206***	*0.2201*	***0.0877***	*0.5153*	*0.1527*	*0.2497*	*0.8173*	*0.2642*	*0.2908*	*0.1753*
Post-publication decay	0.2038				0.1647						
	(1.1102)				(0.4220)						
	0.2699				*0.6740*						
Sample selection bias		-0.0318									
		(-0.3206)									
		0.7493									
Institutional trading	1.2286	8.2979	0.7045	0.7328	0.3234			-0.0008			
	(0.5832)	(1.6151)	(0.7979)	(1.0662)	(0.1008)			(-0.1553)			
	0.5612	*0.1098*	*0.4270*	*0.2892*	*0.9200*			*0.8769*			
Time trend	**-0.2095**				**-0.1743**						
	(-1.6955)				**(-2.4671)**						
	0.0935				***0.0156***						

Notes: estimates of the final time-series model for each of the anomalies via TSLS. T-stats are calculated using the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix and presented (in parentheses), while the corresponding p-values are reported *in italics*. Significant results (at 10%) are reported **in bold**.

5. Conclusion

This study has examined the joint impact of post-publication decay, data-snooping bias, institutional trading, time trend and, most importantly, academic attention on the disappearance of ten most notable stock market anomalies. It has proposed original measures of academic attention attracted by stock market anomalies using a Google Scholar search algorithm based on relevant words and collocations that are shown to explain the diminishing abnormal returns better than the existing approaches highlighted in the existing literature. The method developed in this study allows one to empirically distinguish between behavioural anomalies and "risk factors in disguise". Monday effect, Friday effect, holiday effect, turn-of-the-month effect, and value effect, are shown to be mostly behavioural, decreasing significantly as they gain academic appreciation. In contrast, January effect, size effect, investment, and momentum, are shown to be relevant systematic risk factors as they do not decrease neither post-publication nor with time. The results for the profitability anomaly are uncertain as the intercepts for the factor are insignificant in most estimations. Data-snooping bias that has recently gained substantial popularity as the explanation of anomalies is shown to be present only in the case of Friday effect, while post-publication decay is notable in case of Monday and Holiday effects only, and these estimators cease to be significant when controlled for other factors. Institutional trading does decrease the magnitude for value effect as well as all calendar anomalies except January effect, yet the coefficients are not significant when controlled for academic attention. Among all of the behavioural anomalies, only holiday effect is shown to have been disappearing regardless of academic attention, which can be attributed to the relative simplicity of the anomaly.

The findings of the study have broad implications for academicians and practitioners alike. First, the study has emphasised the crucial role academic research plays in promoting market efficiency, especially in identifying conceptually and computationally complex stock return regularities. It has manifested the role of academia as the important information transmission channel shaping the understanding of the stock market by its participants that is independent of institutional trading. Second, the importance of the distinction between behavioural and risk-related anomalies has been highlighted. It is crucial for forecasting and modelling, suggesting that models based on more robust systematic risk factors (such as size and momentum) would have higher explanatory and predictive power. Moreover, the approach developed by this study allows one to distinguish between these two types of anomalies empirically. Third, the significance of different academic attention measures can be used to interpret the nature of the market learning process, primarily the degree of information retention by market participants. Finally, the results imply that a trader who has discovered a stock market anomaly, especially if it is relatively hard to identify or measure, might generate economic profit from it as long as it has not gained significant academic attention.

The limitations of the study are mainly associated with data availability. First, the analysis has been performed on an annual frequency as Google Scholar allows to search for articles and citations on an annual basis only which, in turn, limits the frequency of the academic attention variables. Further research might investigate the same relationships on a higher frequency (e.g., monthly) especially for the fundamental anomalies, Monday, Friday, and turn-of-the-month effect. Second, the study has a US focus as most of the research on anomalies has historically been performed by American scholars and published in English. The approach developed by the study can nevertheless be replicated, for example, on an emerging market using articles written in the native language of the country to proxy academic attention. Third, the study has covered only ten most notable anomalies well-known among academicians and practitioners. Further research could expand the sample to include some stock return regularities that have been recently discovered and have not yet gained such a wide appreciation to test whether the conclusions of this study still hold. Finally, new research could include more control variables that are not applied in this study, such as market sentiment or liquidity.

6. References

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Appendix: Visual representation of the anomalies

Figure A1. Average daily Monday effect

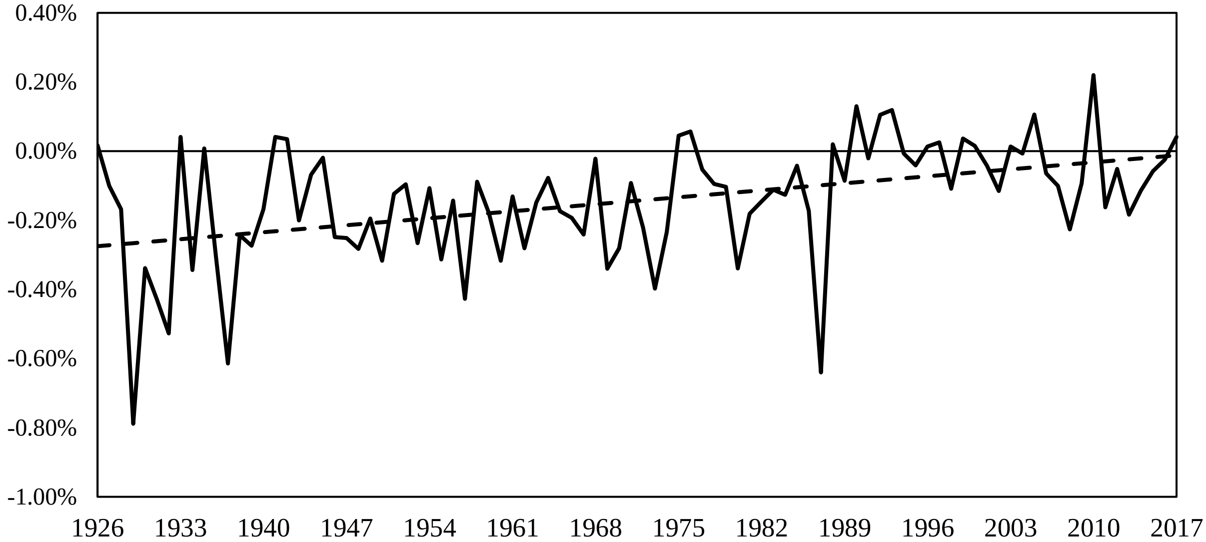

Figure A2. Average daily Friday effect

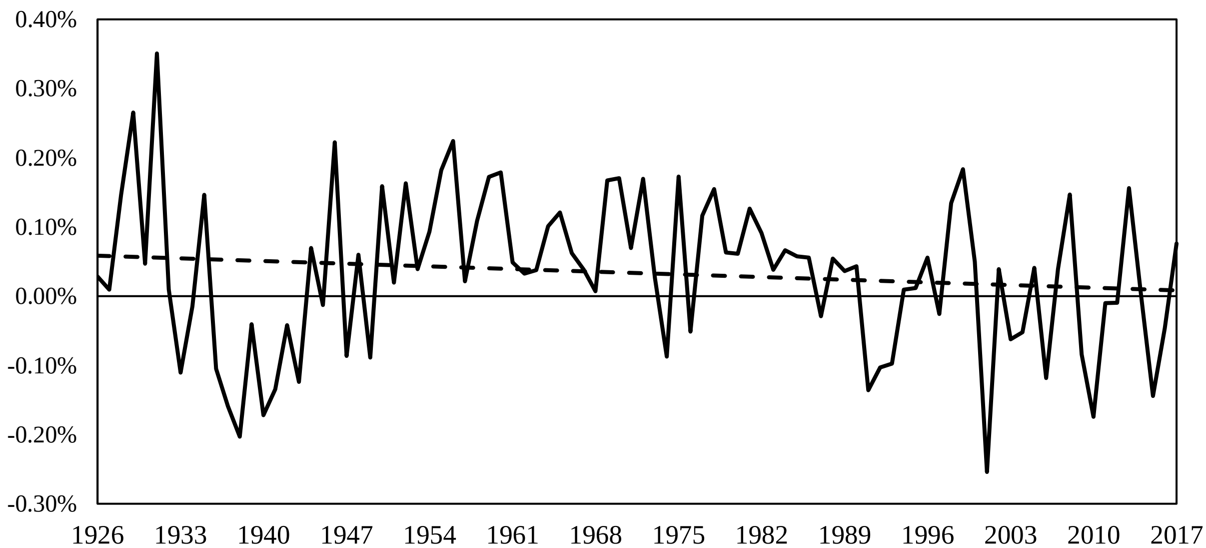

Figure A3. Average daily turn-of-the-month effect (based on three first and four last trading days of the month)

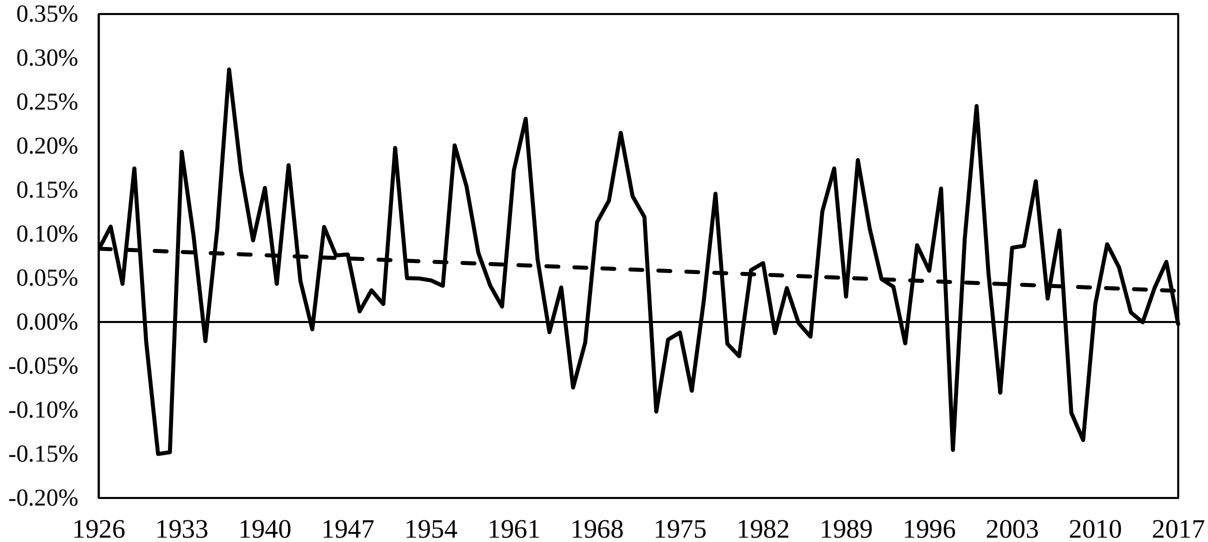

Figure A4. Average daily turn-of-the-month effect (based on the last day of the month and the first two weeks of the following month)

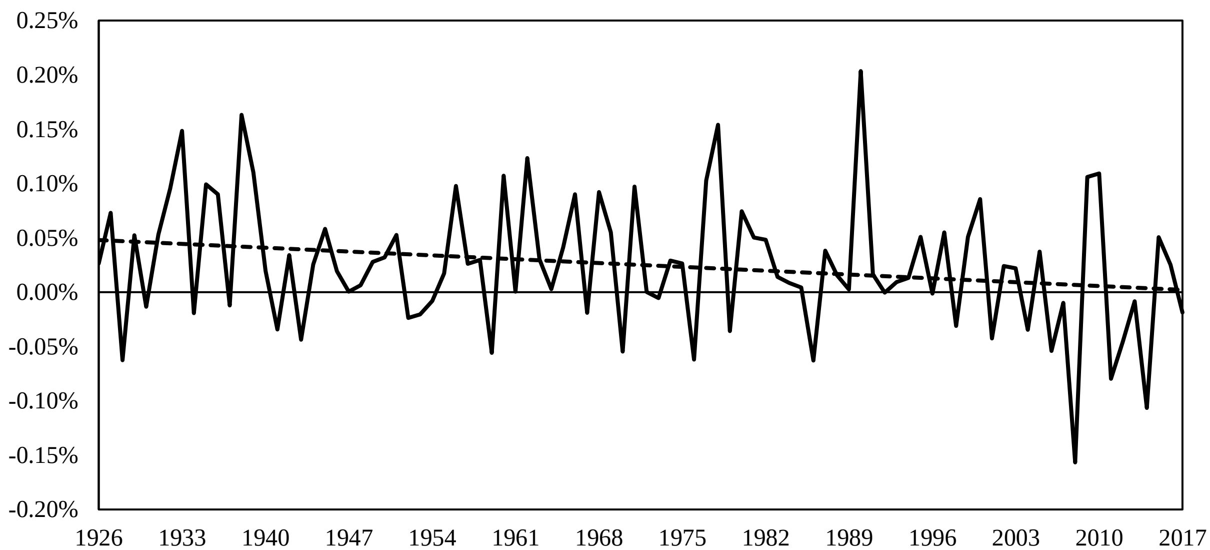

Figure A5. Average daily holiday effect (based on stock market returns on the trading days preceding New Year, Christmas and Independence Day)

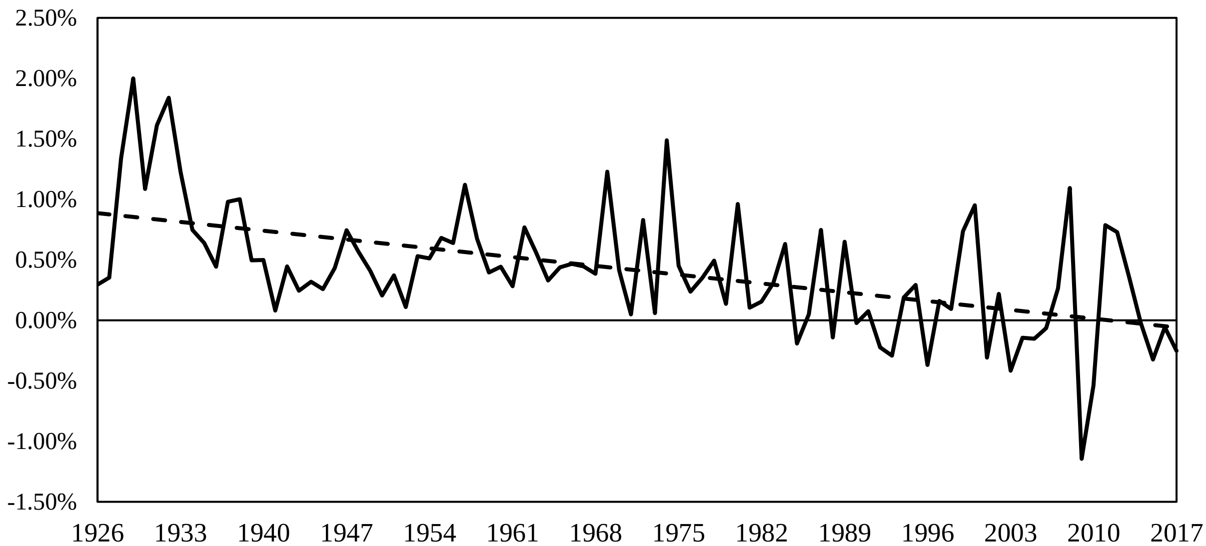

Figure A6. Monthly January effect

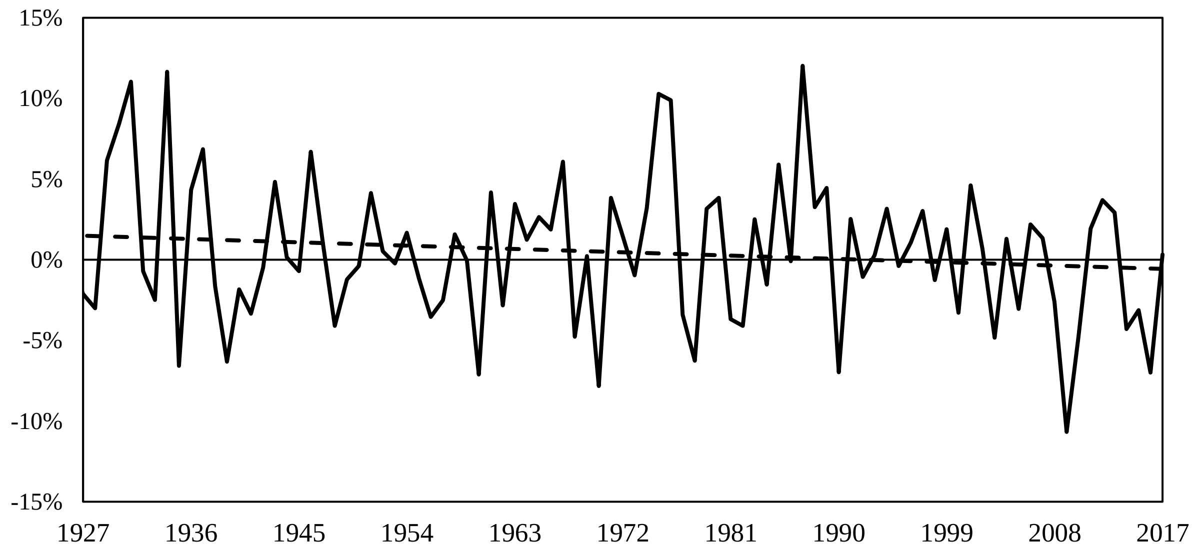

Figure A7. Annual small-minus-big (size) effect

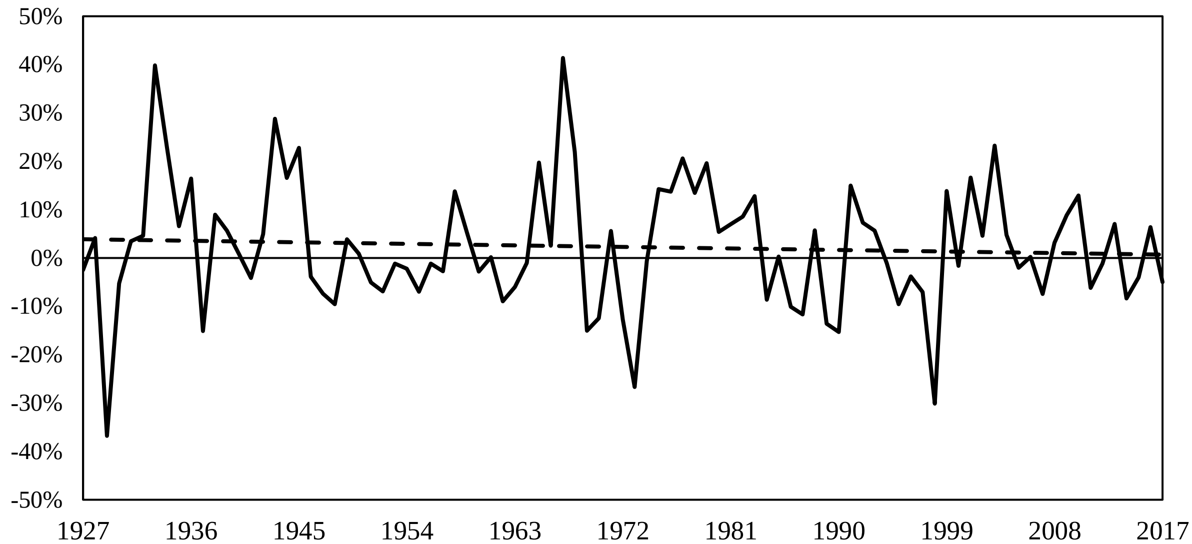

Figure A8. Annual high-minus-low (value) effect

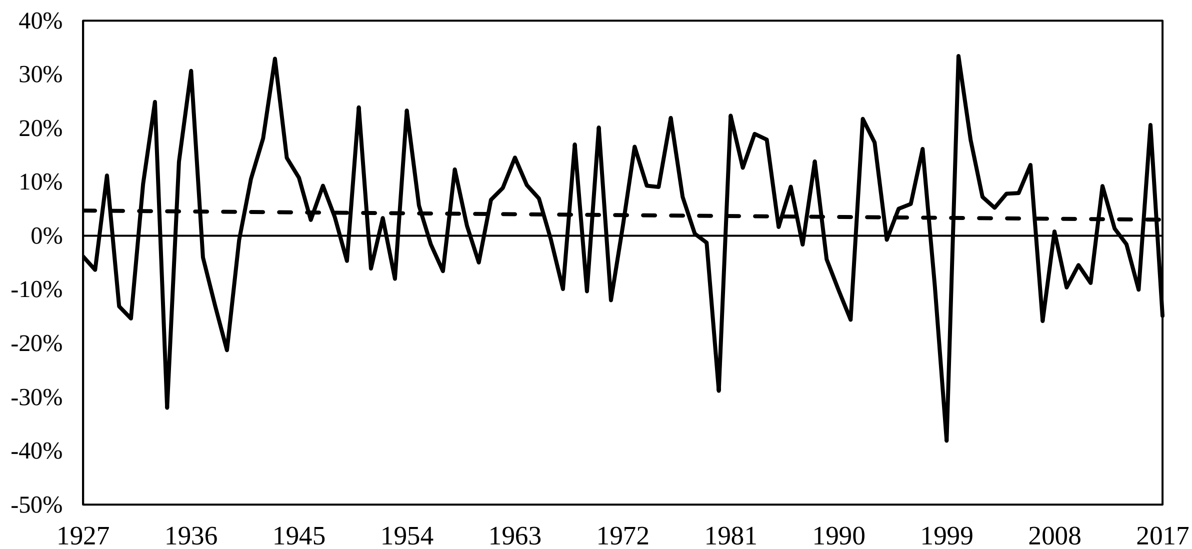

Figure A9. Annual winners-minus-losers (momentum) effect

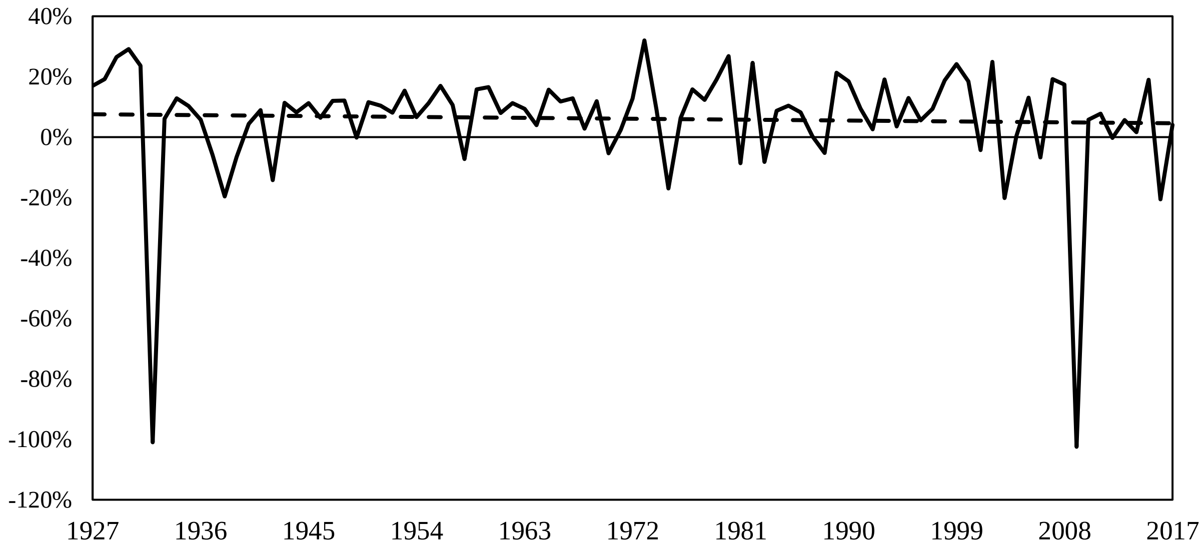

Figure A10. Annual robust-minus-weak (operating profitability) effect

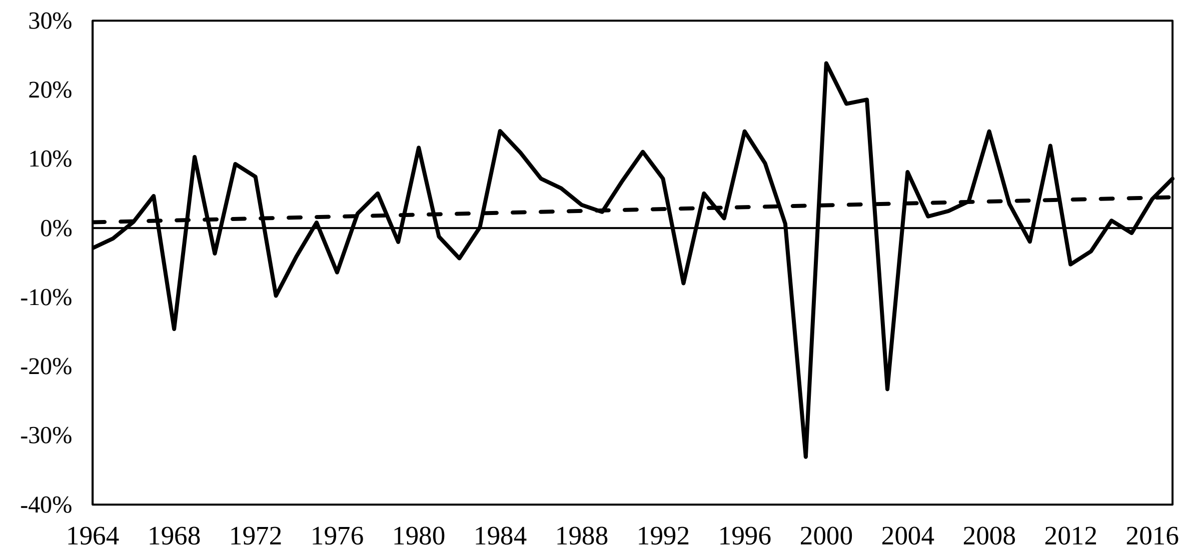

Figure A11. Annual conservative-minus-aggressive (investment) effect

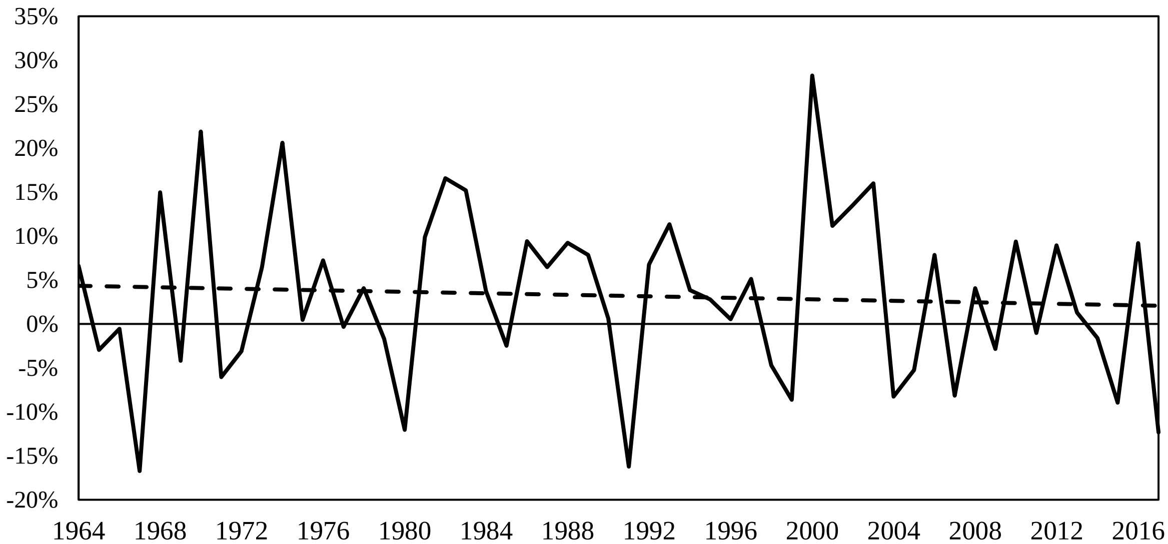

Figure A12. The dynamics of publications related to major anomalies

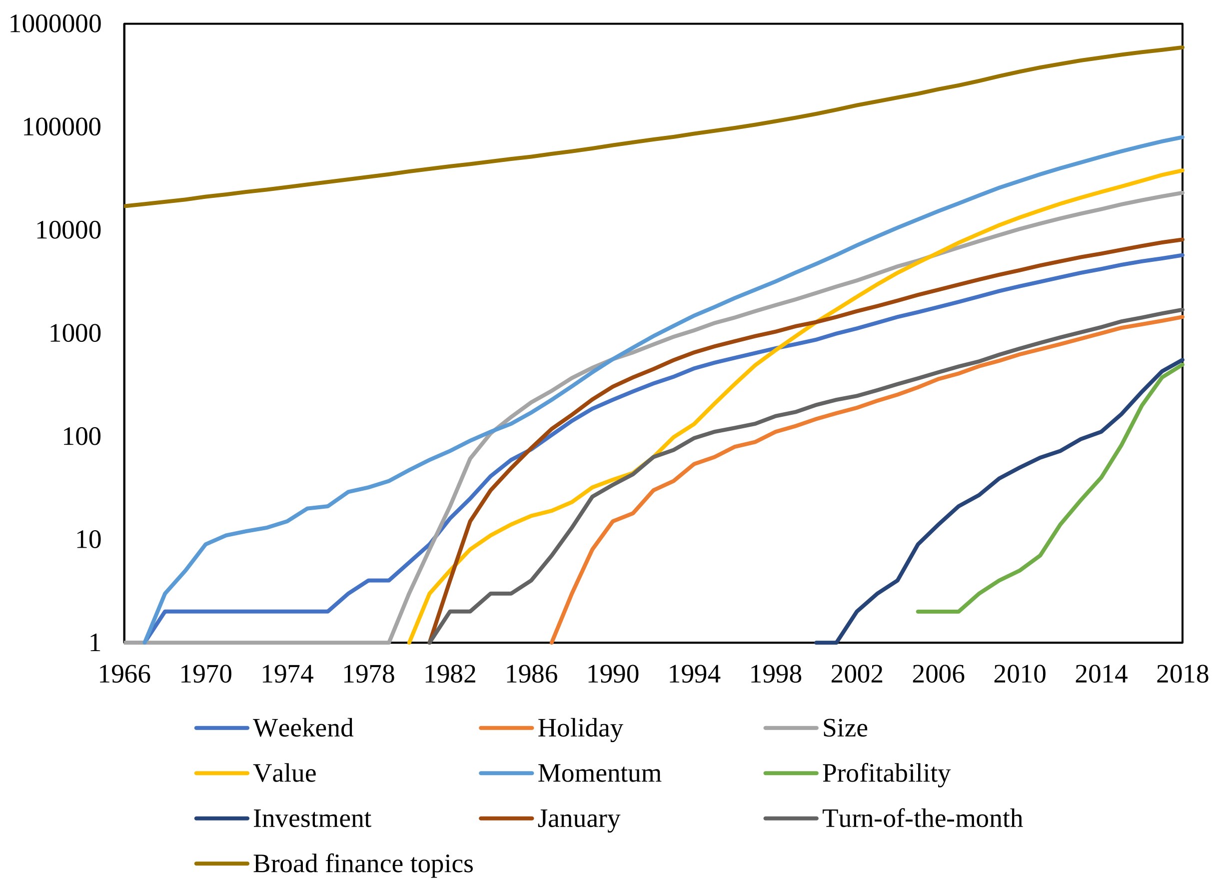

Figure A13. The dynamics of citation count attracted by major anomalies