Where Have the Profits Gone? Market Efficiency and the Disappearing Equity Anomalies in Country and Industry Returns

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Abstract

We are the first to demonstrate the decline in the predictability of country and industry returns in recent years. We examine 53 anomalies in country and industry indices from 64 markets for the years 1973–2018. The profitability of the strategies has significantly decreased during the last decade, driven particularly by the disappearance of value and reversal effects. The phenomenon is strongest in large developed markets. Neither changes in country- and industry-specific risks, nor investor learning from the academic literature is able to explain the effect. Our findings support the view that the fall in return predictability is caused by the overall improvement in market efficiency.

Keywords: equity anomalies, return predictability, international investment, country returns, industry returns, investor learning, market efficiency, value, size, momentum, low-risk, seasonality, long-run reversal, behavioural finance.

JEL codes: G11, G12, G14, G15, G41.

1. Introduction

Equity anomalies are a driving force of asset pricing research. Because equity anomalies can be directly translated into profitable investment strategies, anomaly research is one of the workhorses propelling the development of finance. Not surprisingly, some recent surveys literally enumerate hundreds of such return patterns in stock markets (see, e.g., Harvey, Liu, and Zhu 2016; Hou, Xue, and Zhang 2017; Jacobs and Muller 2018).

Paradoxically, equity anomalies can also be rather unreliable. Once broadly acknowledged, they tend to quickly disappear (Dimson and Marsh 1999). Due to investor learning, improved liquidity, or an increase in market efficiency, anomaly profitability is decreasing. The decline in the return predictability for the stock markets has been particularly pronounced in the last decade. Furthermore, it has affected not only individual well-established anomalies, such as size or momentum (van Dijk 2011; Bhattacharya, Li, and Sonaer 2017), but also the broad range of anomalies in general (McLean and Pontiff 2015; Jacobs and Müller 2018; Tobek and Hronec 2018). Simply put, the profitability of equity anomalies has markedly decreased.

The previous research on the fall in return predictability has concentrated mainly on firm-level anomalies. Meanwhile, numerous return patterns—such as value, momentum, seasonality, or low-risk—are omnipresent phenomena, observable not only in stocks, but also in other asset classes (Asness, Moskowitz, and Pedersen 2013; Frazzini and Pedersen 2014; Geczy and Samonov 2017; Keloharju, Linnainmaa, and Nyberg 2016; Fahiz, Boons, and Tamoni 2018). In fact, many of such phenomena help to predict future returns on country and equity indices (Balvers and Wu 2006; Keppler and Traub 1993; Kim 2012).

The study of the index-level equity anomalies is particularly important from a practical perspective. Since the proliferation of index-tracking investment vehicles in recent years, such as ETFs, index funds, or simple futures, investors can now more easily than ever before move their capital around, and do so across borders too. In this climate of one-click access to international equities, the index level return regularities provide investors a viable tool for equity allocation across markets and industries around the world.

The investor perspective on international equity markets, combined with the disappointing findings on firm-level return predictability, raises some important questions: Have the index-level equity anomalies shared the same fate as their stock-level counterparts? Has the return predictability of country and industry equity indices declined? Have the anomaly strategies become less profitable? If so, then why has it happened? The main objective of this article is to answer these questions. From a theoretical angle, the same arguments for the decline in return predictability which work at the stock level—that is, improved liquidity and efficiency or investor learning—could also be applied to countries and industries. Furthermore, the decrease in profits on the quantitative country selection strategies has already been signaled by some market practitioners (Evans and Schmitz 2015). Nevertheless, surprisingly, we are not aware of any paper that would attempt to address these questions from an academic perspective. Thus, our paper aims to fill this gap.

In this article, our goal is to contribute in two ways. First, we examine whether the recent years have displayed any significant change in the profitability of equity anomalies in country and industry indices. To this end, we replicate 53 anomaly strategies from the finance literature, using samples from 64 countries and 793 industry portfolios for the years 1973–2018. The anomalies belong to six major groups of well-researched return patterns: value, size, momentum, reversal, low-risk, and seasonality. Subsequently, using different specification and robustness checks, we examine the profitability in different subperiods to see whether recent years have brought any change in the return predictability. As far as we are concerned, there is no study in the finance literature to date that has examined this issue comprehensively.

Second, we ponder the possible reasons for the potential decline of index return predictability in recent years. We put forward and examine the following three hypotheses. First, we postulate that the changes in profitability may result from the time-series variation in the country- or industry-specific risk, which may in turn drive anomaly returns (Erb, Harvey, and Viskanta 1995; Zaremba 2016). Consequently, we introduce additional *ad hoc* asset pricing factors, accounting for country liquidity and idiosyncratic risk, and examine the extent to which they explain the time-series variation in anomaly returns. Next, we follow the ideas of McLean and Pontiff (2015) and Jacobs and Müller (2018) in evaluating whether investor learning from academic research contributes to the "destruction" of the index-level return predictability. We therefore run panel regressions with additional variables controlling for the research publications dates. Finally, we examine whether the decrease in return predictability could be linked to changes in the efficiency of the global markets. To this end, we follow Griffin, Kelly, and Nardari (2010) along with Bhattacharya, Li, and Sonaer (2017), who calculate the DELAY measure, reflecting the responsiveness of stock returns to past market payoffs.

The major findings of our study can be summarized as follows. First, we document a significant drop in return predictability at the country and industry levels in recent years. The profitability of the index-level equity anomalies has declined remarkably through the last 14 years. The most affected strategy categories—such as long-run reversal and value—no longer produce any significant profit. The size and momentum effects are less affected, whereas the performance of low-risk anomalies remain robust in all the tested subperiods.

Second, we observe that the decline in the profitability of the anomalies is particularly pronounced in large developed markets with low idiosyncratic risk, clearly linking the decrease in the return predictability to market efficiency.

Third, we demonstrate that the sole changes in the country- and industry-specific risks or investor learning from the academic literature are not sufficient in explaining the decline in the profitability of equity anomalies. The effect is still visible after controlling for these factors. On the other hand, the test by Griffin, Kelly, and Nardari (2010) indicates a surge in the overall efficiency of international equity markets during recent years. This observation supports the hypothesis that it is the improvement in informational efficiency that has contributed to the decline in the anomaly profitability.

This article adds to two major strains of the academic literature. First, we provide new insights into the rapidly growing literature on time-varying return predictability and falling profitability of equity anomalies (Bhattacharya, Li, and Sonaer 2017; Chordia, Roll, and Subrahmanyam 2011; Dimson and Marsh 1999; Jacobs 2016; Jacobs and Müller 2018; McLean and Pontiff 2015; Schwert 2003; Tobek and Hronec 2018; van Dijk 2011). We are the first to examine a similar phenomenon for countries and industries, as well as propose and test some potential explanations.

Second, we extend the research on cross-sectional patterns in country and industry returns (e.g., Asness, Liew, and Stevens 1997; Asness, Moskowitz, and Pedersen 2013; Bali and Cakici 2010; Balvers and Wu 2006; Balvers, Wu, and Gilliland 2000; Bhojraj and Swaminathan 2006; Fahiz, Boons, and Tamoni 2018; Frazzini and Pedersen 2014; Geczy and Samonov 2017; Harvey 2000; Keloharju, Linnainmaa, and Nyberg 2016; Keppler and Traub 1993; Kim 2012; Macedo 1995; Richards 1997; Umutlu 2015). We comprehensively reexamine these signals, allowing for comparison of their performance and inferences about the time-series variation of their profitability.

The remainder of the study is structured as follows. Section 2 presents the data and the sample-tested equity strategies. Section 3 concentrates on the time-series variation in the anomaly returns, while Section 4 reports on the additional subperiod and subsample analyses. Section 5 focuses on potential explanations of the decline of the index-level return predictability. Finally, Section 6 concludes the study.

2. Data and the Sample of Equity Strategies

We calculate the returns on equity anomalies based on the Datastream Global Equity Indices downloaded from the Thomson Reuters Datastream. In particular, we focus on two categories of indices, representing the country and industry portfolios. The country sample includes all 64 equity markets covered by the Datastream, encompassing developed, emerging, and frontier economies. The industry sample splits the country equity markets into 19 supersectors, as classified by the Industry Classification Benchmark: automobiles and parts, banks, basic resources, chemicals, construction and materials, financial services, food and beverage, healthcare, industrial goods and services, insurance, media, oil and gas, personal and household goods, real estate, retail, technology, telecommunications, travel and leisure, and utilities (FTSE Russel 2018). Importantly, we exclude sector baskets representing investment vehicles rather than actual companies, i.e., real estate investment trusts (ID 8670), equity investment instruments (ID 8980), and non-equity investment instruments (ID 8990). Since not each supersector is available in each country, our initial sample includes 1105 industry portfolios.

The sample period for returns covers a time span from February 1973 to August 2018, relying on all the data available in the Datastream. The first 36 months are used solely for estimating our return predictive variables for the anomalies. This means that the actual period of the investigated anomaly returns runs from February 1976 to August 2018. Similar to numerous cross-national studies (e.g., Fama and French 2012), all the price and return data are converted to U.S. dollars. Consistent with this framework, the risk-free rate is proxied using the benchmark U.S. 3-month T-bill rate, obtained from French (2018).

We clean the data with a few basic dynamic filters aimed at assuring the quality of our sample and aligning it with investors' perspectives. First, we include only the index-month observations when both the return in month t and its capitalization at the end of t-1 are available.

Second, we drop the industry portfolios with the total capitalization below 500 USD million at the end of *t*-1. Third, to control for the potential errors in the database we exclude the observations with monthly returns below –98% or above 500%. The filters significantly affect the number of considered industries, limiting it to 793. The final number of monthly return observations amounts to 22,793 and 212,199 for countries and industries, respectively. Tables 1 and 2 report the basic statistical properties of the country and industry indices examined in this study.

[Insert Table 1 here]

[Insert Table 2 here]

To investigate the changes in return predictability, we replicate 53 index-level anomaly strategies. We focus only on the broadly acknowledged and well-established patterns in the cross-section of returns, which have been established across many asset classes and during long periods. The strategies are based on the six major groups of return predictive variables that have been documented to play a significant role in forecasting index returns: value (Macedo 1995; Kim 2012), size (Keppler and Traub 1993; Zaremba and Umutlu 2018), seasonality (Keloharju, Linnainmaa, and Nyberg 2016), reversal (Balvers, Wu, and Gilliland 2000; Spierdijk, Bikker, and van der Hoek 2012), momentum (Bhojraj and Swaminathan 2006; Balvers and Wu 2006), and low-risk (Frazzini and Pedersen 2014). For robustness, within each category, we implement the strategies using a number of alternative specifications and approaches, inspired by both academic and practitioner literature on the firm-level return patterns. When it is suitable, to assure robustness, we relax the formulas from the original papers and use some alternative definitions or formation periods. For the value, in particular, we use a range of different valuation ratios; for size, we use a few differently sized proxies, such as capitalization, enterprise value, or total assets; for seasonality– a number of different measurement widnows, and risk-adjustment and alternative formation period for the long-run reversal. The momentum class encompasses a broad array of trend-following, breakthrough, pure, and adjusted momentum strategies. Finally, the low-risk signals are based on different systematic or non-systematic risk measures, estimated during various periods. A detailed description of the return-predictive variables, as well as implementation methods of the examined sample of the index-level anomalies, is outlined in Table A1 in the Internet Appendix.

The individual strategies are implemented using a consistent procedure. First, we rank all of the indices—representing countries or industries—on a return predictive variable associated with a particular anomaly. Subsequently, we select quintile portfolios, including the indices with the highest and lowest signals. For robustness, we weigh the portfolios using two alternative methods: equally and according to the capitalization. Finally, we form zero-investment strategies, going long for the indices with the highest return predictive variables and simultaneously shorting the countries or industries with the lowest return predictive variables. If the anomaly-associated variable can predict future payoffs, the strategies should display abnormal returns.

Apart from the individual strategies, we also derive the composite strategies. Here, we equally average all of the returns within each anomaly category: value, size, seasonality, reversal, momentum, and low-risk. The aim of computing the composite strategies is to minimize the influence of noise and purge on the underlying anomaly profits.

Since some of the strategies are based on the patterns underlying the popular asset pricing models, we evaluate their performance with the simple world CAPM of Sharpe (1964) and Lintner (1965), which incorporates only the global market risk:

$$R_{i,t} = \alpha_i + \beta_{MKT,i}\, MKT_t + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the excess return on a long-short anomaly portfolio i in month t, $\varepsilon_{i,t}$ represents the error term, while α_i and β_{MKTt} denote the estimated regression parameters. MKT_t is the excess return on the global equity portfolio, i.e., the value-weighted portfolio of all of the 64 country indices considered in the study.

The performance of the equity anomalies is reported in Tables A2 and A3 in the Internet Appendix, while Table 3 presents the returns on the composite strategies. For the equally-weighted portfolios (Table 3, Panel A), almost all of the composite strategies produce significant raw and CAPM-adjusted returns, both for countries and industries. The notable exception is the seasonality strategy, with profits not significantly departing from zero. The detailed outcomes for the individual strategies in Table 2 reveal that it admittedly works slightly better for industry portfolios—especially in the cases of long-run sorting periods—but the profitability is still not particularly impressive. In fact, this matches the observations of Keloharju, Linnainmaa, and Nyberg (2016), who examined the seasonality effect across a few asset classes and found that it was relatively weak for the equity indices. Nevertheless, despite the weak performance of the seasonality anomalies, the overall profitability of the *Total* portfolio aggregating all the strategies is particularly strong: its alphas amount to 0.51% (*t*-stat = 6.69) and 0.53% (*t*-stat = 8.03), when implemented within the country and industry universes, respectively.

[Insert Table 3 here]

The profitability of the composite value-weighted anomaly portfolios (Table 3, Panel B) is somewhat weaker. It corroborates the arguments of Hong, Lim, and Stein (2000), among others, that certain behaviourally-driven equity anomalies are more pronounced among assets with small capitalization, as these market segments are less efficient. The decline in profitability relative to the equally-weighted scheme has affected the reversal strategies and the size effect in particular. The composite size anomalies no longer produce significant mean raw or abnormal returns in the country setting, while the profits from the long-term reversal composite portfolios do not significantly depart from zero either within the country or industry sample. The overall alpha on the *Total* portfolio of all of the 52 strategies equals to 0.33% (*t*-stat = 3.62) and 0.41% (*t-stat* = 4.83) for the country and industry portfolios, respectively.

3. Time-Series Variation in the Profitability of Index-Level Anomalies

Having established the basic properties of the country- and industry level equity anomalies, we now continue with examining the dynamics of their profitability. Figure 1 depicts the profitability of the *Total* portfolio, aggregating the returns on all of the 53 anomalies. In this regard, Panel A of Figure 1, which shows the cumulative returns on the long-short strategies, demonstrates that capital appreciation has been relatively stable through the long-run. Nonetheless, the last 10–15 years seem to have brought on some weakening in the profit generation process, and the figure has visibly flattened, particularly in the case of the value-weighted portfolios.

[Insert Figure 1 here]

Panel B of Figure 1 takes another perspective on the same phenomenon—it displays rolling 10-year average returns on the anomaly portfolios. During the most recent decade, the profitability of the value-weighted portfolios, both of countries and industries, has virtually declined to zero. The equally-weighted strategies still retained some value in this period, although their performance record was the poorest from the start of the measurement period.

Figures A1 and A2 present the results from Figure 1, digging into the performance of the particular composite strategies. Examination of the differences across the various classes of anomalies suggests that the decline in profitability was most evident for the reversal strategies. In this case, the long-run profits have turned into massive losses during the last 10–20 years. The effectiveness of equity allocation based on size and value effects is also visible, although less pronounced. For momentum, the decrease in profits is characteristic for the value-weighted strategies, whereas their equally-weighted counterparts appear largely unaffected.

Finally, the low-risk anomalies prove to be the most robust, demonstrating strong profits through the full study period, including the most recent years.

To further investigate the time-series variation in profitability of anomaly returns, we split the full study period into three roughly equal subperiods: 1976–1990, 1991–2004, and 2005–2018, and subsequently examine their performance within.

Table 4 reports the performance of the index-level anomalies within the three subperiods. The outcomes confirm that the return predictability has visibly decreased during the last decade. Let us take the country portfolios as an example. For the equally-weighted portfolios, the alphas on the *Total* strategies, that equally weigh all of the anomalies, amounted to 0.56% and 0.63% in the years 1976–1990 and 1991–2004, respectively, and subsequently decreased to 0.33% in the years 2005–2018. For the value-weighted strategies, the decline in the raw and risk-adjusted returns was even more pronounced. In consequence, neither the mean of returns (0.12%), nor the alpha (0.10%) significantly departed from zero. The storyline of the industry-based portfolios is quite similar.

[Insert Table 4 here]

To verify whether the average returns or alphas in the last subperiod significantly deviate from their counterparts in the earlier years, we run the following regressions:

$$R_{i,t} = \beta_{0,i} + \beta_{M,i} M_t + \varepsilon_{i,t}, \tag{2}$$

$$R_{i,t} = \beta_{0,i} + \beta_{MKT,i} MKT_t + \beta_{M,i} M_t + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the return on the composite long-short anomaly portfolio *i* in month *t*, $\varepsilon_{i,t}$ represents the error term, and $\beta_{0,i}$, $\beta_{MKT,i}$, and $\beta_{M,i}$ are the regression coefficients. M_t represents the dummy variable equal to one, if month *t* belongs to a considered subperiod. The models (2) and (3) refer to the changes in the mean returns and alphas, respectively.

Importantly, the results of the formal investigations with regression model (3), demonstrated in Table 5, confirm the weakening profitability within the last subperiod (2005–

2018). For all our specifications, i.e., for value-weighted and equally-weighted portfolios of countries and industries, the last subperiod displays a significantly lower profitability than the long-term average, both on the raw and risk-adjusted basis.

[Insert Table 5 here]

Consistent with our initial observations, the deterioration of profitability is the strongest for the reversal anomalies. Again, let the countries serve as an example: the alpha on the composite equally-weighted (value-weighted) *Reversal* portfolio drops from 1.19% (1.27%) in the years 1976–1990 to –0.24% (–0.49%) in the years 2005–2018. Similarly, the value strategies—once profitable—markedly suffered in the last subperiod. After a significant decline in the profitability (confirmed by the outcomes in Table 5), the alphas decreased to only 0.02% and 0.03% for the equally-weighted and value-weighted strategies, respectively, no longer significantly departing from zero. Finally, as in Bhattacharya, Li, and Sonaer (2017), the outcomes in Tables 4 and 5 point to a significant deterioration in the momentum performance. This, however, refers only to the value-weighted portfolios, whereas the effect is less pronounced for the equally-weighted strategies.

So far, our results indicate that the recent years have brought on a remarkable decline in the profitability of the composite equity anomalies at the index-level. To provide some additional insights, we conduct two supplementary tests. First, as we report in Table A4 of the Internet Appendix, we check whether our results are dependent on some specific portfolio construction methods. Consequently, we replicate the analysis based on the anomaly portfolios formed in the 10% and 30% of the most extreme countries or industries in each leg (as opposed to the 20% benchmark in the default approach). As demonstrated in Table A4, this operation has had no qualitative influence on the results.

Next, we apply the test, represented by regression equation (3), not only to the composite anomalies but also to the 53 individual strategies displayed in Tables A1–A3. In particular, we focus on the question of whether the profitability generated off particular strategies has significantly dropped in the last subperiod, i.e., 2005–2018. The insights provided in Table A5 confirm that the drop in the returns has most significantly affected the reversal strategies and, to a lesser extent, the value anomalies. In the latter case, the drop in payoffs has predominantly influenced the country portfolios. As for the momentum anomalies, although the majority of the regression coefficients are negative, only some of them, such as *RMOM* or *VARMOM*, significantly depart from zero. Finally, the low-risk or seasonality anomalies do not demonstrate any visible decrease in the average returns or alphas.

4. Further Robustness Checks: Subsample and Subperiod Analysis

Our considerations in Section 2 demonstrate that return predictability stemming from equity anomalies at the index level has significantly deteriorated during the recent years. To assure the robustness of this finding and provide additional insights, we now investigate this phenomenon within the subsamples and for the particular time frames.

4.1. Performance within Subsamples

Let us start with the subsample analysis. A number of recent studies indicate that the equity anomalies are particularly pronounced in certain market segments. Since the behavioural view on equity anomalies is such that they reflect limited investor rationality that cannot be easily arbitraged away, some studies argue that the anomalies are the strongest among assets which are difficult to arbitrage and in market segments where new information is absorbed less efficiently (e.g., Arena, Haggard, and Yan 2008; Brav, Heaton, and Li 2010; Hong, Lim, and Stein 2000; Jiang, Lee, and Zhang 2005; Li, Rodney, and Sullivan 2011; Li, Sullivan, and Garica-Feijóo 2014; Stambaugh, Yu, and Yuan 2015). Moreover, due to similar reasons, there may be differences in the price efficiency between the developed and emerging markets (Bekaert and Harvey 2002; Bhattacharya, Daouk, Jorgenson, and Kehr 2000; Griffin, Kelly, and Nardari 2010), which also applies to the index-level studies (Zaremba and Miziołek 2017).

Inspired by these ideas, we examine the decline of the performance of equity anomalies within three subsamples of the main sample, splitting it based on the capitalization, idiosyncratic volatility, and market development. Each month, we divide the sample into two equal subsamples based on the following characteristics: (a) the median aggregate capitalization of the index portfolio at the end of month *t*-1, (b) the median idiosyncratic risk from the CAPM, estimated through the trailing 60-month period, and (c) classification into developed or emerging markets, according to Thomson Reuters. Subsequently, we apply regression model (3) within the pairs of subsamples. The results of these examinations are reported in Table 6.

[Insert Table 6 here]

The decline in profitability is visibly higher in the following three categories of assets: developed countries, large capitalization markets or indices, and universes with a low-idiosyncratic risk. Within these segments, the decline of profitability on the *Total* portfolio (aggregating all of the examined anomalies) in the years 2005–2018 was significant in all of the cases and for all of the examined specifications, i.e., for both equally- and value-weighted portfolios as well as across countries and industries. On the other hand, for the small, high-idiosyncratic risk indices from the emerging markets, the decrease in profitability was also visible. However, it was too small to be considered significant.

The observations in Table 6 clearly highlight the link between the deterioration of return predictability and market efficiency. Unfortunately, they also have rather pessimistic implications for equity investors pursuing international quantitative strategies. Our findings mean that in large and developed markets, which at the same time are the most accessible for investors, the country and index allocation strategies have not worked well recently. These markets are inherently more likely to be covered by futures and exchange-traded funds, which are characterized by low trading costs and minimal capital mobility constraints. On the other hand, in market segments that are not easily accessible (due to regulatory barriers, high transaction costs, or lack of coverage with convenient investment vehicles), the deterioration in return predictability has not been as profound.

4.2. Performance within Subperiods

We now turn to the role of the specific market states or calendar periods in explaining the fall in returns on the index-level equity anomalies. In particular, we consider the role of the following issues. First, a number of studies indicate that certain equity anomalies display some calendar regularities, demonstrating some specific patterns in January. This phenomenon has been investigated with, for example, momentum (Haug and Hirschey 2006), size (Horowitz, Loughran, and Savin 2000; Zaremba and Umutlu 2018), and value (Davis 1994). Therefore, we test the changes in return predictability in January and other months.

Second, a number of studies accentuate that market states, be they bullish or bearish, measured with past returns (Cooper, Gutierrez, and Hameed 2004) or volatility (Wang and Xu 2015), influence the anomaly returns, and the momentum effect may just serve as an example. Motivated by these studies, we split the full study period into a number of subperiods: (a) subperiods of positive and negative total excess return on the market portfolio during the last 12 months, and (b) subperiods of above-median and below-median standard deviation of the excess returns on the market portfolio during the last 12 months. The results of these robustness checks are reported in Table 7.

[Insert Table 7 here]

Panel A of Table 7 suggests that the fall in return predictability was stronger following the bear markets than in the bull markets. Although in both the subperiods the change in the profitability of the *Total* anomaly portfolio was negative, the effect was robustly significant only for the bear markets. A detailed analysis shows that the drop was the highest for the momentum strategies. For example, taking the value-weighted portfolios into consideration, the alpha on the composite momentum portfolio in the years 2005–2018 was lower by -1.43% (-1.12%) in the country (industry) setting compared to the long-run norm. This may be linked to the famous "momentum crash" following the global financial crisis of 2008–09, which has had a detrimental impact on the performance of trend-following strategies (Daniel and Moskowitz 2016).

Panel B of Table 7 focuses on the return predictability, following high and low market volatility. The decrease appears to be slightly larger in the high volatility markets. Taking the value-weighted country (industry) *Total* portfolios as an example, the influence of the years 2005–2018 on the market adjusted returns amounts to -0.47% (-0.40%) in the high volatility states, and -0.23% (-0.33%) in the low volatility states. The differences are visible though not dramatic.

Finally, Panel C of Table 7 presents the $\beta_{M,t}$ coefficients for January and the remaining months. Indeed, the coefficient for the *Total* portfolio, aggregating all the anomalies, was significant only for the other months and not for January. Here, the lack of significance, however, stems from a much smaller number of monthly observations for the January subsamples than those in the other months. In fact, the mere value of the coefficient is similar in both the subperiods, so it does not seem that calendar seasonalities have played any major role in the weakening of the return predictability of country and industry indices.

5. Possible Explanations for the Decline in Return Predictability

So far, we have demonstrated that the return predictability at the index level has markedly decreased through recent years. Let us now move on to explaining the cause of this change. As already mentioned, we consider three potential explanations for the fading anomaly profitability: (1) time-series variation country- and industry-specific risks, (2) investor learning from research discoveries, and (3) overall improvement in market efficiency.

5.1. Time-Varying Country- and Industry-Specific Risks

Erb, Harvey, and Viskanta (1995) and Zaremba (2016) argue that profits on certain country-level equity anomalies are merely a compensation for the country-specific type of risk. Hence, the decline in the anomaly profitability could result from time-series variation in these risks. To check this, we extend regression model (3) to account for the two additional non-diversifiable risks: liquidity and idiosyncratic volatility.

We measure liquidity in month t, LIQ_t, similarly as in Datar, Nauk, and Radcliffe (1998), as a ratio of total dollar volume to total market capitalization in month t-1. The second variable, $IVOL_t$, is the idiosyncratic risk from the CAPM estimated during months t-60 to t-1. Having obtained these return predictive variables, we follow the concepts in the study of Fama and French (1993) and design the factors as zero-investment long-short value-weighted portfolios, including 30% of the indices in their long and short legs. To form our *ad hoc* liquidity factor —denoted as "illiquid minus liquid" (IML)— each month we rank all the markets on LIQ_t. Subsequently, we sort the indices into tertiles based on the LIQ_t. variable. Next, we value-weight the portfolios in the tertiles with the highest and lowest LIQ_t to obtain portfolios of indices. Finally, the IML factor portfolio is a zero-investment strategy that goes long (short) the assets with the lowest (highest) liquidity measured with LIQ_t. Importantly, the factors used to evaluate country and industry strategies are derived separately from the samples of country and industry indices, respectively. In other words, when we evaluate the country-based strategies, the factors are composed of country indices, and for the evaluation of industry-based portfolios we use factors formed of industry indices.

The idiosyncratic volatility factor—called "risky minus safe" (RMS)— is formed in an analogous way as IML, but the underlying sorting variable is $IVOL_t$. Concretely, RMS buys (sells) a value-weighted tertile portfolio indices with the highest (lowest) $IVOL_t$.

Our extended model is represented by regression equation (4):

$$R_{i,t} = \alpha_i + \beta_{MKT,i}\, MKT_t + \beta_{IML,i}\, IML_t + \beta_{RMS,i}\, RMS_t + \varepsilon_{i,t}, \tag{4}$$

where β_{IMLi}, and $\beta_{RMS,i}$, represent measures of exposure to risk *IML* and *RMS* risk factors.

Table 8 reports on the application of the three-factor model (4) to the composite equity anomalies. Some of the anomalies, indeed, display significant exposure to the liquidity and idiosyncratic risk factors. For example, the value, size, reversal, and low-risk strategies demonstrate some bias toward illiquid countries and industries. Here, too, the size strategies are more heavily allocated in the indices of high idiosyncratic volatility. Nonetheless, the additional risk factors are not able to explain the performance of the anomalies on the whole. The *Total* portfolios, aggregating all the anomalies in the equally- or value-weighted country or industry settings, continue to produce significant abnormal returns during the entire study period.

[Insert Table 8 here]

The investigation in Table 9 goes one step further by including the dummy variable representing the years 2005–2018 in the considered model:

$$R_{i,t} = \alpha_i + \beta_{M,i} M_t + \beta_{MKT,i} MKT_t + \beta_{IML,i} IML_t + \beta_{RMS,i} RMS_t + \varepsilon_{i,t}. \tag{5}$$

By doing so, we aim to test whether the return predictability has decreased in the years 2005–2018, even after accounting for the role of the index-specific liquidity and idiosyncratic risk.

[Insert Table 9 here]

The results in Table 9 do not support the idea that the decrease in profitability stemmed from the changes in index-specific risk. Although the IML and RMS factors may strive to explain part of the time-series variation, they can most certainly not tell the entire story behind the recent fall in the return predictability. The examination of the payoffs of the *Total* portfolio $\beta_{M,t}$ reveals that the alphas have significantly decreased for both the value- and equally-weighted strategies in both the country and industry universes. Indeed, there is some variation for the particular strategies. For example, although the fall in the profitability is still the strongest for the reversal effect, the decline in the performance of the value strategies is no longer significant. Nevertheless, the overall picture is clear: the average anomaly performance has decreased, even after accounting for illiquidity and idiosyncratic volatility risks. In other words, the variation in these risks does not explain the decline in the performance of the index-level anomalies.[1]

5.2. Investor Learning from Research Discoveries

McLean and Pontiff (2015) indicate that the fall in the predictability of firm-level returns may result from investor learning from academic publications, and Jacobs and Muller (2017) as well as Tobec and Hronec (2018) follow up on this concept. The underlying idea is that investors pursue strategies allowing them to capitalize on the discovered return patterns, thus contributing to their extinction. To verify this conjecture, we closely follow the methodology of McLean and Pontiff (2015) and run a panel regression. In doing so, we include a dummy variable representing the post-publication period, *PUBt*, which is equal to one in each month, starting from the first year following the publication, and zero otherwise. Subsequently, as in McLean and Pontiff (2015), we run the random effects panel regressions aimed at examining the role of the post-publication period for returns, but on a stand-alone basis, and also after controlling for all the other risk factors and variables:

$$R_{i,t} = \alpha_i + \beta_{PUB}\, PUB_{i,t} + \varepsilon_{i,t}, \tag{6}$$

$$R_{i,t} = \alpha_i + \beta_{PUB}\, PUB_{i,t} + \beta_{M,i}\, M_t + \beta_{MKT,i}\, MKT_t + \beta_{IML,i}\, IML_t + \beta_{RMS,i}\, RMS_t + \varepsilon_{i,t}, \tag{7}$$

where $R_{i,t}$ is the returns on an individual anomaly (out of 53) i in month t, and β_{PUB} represents the decline in profitability for the post-publication date.

[1] Table A6 in the Online Appendix additionally reports the results of regression model (3), which is estimated within the three investigated subperiods: 1976–1990, 1991–2004, and 2005–2018. The results point to a consistent conclusion: the decline in the profitability is visible.

Contrary to stock-level studies, defining a publication date for the index-level return patterns is not straightforward. First, the investors could have possibly picked up on an anomaly once it had been documented at the level of individual securities, and not necessarily only after a parallel effect had been documented at the index level. Second, not all of the variants of the stock-level anomalies have been researched at the country level. For example, although the classical 12-month momentum effect has been frequently researched for industries and countries, it is not necessarily true for all its variants, such as the intermediate momentum effect of Novy-Marx (2013). Third, if some anomalies are closely related to each other and follow the same pattern, such as the regular momentum effect of Jegadeesh and Titman (1993) and the residual momentum effect of Blitz, Huij, and Martens (2011), pursuing one of them may lead to a decrease in the profitability of the other. Last but not least, some anomalies may be, in fact, only the manifestations of other anomalies. For example, although Moskowitz, Ooi, and Pedersen (2012) indicate that the time-series momentum is an independent return anomaly, Goyal and Jegadeesh (2018) argue that it is only a variant of the classical cross-sectional momentum with the time-varying equity exposure.

Consequently, to assure the robustness and reliability of our results, we consider the following three different definitions of the "publication date". The first approach assumes the actual publication date of the article on a given anomaly at the firm level, according to the dates indicated explicitly in Table A1 in the Online Appendix. The second framework takes the publication date of the first representative anomaly in each class, i.e., value, momentum, size, etc., at the firm level. Here, the six considered articles are Basu (1977) for value, Banz (1981) for size, Jegadeesh and Titman (1993) for momentum, DeBondt and Thaler (1985) for reversal, Ang, Hodrick, Xing, and Zhang (2006) for low risk, and Heston and Sadka (2008) for cross-sectional seasonality. The third method relies on using the publication dates of the first representative parallel anomalies in each class, documented at the index level. The six papers that we take into account for this category are Macedo (1995) for value; Keppler and Traub (1993) for size; Asness, Liew, and Stevens (1997) for momentum; Richards (1997) for reversal; Frazzini and Pedersen (2014) for low risk; and Keloharju, Linnainmaa, and Nyberg (2016) for seasonality. The results of the panel regressions are displayed in Table 10.

[Insert Table 10 here]

Panel A of Table 10 shows the results of simple regressions (6). For robustness, we demonstrate the outcomes for countries and industries, using two weighting methods and three different publication date definitions. At first glance, it may appear that the publication date indeed exerts some effect on the level of abnormal returns on the anomalies. The β_{PUB} coefficients are negative and significant across all the specifications. Theoretically, it may seem as if the publication date indeed could have an impact on future performance. Nonetheless, the outcomes in Panel B of Table 10 shed additional light on this issue.

Once we control for the additional risk factors and the dummy variable representing the period 2005–2018, the role of the publication date becomes predominantly irrelevant. Meanwhile, the β_M coefficients retain their significance across all of the specifications. In other words, once we jointly control for the period 2005–2018 and the post-publication date, it is the 2005–2018 time frame which prevails, no matter how we define the publication date. The research discoveries do not seem to be the major source of the decline in index return predictability. Summing up, our evidence does not support the idea that investor learning leads to the decline in the profitability of anomalies.

5.3. Overall Improvement in Market Efficiency

Our final conjecture stipulates whether it is the general improvement in market efficiency that contributes to the decline in the return predictability. By definition, in a more efficient market, it is much more difficult to predict future payoffs on securities, and the same applies to portfolios of these securities. Thus, the decline in the anomaly profitability can be interpreted as evidence of improvement in market efficiency. The reason for that may be, for instance, that new information gets impounded into prices faster in the more recent years. To check this, we use the *DELAY* measure by Griffin, Kelly, and Nardari (2010), which reflects the degree of response of equity returns to past market returns. In particular, we follow the implementation by Bhattacharya, Li, and Sonaer (2017).

We compute the *DELAY* measure by subtracting the adjusted R^2 coefficient on the unrestricted market model (R^2_{UNR}) from the R^2 of the restricted model (R^2_R):

$$DELAY = R^2_{UNR} - R^2_R. \quad (8)$$

Both models are derived from monthly data. The unrestricted model assumes regressing the portfolio *i* return on the contemporaneous market return, as well as four monthly lags of the market return:

$$R_{i,t} = \beta_{0,i} + \beta_{1,i}MKT_t + \beta_{2,i}MKT_{t-1} + \beta_{3,i}MKT_{t-2} + \beta_{4,i}MKT_{t-3} + \beta_{5,i}MKT_{t-4} + \varepsilon_{i,t}. \quad (9)$$

In the restricted model, all the coefficients on the lagged market returns are constrained to zero, and thus, as a result, the model takes the form of equation (1). Closely following Bhattacharya, Li, and Sonaer (2017), we apply this test to five portfolios from one-way sorts on index market capitalization. Furthermore, we apply this test to both equally- and value-weighted portfolios of countries and industries. In particular, we calculate the test for the *DELAY* measures for the years 2005–2018 and compare with its counterpart for the earlier years. The outcomes of these tests are illustrated in Figure 2.

[Insert Figure 2 here]

In line with our conjectures, the *DELAY* measure was lower in the years 2005–2018 than in the earlier period. Admittedly, there was some variation in its absolute value. The *DELAY* was visibly higher for the small markets and industries than for their large counterparts. This, as we have already noted, is intuitively understandable, since the small assets are usually characterized by, e.g., higher limits to arbitrage. Nonetheless, the decline in the *DELAY* measure was visible for nearly all the size groups, for both equally- and value-weighted portfolios, as well as across countries and in industries. To conclude, the market efficiency has clearly improved, and this phenomenon may have rightfully contributed to the decreased return predictability. Observations from our last round of tests support the hypothesis that the decline in anomaly profitability may have been driven by the improvement in overall market efficiency around the globe.

6. Concluding Remarks, Limitations, and Areas for Future Research

In this study, we aim at examining the time-series variation in the return predictability at the country and industry level, measured with the profitability of index-level anomalies. To this end, we investigate 64 country indices and 793 industry portfolios for the years 1973–2018. We show that the abnormal returns on the anomaly strategies have markedly decreased in recent years, and the decline has affected reversal and value strategies, in particular. The change in the payoffs was particularly pronounced in large, developed markets characterized by low idiosyncratic risk.

We also test the three potential sources of this effect. We demonstrate that the decline in profitability cannot be fully explained by either time-series changes in the country and industry-specific risks, or by investors learning from the academic literature. Our results support the idea that the fall in return predictability results from the overall improvement in the efficiency of international equity markets.

Our results contribute to the existing body of literature from both the academic and practitioner perspectives. On the one hand, they provide new insights into asset pricing, return predictability, and market efficiency at the country and industry level. On the other hand, they have explicit implications for the investment practice. Quantitative portfolio managers with an international mandate should be careful when implementing country or industry selection strategies based on such concepts as reversal, value, or momentum. Although these approaches used to work well in the past, they may be disappointing today and in the future.

One of the limitations of this paper, which creates potential opportunities for future research on the topic discussed, is the rather weak link between the improved market efficiency and the falling profitability of the anomalies. In particular, we left open the question of the particular mechanism that links the efficiency with the anomaly performance. Future studies may, for instance, focus on an increase in arbitrage capital in particular markets to disentangle this issue further. The Achilles' heel of this idea is that the relevant data—in particular for distant historical periods and emerging markets—is hardly available.

The concept of market efficiency is also closely linked to trading costs. Lower transaction costs facilitate more active trading and thus contribute to improved market efficiency. In an extreme case, the post-cost profitability of anomalies might have remained largely unchanged, whereas the pre-cost profitability might have indeed decreased. Again, the data shortage on the inter-country and intra-country trading costs for certain frontier and emerging countries, as well as for distant historical periods, makes examining this issue difficult within the scope of this paper.

Researching the issues discussed above may potentially shed light on some other interesting questions: What is the source of cross-sectional differences in the decline of profitability? Why did the return predictability by long-run reversal diminish more severely than for low-risk or momentum? Is it due to changes in trading costs or investor activity?

Finally, the ideas researched in our study may be extended also to other asset classes. Many of the investigated strategies have their counterparts in, e.g., corporate bonds or commodities. Do these assets also experience a decline in return predictability? As of now, this question remains unanswered.

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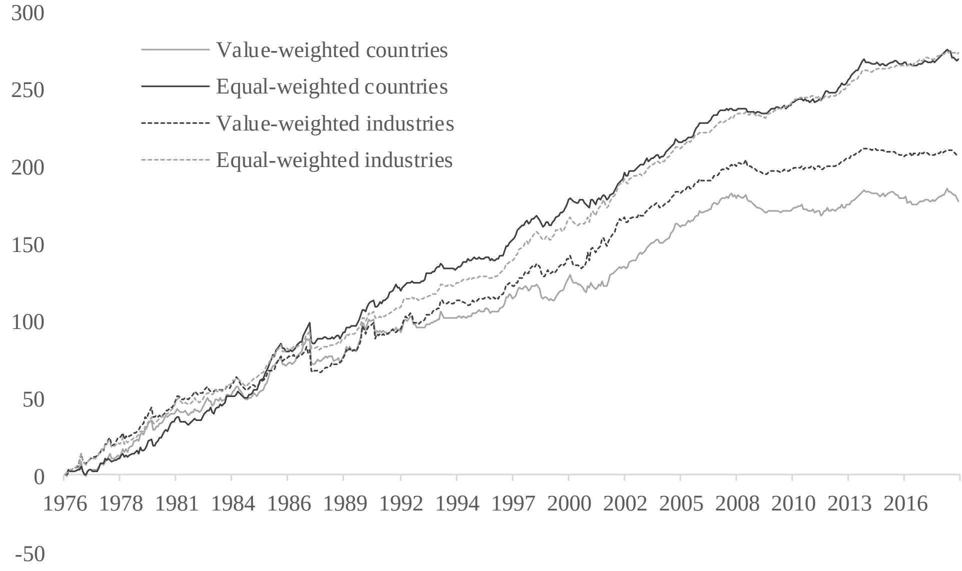
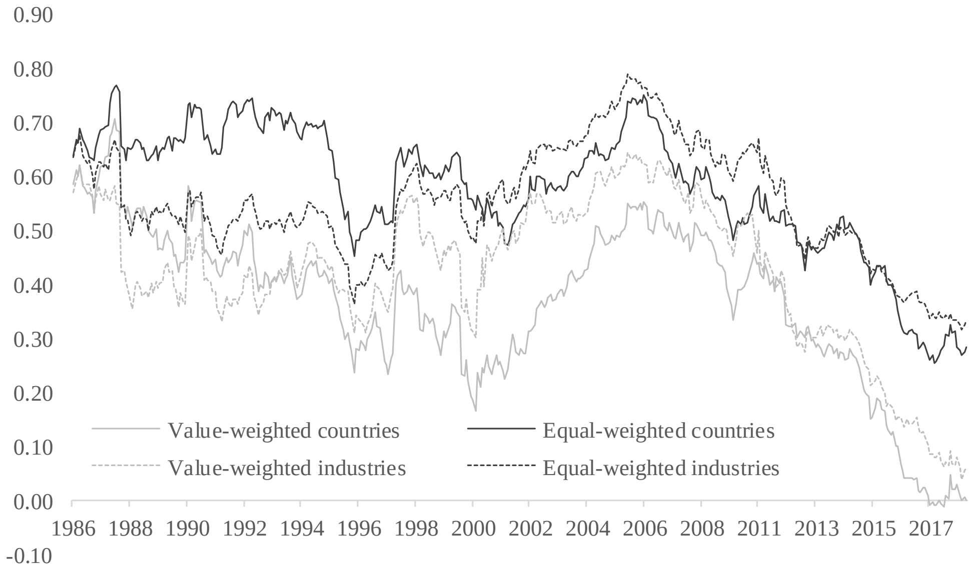
Figures



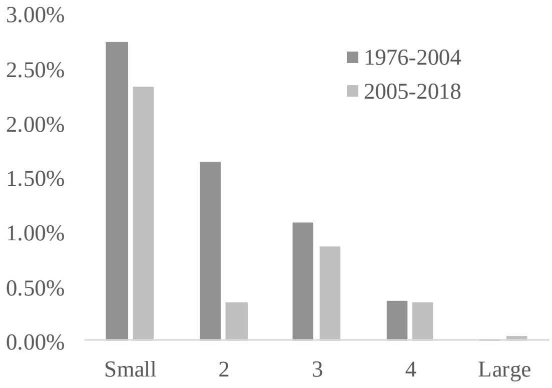
Panel A: Cumulative Returns.



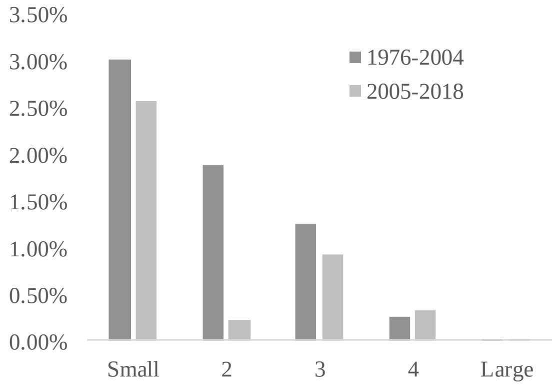
Panel B: Trailing 10-Year Average Returns.

Figure 1: *Time-Series Variation in Returns on Composite Equity Allocation Strategies*

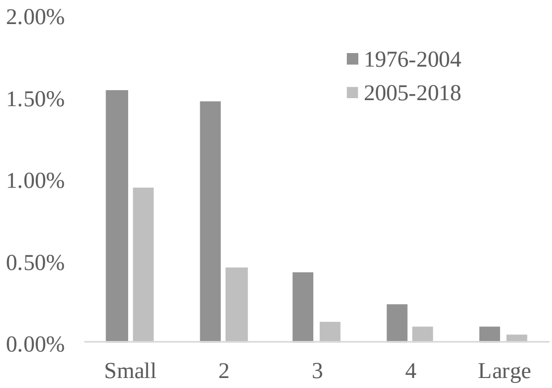
Note. The figure presents the cumulative raw returns (expressed in percentages, cumulated additively) on composite international long-short value-weighted and equity-weighted portfolios of countries and industries. The composite strategies equally weigh all of the 53 individual strategies described in Section 2.



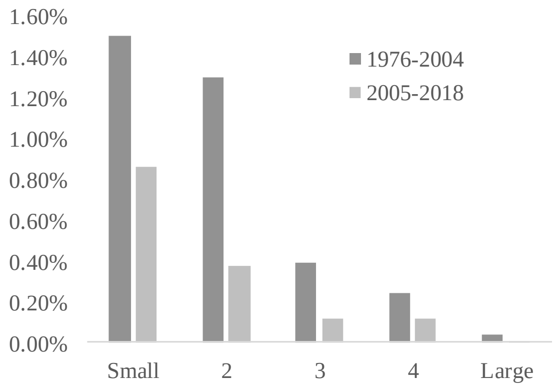
Panel A: Equally-Weighted Portfolios of Countries



Panel B: Value-Weighted Portfolios of Countries



Panel C: Equally-Weighted Portfolios of Industries



Panel D: Value-Weighted Portfolios of Industries

Figure 2: *Changes in Measures of DELAY in International Markets*

Note. This figure demonstrates the DELAY measures for the equally-weighted and value-weighted size quintiles of countries and industries. The DELAY measures are calculated by subtracting the adjusted R^2 of the unrestricted market model from the adjusted R^2 of the restricted model, as described in Section 5. The restricted model considers only the contemporaneous market return, whereas the unrestricted model also incorporates the four monthly lags. The DELAY measures are estimated separately for the last subperiod from Table 6 (2005–2018) compared to the earlier years (1976–2004). The DELAY measures are reported in percentages.

Tables

Table 1

Statistical Properties of the Sample of Country Indices

Country	R	Vol	N	MV	Country	R	Vol	N	MV
Argentina	0.50	9.85	300	3.73	Malta	0.38	4.89	223	0.34
Australia	0.66	6.96	547	41.49	Mexico	1.09	7.97	351	21.48
Austria	0.83	7.02	416	5.99	Morocco	0.85	4.87	293	3.32
Bahrain	0.28	3.52	176	1.90	Netherlands	0.68	5.40	547	30.99
Belgium	0.60	5.67	547	13.14	New Zealand	0.73	6.10	367	3.22
Brazil	0.97	10.25	289	53.82	Nigeria	0.28	7.18	107	4.66
Bulgaria	0.53	9.05	167	0.31	Norway	0.80	7.67	463	10.25
Canada	0.50	5.34	547	61.92	Oman	0.35	4.52	154	1.81
Chile	1.04	6.40	349	11.28	Pakistan	0.79	9.07	313	2.56
China	1.16	10.11	301	29.62	Peru	0.82	6.34	295	4.02
Colombia	0.78	7.74	317	7.16	Philippines	0.87	8.20	371	7.38
Croatia	0.54	7.42	154	2.12	Poland	0.60	9.78	293	7.93
Cyprus	0.34	11.40	308	0.57	Portugal	0.32	6.03	343	5.48
Czechia	0.98	8.46	297	2.76	Qatar	1.08	8.55	176	11.07
Denmark	0.76	5.71	547	9.46	Romania	1.12	11.21	223	1.39
Egypt	0.73	8.64	263	3.67	Russia	1.41	11.93	247	41.97
Finland	0.81	7.93	365	13.79	Singapore	0.57	7.95	547	16.19
France	0.73	6.48	547	81.18	Slovenia	0.43	5.94	236	0.70
Germany	0.56	5.84	547	70.92	South Africa	0.80	8.00	547	15.64
Greece	0.30	10.45	343	6.08	South Korea	0.78	10.06	371	41.37
Hong Kong	0.95	9.33	547	58.74	Spain	0.67	6.49	377	42.90
Hungary	1.07	9.87	300	1.92	Sri Lanka	0.62	7.61	339	0.58
India	1.09	9.73	343	53.06	Sweden	0.95	6.90	439	25.23
Indonesia	0.53	10.72	340	12.86	Switzerland	0.64	4.97	547	51.22
Ireland	0.69	6.54	524	4.21	Taiwan	0.66	9.73	363	32.41
Israel	0.55	6.40	307	8.22	Thailand	1.14	9.78	379	11.40
Italy	0.50	7.40	547	32.74	Turkey	1.24	14.98	367	9.56
Japan	0.40	5.87	547	248.95	UAE	1.10	7.85	176	14.31
Jordan	0.12	4.72	146	2.50	UK	0.63	6.19	547	151.50
Kuwait	0.44	5.35	176	8.61	USA	0.56	4.38	547	797.15
Luxembourg	0.68	5.59	319	2.63	Venezuela	3.46	24.66	295	1.35
Malaysia	0.81	7.96	391	16.64	Vietnam	0.33	8.22	136	3.88

Note. The table presents the sample of the DS country equity indices examined in this study. *R* is the mean monthly excess return, *Vol* is the standard deviation, *N* is the number of monthly observations, and *MV* is the mean market value of the stocks in the index portfolio expressed in USD billion.

Table 2

Statistical Properties of the Sample of Industry Indices

Industry	R	Vol	N	MV
Oil & Gas	0.52	9.97	254.23	3.82
Chemicals	0.88	10.77	244.96	1.41
Basic Resources	0.46	11.01	270.98	1.92
Construction & Materials	0.46	9.84	271.66	0.96
Industrial Goods & services	0.69	10.12	283.20	4.05
Automobiles & Parts	0.40	10.24	243.14	2.14
Food & Beverage	0.55	9.14	278.44	1.95
Personal & Household Goods	0.48	8.90	233.86	2.46
Healthcare	0.54	8.68	261.78	4.32
Retail	0.48	8.90	229.96	2.44
Media	1.34	11.25	245.85	1.63
Travel & Leisure	0.51	9.19	196.31	1.07
Telecommunications	0.60	9.81	262.25	2.80
Utilities	0.69	8.55	259.65	2.39
Banks	0.73	9.65	313.70	4.98
Insurance	0.46	9.15	249.53	2.29
Real Estate Investment & Services	0.75	10.33	219.81	1.41
Financial Services	0.15	10.10	224.67	2.01
Technology	0.37	11.73	222.58	5.45

Note. The table presents the sample of the DS industry equity indices examined in this study. *R* is the mean monthly excess return, *Vol* is the standard deviation, *N* is the number of monthly observations, and *MV* is the mean market value of the stocks in the index portfolio expressed in USD billion. To obtain the values reported in the table, we first compute the time-series averages for the individual industries, and, subsequently, we calculate cross-sectional averages across the 64 considered countries.

Table 3

Returns on Composite Anomaly Portfolios

	Countries				Industries			
	R	t-stat$_R$	α	t-stat$_\alpha$	R	t-stat$_R$	α	t-stat$_\alpha$
Panel A: Equally-Weighted Strategies								
Value	0.55***	*(4.59)*	0.57***	*(4.10)*	0.49***	*(6.70)*	0.51***	*(4.78)*
Size	0.38***	*(2.79)*	0.48***	*(2.64)*	0.35***	*(3.51)*	0.40***	*(3.48)*
Seasonality	-0.04	*(-0.19)*	-0.08	*(-0.41)*	0.22*	*(1.68)*	0.20	*(1.52)*
Reversal	0.50***	*(3.27)*	0.49**	*(2.56)*	0.38***	*(2.78)*	0.39**	*(2.29)*
Momentum	0.79***	*(4.70)*	0.85***	*(4.49)*	0.81***	*(5.36)*	0.90***	*(5.40)*
Low-Risk	0.45***	*(4.42)*	0.26**	*(2.16)*	0.44***	*(5.11)*	0.28***	*(2.94)*
Total	0.53***	*(8.06)*	0.51***	*(6.69)*	0.54***	*(8.60)*	0.53***	*(8.03)*
Panel B: Value-Weighted Strategies								
Value	0.48***	*(3.98)*	0.47***	*(2.95)*	0.31***	*(2.73)*	0.35**	*(2.28)*
Size	0.23	*(1.26)*	0.30	*(1.45)*	0.28***	*(2.62)*	0.29**	*(2.05)*
Seasonality	-0.18	*(-0.76)*	-0.23	*(-1.04)*	0.11	*(0.65)*	0.04	*(0.24)*
Reversal	0.20	*(0.92)*	0.24	*(1.02)*	0.07	*(0.33)*	0.16	*(0.69)*
Momentum	0.41**	*(2.26)*	0.48***	*(2.75)*	0.62***	*(3.47)*	0.71***	*(4.34)*
Low-Risk	0.45***	*(4.42)*	0.26**	*(2.16)*	0.44***	*(5.11)*	0.28***	*(2.94)*
Total	0.35***	*(4.25)*	0.33***	*(3.62)*	0.40***	*(5.20)*	0.41***	*(4.83)*

Note. The table reports the returns on the composite equally-weighted and value-weighted long-short anomaly portfolios of the country and industry indices. The first column indicates the category of the strategy. *R* is the mean monthly return, α is the abnormal return from the CAPM, and t-stat$_R$ and t-stat$_\alpha$ are the corresponding bootstrap and Newey-West (1987) adjusted t-statistics. The composite strategies that equally weigh all of the individual anomaly portfolios are outlined in Tables A1-A3 in the Internet Appendix. The asterisks ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4

Returns on Composite Strategies within Subperiods

	Equally-Weighted Portfolios						Value-Weighted Portfolios					
	1976-1990		1991-2004		2005-2018		1976-1990		1991-2004		2005-2018	
	R	α	R	α	R	α	R	α	R	α	R	α
Panel A: Countries												
Value	0.62***	0.70***	0.92***	0.97***	0.09	0.02	0.57*	0.69**	0.70***	0.68***	0.17	0.03
	(2.69)	*(2.93)*	*(4.27)*	*(4.87)*	*(0.46)*	*(0.08)*	*(1.79)*	*(1.97)*	*(3.14)*	*(3.05)*	*(1.05)*	*(0.19)*
Size	0.29	0.35	0.57**	0.72**	0.29*	0.36	0.05	0.14	0.46	0.57	0.18	0.19
	(1.22)	*(1.09)*	*(2.19)*	*(2.23)*	*(1.78)*	*(1.55)*	*(0.12)*	*(0.38)*	*(1.56)*	*(1.42)*	*(0.86)*	*(0.78)*
Seasonality	-0.03	-0.14	-0.27	-0.30	0.16	0.19	-0.01	-0.15	-0.64*	-0.67*	0.12	0.13
	(-0.16)	*(-0.36)*	*(-0.75)*	*(-0.78)*	*(0.68)*	*(0.85)*	*(-0.08)*	*(-0.32)*	*(-1.87)*	*(-1.89)*	*(0.60)*	*(0.60)*
Reversal	1.17***	1.19***	0.47	0.47	-0.21	-0.24	1.20***	1.27***	-0.08	-0.14	-0.59*	-0.49
	(3.83)	*(4.49)*	*(1.06)*	*(1.16)*	*(-0.81)*	*(-0.95)*	*(2.73)*	*(3.15)*	*(-0.37)*	*(-0.32)*	*(-1.70)*	*(-1.57)*
Momentum	0.96***	0.90**	0.77***	0.88**	0.61**	0.75***	0.69**	0.65*	0.50	0.60*	0.02	0.14
	(3.29)	*(2.49)*	*(2.84)*	*(2.49)*	*(2.42)*	*(3.61)*	*(1.98)*	*(1.90)*	*(1.56)*	*(1.86)*	*(-0.27)*	*(0.66)*
Low-risk	0.28	0.07	0.53***	0.35	0.55***	0.35***	0.28	0.07	0.53***	0.35	0.55***	0.35***
	(1.25)	*(0.32)*	*(2.60)*	*(1.44)*	*(3.45)*	*(2.66)*	*(1.25)*	*(0.32)*	*(2.60)*	*(1.44)*	*(3.45)*	*(2.66)*
Total	0.61***	0.56***	0.62***	0.63***	0.34***	0.33***	0.52***	0.48**	0.39***	0.38***	0.12	0.10
	(4.46)	*(3.58)*	*(5.92)*	*(4.99)*	*(3.52)*	*(3.33)*	*(2.69)*	*(2.26)*	*(3.06)*	*(2.64)*	*(1.25)*	*(1.14)*
Panel B: Industries												
Value	0.34**	0.41***	0.75***	0.81***	0.39***	0.31**	0.08	0.23	0.76***	0.84***	0.10	-0.01
	(2.14)	*(2.64)*	*(5.11)*	*(4.56)*	*(3.58)*	*(2.21)*	*(0.33)*	*(0.97)*	*(3.69)*	*(3.17)*	*(0.77)*	*(-0.08)*
Size	0.17	0.22	0.49***	0.54**	0.40***	0.45***	0.23	0.29	0.42**	0.44	0.20	0.15
	(1.03)	*(1.10)*	*(2.94)*	*(2.22)*	*(3.23)*	*(3.56)*	*(1.16)*	*(1.46)*	*(2.25)*	*(1.44)*	*(1.19)*	*(0.87)*
Seasonality	0.35	0.30	-0.06	-0.08	0.37***	0.36**	0.20	0.02	-0.12	-0.13	0.25	0.23
	(1.38)	*(1.18)*	*(-0.13)*	*(-0.30)*	*(2.75)*	*(2.56)*	*(0.54)*	*(0.04)*	*(-0.39)*	*(-0.55)*	*(1.18)*	*(1.08)*
Reversal	0.71**	0.78***	0.52	0.52	-0.12	-0.15	0.68*	0.86**	-0.04	-0.01	-0.49	-0.42
	(2.53)	*(3.16)*	*(1.55)*	*(1.48)*	*(-0.42)*	*(-0.58)*	*(1.66)*	*(2.07)*	*(-0.14)*	*(-0.02)*	*(-1.58)*	*(-1.44)*
Momentum	0.93***	0.90***	0.85***	0.99***	0.63***	0.78***	0.83**	0.84**	0.74**	0.86**	0.28	0.41*
	(3.39)	*(2.90)*	*(2.83)*	*(2.99)*	*(3.11)*	*(4.52)*	*(2.51)*	*(2.53)*	*(2.09)*	*(2.46)*	*(1.02)*	*(1.93)*
Low-risk	0.37**	0.18	0.63***	0.51***	0.33***	0.17	0.37**	0.18	0.63***	0.51***	0.33***	0.17
	(2.00)	*(0.94)*	*(3.90)*	*(2.66)*	*(2.78)*	*(1.56)*	*(2.00)*	*(0.94)*	*(3.90)*	*(2.66)*	*(2.78)*	*(1.56)*
Total	0.57***	0.54***	0.64***	0.67***	0.39***	0.38***	0.51***	0.51***	0.54***	0.56***	0.16**	0.14**
	(4.42)	*(3.74)*	*(5.80)*	*(5.83)*	*(6.35)*	*(6.47)*	*(3.13)*	*(2.76)*	*(3.85)*	*(3.99)*	*(2.12)*	*(2.16)*

Note. The table reports the returns on the composite equally-weighted long-short anomaly portfolios of the country and industry indices. The composite portfolios equally weigh all of the strategies in a given class: *Value*, *Size*, *Seasonality*, *Reversal*, *Momentum*, and *Low-Risk*, and the *Total* portfolio equally weighs all the 53 strategies considered in the study. *R* is the mean monthly return, *α* is the abnormal return from the CAPM, and the numbers in brackets are the corresponding bootstrap and Newey-West (1987) adjusted *t*-statistics for R and α, respectively. *Panels A* and *B* present the results for the portfolios of countries and industries, respectively. The vertical sections demonstrate outcomes for the subperiods 1976–1990, 1991–2004, and 2005–2018, respectively. The asterisks ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5

Decline in Profitability in the Years 2005 – 2018

	Panel A: Countries				*Panel B: Industries*			
	Equal-weighted portfolios		Value-weighted portfolios		Equal-weighted portfolios		Value-weighted portfolios	
	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)
Value	-0.67**	-0.67**	-0.46*	-0.46*	-0.15	-0.15	-0.31	-0.31
	(-2.42)	*(-2.37)*	*(-1.67)*	*(-1.65)*	*(-0.80)*	*(-0.77)*	*(-1.24)*	*(-1.18)*
Size	-0.14	-0.13	-0.07	-0.06	0.07	0.07	-0.12	-0.12
	(-0.42)	*(-0.39)*	*(-0.18)*	*(-0.16)*	*(0.33)*	*(0.35)*	*(-0.49)*	*(-0.47)*
Seasonality	0.31	0.30	0.43	0.43	0.22	0.22	0.20	0.20
	(0.87)	*(0.87)*	*(1.20)*	*(1.19)*	*(1.02)*	*(1.02)*	*(0.62)*	*(0.61)*
Reversal	-1.04***	-1.04***	-1.16***	-1.16***	-0.74**	-0.74**	-0.82**	-0.82**
	(-3.03)	*(-3.03)*	*(-2.69)*	*(-2.72)*	*(-2.28)*	*(-2.28)*	*(-1.99)*	*(-2.05)*
Momentum	-0.27	-0.26	-0.58*	-0.58*	-0.26	-0.26	-0.51*	-0.50*
	(-0.78)	*(-0.79)*	*(-1.78)*	*(-1.72)*	*(-0.89)*	*(-0.86)*	*(-1.68)*	*(-1.68)*
Low-risk	0.15	0.13	0.15	0.13	-0.16	-0.17	-0.16	-0.17
	(0.46)	*(0.68)*	*(0.46)*	*(0.68)*	*(-0.64)*	*(-1.08)*	*(-0.64)*	*(-1.08)*
Total	-0.27*	-0.27**	-0.33**	-0.33**	-0.21**	-0.21**	-0.36***	-0.36***
	(-1.94)	*(-2.04)*	*(-2.14)*	*(-2.25)*	*(-2.04)*	*(-2.05)*	*(-2.85)*	*(-2.83)*

Note. The table reports the values of the $\beta_{M,i}$ coefficients along with the Newey-West adjusted *t*-statistics (in brackets) from the regression equations (A) and (B), as indicated by the columns' captions:

$$R_{i,t} = \beta_{0,i} + \beta_{M,i} M_t + \varepsilon_{i,t}, \qquad \text{(A)}$$

$$R_{i,t} = \beta_{0,i} + \beta_{MKT,i} MKT_t + \beta_{M,i} M_t + \varepsilon_{i,t}, \qquad \text{(B)}$$

respectively, where $R_{i,t}$ is the return on a composite long-short anomaly portfolio *i* in month *t*, $\varepsilon_{i,t}$ represents the error term, and $\beta_{0,t}$, $\beta_{MKT,t}$, and $\beta_{M,t}$ are estimated regression coefficients. MKT_t denotes the excess return on the global equity portfolio, and M_t is the dummy variable equal to one, if month *t* belongs to the subperiod 2005–2018, or zero otherwise. *EW* and *VW* refer to the equally-weighted and value-weighted anomaly portfolios, respectively. The composite portfolios equally weigh all of the strategies in a given class: *Value*, *Size*, *Seasonality*, *Reversal*, *Momentum*, and *Low-Risk*, and the *Total* portfolio equally weighs all the 53 strategies considered in the study. *Panels A* and *B* present the results for the portfolios of countries and industries, respectively. The asterisks ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6

Changes in Profitability of Index-Level Strategies – Subsample Analysis

	Countries				Industries			
	EW	VW	EW	VW	EW	VW	EW	VW
	Panel A: Developed vs. Emerging Markets							
	Developed markets		Emerging markets		Developed markets		Emerging markets	
Value	-0.68***	-0.43*	-0.69*	-0.54	-0.27	-0.35	-0.15	-0.49
	(-3.40)	*(-1.82)*	*(-1.68)*	*(-1.14)*	*(-1.19)*	*(-1.30)*	*(-0.59)*	*(-1.41)*
Size	-0.34	-0.16	-0.32	-0.30	0.11	-0.12	-0.01	-0.21
	(-1.53)	*(-0.62)*	*(-0.70)*	*(-0.59)*	*(0.50)*	*(-0.49)*	*(-0.05)*	*(-0.76)*
Seasonality	0.16	0.01	0.39	-0.06	0.01	0.17	0.35	0.38
	(0.61)	*(0.04)*	*(0.77)*	*(-0.15)*	*(0.03)*	*(0.55)*	*(0.92)*	*(0.82)*
Reversal	-1.07***	-0.61	-0.29	-0.53	-0.71**	-0.77**	-0.33	-0.53
	(-3.22)	*(-1.57)*	*(-0.68)*	*(-1.35)*	*(-2.18)*	*(-2.00)*	*(-0.89)*	*(-1.33)*
Momentum	-0.69**	-0.82***	0.21	-0.27	-0.54*	-0.60**	0.53	0.32
	(-2.30)	*(-2.60)*	*(0.55)*	*(-0.61)*	*(-1.89)*	*(-2.22)*	*(1.44)*	*(0.79)*
Low-risk	-0.13	-0.13	0.29	0.29	-0.31***	-0.31***	0.14	0.14
	(-1.03)	*(-1.03)*	*(1.60)*	*(1.60)*	*(-2.60)*	*(-2.60)*	*(1.57)*	*(1.57)*
Total	-0.51***	-0.46***	-0.04	-0.21	-0.37***	-0.43***	0.16	0.00
	(-4.99)	*(-3.67)*	*(-0.21)*	*(-1.04)*	*(-3.80)*	*(-3.72)*	*(1.13)*	*(-0.01)*
	Panel B: Large vs. Small Markets							
	Large markets		Small markets		Large markets		Small markets	
Value	-0.50*	-0.38	-0.79**	-0.43	-0.32	-0.32	0.02	0.08
	(-1.93)	*(-1.38)*	*(-1.99)*	*(-1.10)*	*(-1.43)*	*(-1.17)*	*(0.11)*	*(0.40)*
Size	-0.03	-0.10	0.41	0.74	0.07	-0.08	0.18	0.15
	(-0.11)	*(-0.32)*	*(1.01)*	*(1.49)*	*(0.40)*	*(-0.35)*	*(1.15)*	*(1.14)*
Seasonality	0.36	0.61*	0.17	-0.29	0.04	-0.01	0.31	0.34
	(1.15)	*(1.87)*	*(0.32)*	*(-0.67)*	*(0.17)*	*(-0.02)*	*(1.09)*	*(1.12)*
Reversal	-0.72*	-0.70	-0.84*	-0.74	-0.83**	-0.79**	-0.57	-0.69*
	(-1.92)	*(-1.64)*	*(-1.78)*	*(-1.61)*	*(-2.47)*	*(-2.02)*	*(-1.58)*	*(-1.86)*
Momentum	-0.53*	-0.39	0.06	-0.26	-0.47	-0.52*	-0.03	-0.18
	(-1.77)	*(-1.33)*	*(0.13)*	*(-0.51)*	*(-1.56)*	*(-1.80)*	*(-0.07)*	*(-0.52)*
Low-risk	-0.08	-0.08	0.18	0.18	-0.12	-0.12	-0.05	-0.05
	(-0.83)	*(-0.83)*	*(1.06)*	*(1.06)*	*(-1.27)*	*(-1.27)*	*(-0.60)*	*(-0.60)*
Total	-0.33***	-0.25**	-0.13	-0.15	-0.32***	-0.37***	-0.05	-0.11
	(-2.88)	*(-2.08)*	*(-0.78)*	*(-0.82)*	*(-2.91)*	*(-3.17)*	*(-0.47)*	*(-0.97)*
	Panel C: High vs. Low Idiosyncratic Risk							
	High idiosyncratic risk		Low idiosyncratic risk		High idiosyncratic risk		Low idiosyncratic risk	
Value	-0.88**	-0.77***	-0.48**	-0.45*	-0.21	-0.51	-0.21	-0.34
	(-2.02)	*(-3.04)*	*(-2.54)*	*(-1.89)*	*(-0.87)*	*(-1.51)*	*(-1.14)*	*(-1.33)*
Size	-0.26	-0.18	-0.34	-0.34	-0.05	-0.22	-0.03	-0.21
	(-0.60)	*(-0.38)*	*(-1.48)*	*(-1.27)*	*(-0.23)*	*(-0.79)*	*(-0.15)*	*(-0.96)*
Seasonality	-0.14	-0.39	0.39	0.36	0.19	0.44	0.18	0.13
	(-0.28)	*(-0.74)*	*(1.48)*	*(1.27)*	*(0.61)*	*(0.99)*	*(1.01)*	*(0.53)*
Reversal	-1.07**	-1.13**	-0.34	-0.60*	-0.76*	-0.93*	-0.47*	-0.73**
	(-2.28)	*(-2.41)*	*(-1.23)*	*(-1.75)*	*(-1.85)*	*(-1.93)*	*(-1.86)*	*(-2.14)*
Momentum	0.05	-0.55	-0.38	-0.53*	0.00	-0.42	-0.36	-0.43*
	(0.12)	*(-1.29)*	*(-1.39)*	*(-1.85)*	*(0.00)*	*(-1.00)*	*(-1.47)*	*(-1.77)*
Low-risk	0.20	0.20	-0.09	-0.09	-0.07	-0.07	-0.10	-0.10
	(1.26)	*(1.26)*	*(-0.68)*	*(-0.68)*	*(-0.78)*	*(-0.78)*	*(-0.88)*	*(-0.88)*
Total	-0.26	-0.42**	-0.26**	-0.34***	-0.13	-0.33*	-0.23**	-0.33***
	(-1.44)	*(-2.45)*	*(-2.56)*	*(-2.74)*	*(-1.07)*	*(-1.85)*	*(-2.57)*	*(-3.19)*

Note. The table reports the values of $\beta_{M,i}$ coefficients along with the Newey-West adjusted *t*-statistics (in brackets) from the regression equation:

$$R_{i,t} = \beta_{0,i} + \beta_{MKT,i} MKT_t + \beta_{M,i} M_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return on a composite long-short anomaly portfolio *i* (equally- or value-weighted) in month *t*, $\varepsilon_{i,t}$ represents the error term, and $\beta_{0,t}$, $\beta_{MKT,t}$, and $\beta_{M,t}$ are the estimated regression coefficients. MKT_t denotes the excess return on the global equity portfolio, and M_t is the dummy variable equal to one, if month *t* belongs to the subperiod 2005–2018, or zero otherwise. The composite portfolios equally weigh all of the strategies in a given class: *Value*, *Size*, *Seasonality*, *Reversal*, *Momentum*, and *Low-Risk*, and the *Total* portfolio equally weighs all the 53 strategies considered in this study. The left and right sides of the table focus on the strategies formed of the country and industry indices, respectively. The long and short legs of the strategies are formed of the 20% of the country or industry indices, and *VW* refers to equally-weighted and value-weighted anomaly portfolios, respectively. The asterisks ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively. The strategies in Panel A are implemented separately in developed and emerging markets, as classified according to Thomson Reuters's approach. The results in Panel B are reported separately for the markets with above-median (*Large*) and below-median (*Small*) aggregate capitalization. Finally, the results in Panel C are reported separately for the markets with above-median (*High idiosyncratic risk*) and below-median (*Low idiosyncratic risk*) idiosyncratic volatility from the CAPM, estimated through the trailing 60-month window.

Table 7

Changes in Profitability of Index-Level Strategies – Subperiod Analysis

	Countries				Industries			
	EW	VW	EW	VW	EW	VW	EW	VW
	Panel A: Bull vs. Bull Markets							
	Bull markets		Bear markets		Bull markets		Bar markets	
Value	-0.65**	-0.21	-0.60	-1.09**	-0.07	-0.13	-0.23	-0.76
	(-1.97)	*(-0.66)*	*(-1.42)*	*(-2.36)*	*(-0.41)*	*(-0.48)*	*(-0.45)*	*(-1.62)*
Size	0.11	0.22	-0.99	-1.00	0.16	-0.02	-0.20	-0.43
	(0.28)	*(0.51)*	*(-1.55)*	*(-1.26)*	*(0.71)*	*(-0.08)*	*(-0.49)*	*(-0.84)*
Seasonality	0.40	0.28	0.05	0.90***	0.16	0.10	0.31	0.39
	(0.91)	*(0.68)*	*(0.11)*	*(2.95)*	*(0.62)*	*(0.25)*	*(0.75)*	*(0.61)*
Reversal	-1.13***	-1.16***	-0.50	-0.98	-0.82**	-0.89**	-0.21	-0.30
	(-3.11)	*(-2.59)*	*(-0.73)*	*(-1.06)*	*(-2.56)*	*(-2.11)*	*(-0.35)*	*(-0.38)*
Momentum	-0.19	-0.33	-0.56	-1.43**	-0.08	-0.31	-0.95	-1.12
	(-0.51)	*(-1.01)*	*(-0.75)*	*(-2.12)*	*(-0.27)*	*(-0.96)*	*(-1.62)*	*(-1.53)*
Low-risk	0.30	0.30	-0.46	-0.46	-0.01	-0.01	-0.63	-0.63
	(1.63)	*(1.63)*	*(-1.06)*	*(-1.06)*	*(-0.07)*	*(-0.07)*	*(-1.36)*	*(-1.36)*
Total	-0.17	-0.15	-0.57**	-0.89***	-0.11	-0.24*	-0.51*	-0.70*
	(-1.13)	*(-0.98)*	*(-2.09)*	*(-2.77)*	*(-1.04)*	*(-1.80)*	*(-1.91)*	*(-1.82)*
	Panel B: High vs. Low Volatility							
	High Volatility		Low Volatility		High Volatility		Low Volatility	
Value	-0.52	-0.47	-0.79*	-0.44	-0.18	-0.55	-0.11	-0.10
	(-1.37)	*(-1.19)*	*(-1.89)*	*(-1.09)*	*(-0.55)*	*(-1.40)*	*(-0.49)*	*(-0.28)*
Size	-0.89*	-0.61	0.47	0.36	-0.02	-0.16	0.13	-0.10
	(-1.95)	*(-1.22)*	*(1.23)*	*(0.70)*	*(-0.06)*	*(-0.45)*	*(0.50)*	*(-0.27)*
Seasonality	0.96**	0.93*	-0.32	-0.11	0.58*	0.53	-0.13	-0.17
	(2.15)	*(1.89)*	*(-0.63)*	*(-0.24)*	*(1.80)*	*(1.02)*	*(-0.44)*	*(-0.43)*
Reversal	-1.02*	-0.94	-1.01**	-1.25**	-0.97*	-0.57	-0.46	-0.92*
	(-1.95)	*(-1.56)*	*(-2.36)*	*(-2.29)*	*(-1.93)*	*(-1.05)*	*(-1.20)*	*(-1.74)*
Momentum	-0.40	-0.86**	-0.12	-0.35	-0.45	-0.61	-0.12	-0.45
	(-0.80)	*(-2.04)*	*(-0.27)*	*(-0.74)*	*(-1.03)*	*(-1.38)*	*(-0.34)*	*(-1.12)*
Low-risk	0.00	0.00	0.23	0.23	-0.22	-0.22	-0.13	-0.13
	(-0.01)	*(-0.01)*	*(0.91)*	*(0.91)*	*(-0.79)*	*(-0.79)*	*(-0.68)*	*(-0.68)*
Total	-0.36**	-0.47**	-0.20	-0.23	-0.32**	-0.40*	-0.13	-0.33**
	(-2.05)	*(-2.29)*	*(-0.98)*	*(-1.17)*	*(-1.96)*	*(-1.94)*	*(-0.93)*	*(-2.25)*
	Panel C: January vs. Other Months							
	January		Other months		January		Other months	
Value	-0.76	0.65	-0.66**	-0.56**	-0.02	0.05	-0.16	-0.34
	(-0.70)	*(1.05)*	*(-2.33)*	*(-1.99)*	*(-0.03)*	*(0.06)*	*(-0.74)*	*(-1.25)*
Size	-0.27	0.74	-0.11	-0.14	0.10	0.29	0.05	-0.18
	(-0.25)	*(0.43)*	*(-0.35)*	*(-0.42)*	*(0.22)*	*(0.33)*	*(0.26)*	*(-0.70)*
Seasonality	-1.85	-1.63*	0.48	0.60	-1.25***	-1.86*	0.33	0.37
	(-1.33)	*(-1.83)*	*(1.31)*	*(1.54)*	*(-3.48)*	*(-1.86)*	*(1.44)*	*(1.20)*
Reversal	-1.98	-1.05	-0.95**	-1.15***	-1.29	-0.81	-0.69**	-0.83**
	(-1.62)	*(-0.90)*	*(-2.54)*	*(-2.61)*	*(-1.54)*	*(-0.74)*	*(-1.96)*	*(-1.98)*
Momentum	0.39	-2.26*	-0.34	-0.44	0.03	-1.17	-0.29	-0.43
	(0.21)	*(-1.87)*	*(-0.95)*	*(-1.29)*	*(0.03)*	*(-0.84)*	*(-0.94)*	*(-1.29)*
Low-risk	1.61*	1.61*	0.00	0.00	0.69	0.69	-0.25	-0.25
	(1.87)	*(1.87)*	*(0.01)*	*(0.01)*	*(1.52)*	*(1.52)*	*(-1.49)*	*(-1.49)*
Total	-0.07	-0.33	-0.30**	-0.34**	-0.04	-0.40	-0.23**	-0.36***
	(-0.29)	*(-0.63)*	*(-2.14)*	*(-2.21)*	*(-0.36)*	*(-1.08)*	*(-2.28)*	*(-2.69)*

Note. The table reports the values of $\beta_{M,i}$ coefficients along with the Newey-West adjusted *t*-statistics (in brackets) from the regression equation:

$$R_{i,t} = \beta_{0,i} + \beta_{MKT,i}\, MKT_t + \beta_{M,i}\, M_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return on composite long-short anomaly portfolio i (equally or value-weighted) in month t, $\varepsilon_{i,t}$ represents the error term, and $\beta_{0,t}$, $\beta_{MKT,t}$, and $\beta_{M,t}$ are the estimated regression coefficients. MKT_t denotes the excess return on the global equity portfolio, and M_t is the dummy variable equal to one, if month *t* belongs to the subperiod 2005–2018, or zero otherwise. The composite portfolios equally weigh all of the strategies in a given class: *Value*, *Size*, *Seasonality*, *Reversal*, *Momentum*, and *Low-Risk*, and the *Total* portfolio equally weighs all the 53 strategies considered in this study. The left and right sides of the table focus on the strategies formed of the country and industry indices, respectively. The long and short legs of the strategies are formed of quintiles of the country or industry indices. *EW* and *VW* refer to equally-weighted and value-weighted anomaly portfolios, respectively. The asterisks ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively. The results in *Panel A* are presented separately for the months following *Bull markets* and *Bear markets*, i.e., when the trailing cumulative 12-month excess return on the market portfolio in months *t*-12 to *t*-1 is positive and negative, respectively. The results in *Panel B* are presented separately for the months with high and low volatility, where the volatility is calculated as the standard deviation of daily returns on the global equities (the DS World Index) within a given month. The *High volatility* and *Low volatility* denote the periods of above-median and below-median standard deviation, respectively. The results in *Panel C* are presented separately for *January* and other calendar months (*Other months*).

Table 8

The Role of Risk Factors for the Performance of Index-Level Long-Short Portfolios

	Equally-Weighted Portfolios					Value-Weighted Portfolios				
	α	β_{MKT}	β_{LIQ}	β_{IVOL}	R^2	α	β_{MKT}	β_{LIQ}	β_{IVOL}	R^2
Panel A: Countries										
Value	0.48***	-0.02	0.27***	-0.11***	14.03	0.30***	0.01	0.54***	-0.02	54.41
	(3.75)	*(-0.50)*	*(8.17)*	*(-2.90)*		*(2.95)*	*(0.32)*	*(11.68)*	*(-0.56)*	
Size	0.47***	-0.20***	0.05	0.17***	12.27	0.25	-0.19***	0.18***	0.34***	32.06
	(2.66)	*(-4.09)*	*(1.10)*	*(4.58)*		*(1.53)*	*(-4.43)*	*(4.09)*	*(8.95)*	
Seasonality	-0.08	0.07	0.01	-0.02	-0.09	-0.22	0.09	-0.03	-0.01	0.31
	(-0.41)	*(1.46)*	*(0.12)*	*(-0.32)*		*(-1.00)*	*(1.63)*	*(-0.49)*	*(-0.19)*	
Reversal	0.45**	0.01	0.12**	-0.04	0.84	0.19	-0.05	0.15*	-0.11	1.58
	(2.31)	*(0.23)*	*(2.02)*	*(-0.67)*		*(0.83)*	*(-0.70)*	*(1.82)*	*(-1.54)*	
Momentum	0.88***	-0.11*	-0.09	0.01	2.14	0.49***	-0.11	-0.05	0.01	1.07
	(4.57)	*(-1.73)*	*(-1.20)*	*(0.09)*		*(2.85)*	*(-1.62)*	*(-0.49)*	*(0.17)*	
Low-risk	0.23**	0.33***	0.09***	0.05	36.36	0.23**	0.33***	0.09***	0.05	36.36
	(2.13)	*(9.46)*	*(3.31)*	*(1.62)*		*(2.13)*	*(9.46)*	*(3.31)*	*(1.62)*	
Total	0.49***	0.03	0.05**	0.01	3.30	0.29***	0.03	0.12***	0.03	12.05
	(6.53)	*(1.05)*	*(2.33)*	*(0.34)*		*(3.45)*	*(0.80)*	*(3.33)*	*(1.15)*	
Panel B: Industries										
Value	0.43***	-0.03	0.27***	0.05	34.34	0.16**	-0.04**	0.59***	0.06**	72.52
	(5.57)	*(-1.13)*	*(9.66)*	*(1.60)*		*(2.00)*	*(-2.14)*	*(16.25)*	*(2.46)*	
Size	0.39***	-0.16***	0.15***	0.19***	21.90	0.25**	-0.11***	0.28***	0.26***	35.30
	(3.83)	*(-4.95)*	*(4.76)*	*(4.99)*		*(2.41)*	*(-3.37)*	*(6.68)*	*(5.48)*	
Seasonality	0.21	0.04	-0.03	0.00	0.02	0.09	0.11	-0.12*	0.01	2.75
	(1.53)	*(0.84)*	*(-0.84)*	*(-0.03)*		*(0.45)*	*(1.57)*	*(-1.90)*	*(0.16)*	
Reversal	0.32*	0.04	0.14**	-0.10*	4.35	0.03	-0.01	0.16	-0.31***	12.20
	(1.91)	*(0.72)*	*(2.42)*	*(-1.74)*		*(0.14)*	*(-0.09)*	*(1.54)*	*(-3.76)*	
Momentum	0.90***	-0.13**	-0.06	-0.06	4.19	0.74***	-0.20***	-0.02	0.08	2.91
	(5.54)	*(-2.07)*	*(-0.94)*	*(-0.79)*		*(4.52)*	*(-2.76)*	*(-0.16)*	*(0.90)*	
Low-risk	0.24**	0.31***	0.11***	-0.04	33.95	0.24**	0.31***	0.11***	-0.04	33.95
	(2.56)	*(6.95)*	*(2.59)*	*(-0.98)*		*(2.56)*	*(6.95)*	*(2.59)*	*(-0.98)*	
Total	0.50***	0.02	0.07***	-0.02	4.69	0.36***	0.00	0.15***	0.02	12.06
	(7.74)	*(0.50)*	*(2.77)*	*(-0.56)*		*(4.45)*	*(-0.07)*	*(3.67)*	*(0.52)*	

Note. The table reports the results of the multiple regression of returns on the composite long-short equity portfolios following the three-factor model (4). β_{MKT}, β_{IML}, and β_{RMS} are the slope coefficients corresponding with *MKT*, *LIQ*, and *IVOL* factors. *MKT* is the excess return on the market portfolio. *IML* and *RMS* are the long-short value-weighted portfolios, going long (short) for 30% of the indices with the lowest (highest) liquidity and the highest (lowest) idiosyncratic volatility, respectively. α is the intercept representing the abnormal return, and R^2 denotes the coefficient of determination. The numbers in parentheses are the Newey-West (1987) adjusted *t*-statistics. The asterisks ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively. α and R^2 are expressed in percentages.

Table 9

The Decline in the Risk-Adjusted Anomaly Returns

	Panel A: Countries				*Panel B: Industries*			
	Equally-weighted portfolios		Value-weighted portfolios		Equally-weighted portfolios		Value-weighted portfolios	
	α	*t*-stat	α	*t*-stat	α	*t*-stat	α	*t*-stat
Value	-0.55**	*(-2.10)*	-0.26	*(-1.44)*	-0.07	*(-0.43)*	-0.16	*(-0.79)*
Size	-0.13	*(-0.44)*	-0.04	*(-0.14)*	0.06	*(0.42)*	-0.11	*(-0.61)*
Seasonality	0.31	*(0.89)*	0.42	*(1.14)*	0.21	*(0.96)*	0.17	*(0.52)*
Reversal	-0.99***	*(-2.89)*	-1.09***	*(-2.59)*	-0.69**	*(-2.12)*	-0.73*	*(-1.84)*
Momentum	-0.30	*(-0.88)*	-0.60*	*(-1.83)*	-0.28	*(-0.98)*	-0.51	*(-1.63)*
Low-risk	0.16	*(0.83)*	0.16	*(0.83)*	-0.15	*(-0.99)*	-0.15	*(-0.99)*
Total	-0.26*	*(-1.93)*	-0.29**	*(-2.12)*	-0.20**	*(-2.01)*	-0.33***	*(-2.78)*

Note. The table reports the values of the $\beta_{M,t}$ coefficients along with the Newey-West adjusted *t*-statistics (in brackets) from the regression equation:

$$R_{i,t} = \beta_{0,i} + \beta_{M,i}\, M_t + \beta_{MKT,i}\, MKT_t + \beta_{IML,i}\, IML_t + \beta_{RMS,i}\, RMS_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return on a composite long-short anomaly portfolio *i* (equally- or value-weighted) in month *t*, $\varepsilon_{i,t}$ represents the error term, and $\beta_{0,i}$, $\beta_{MKT,i}$, $\beta_{IML,i}$, $\beta_{RMS,i}$ and $\beta_{M,t}$ are estimated regression coefficients. MKT_t denotes the excess return on the global equity portfolio, and M_t is the dummy variable equal to one, if month *t* belongs to the subperiod 2005–2018, or zero otherwise. IML_t and RMS_t are the returns on long-short value-weighted portfolios going long (short) for 30% of the indices with the lowest (highest) liquidity and the highest (lowest) idiosyncratic volatility, respectively. The composite portfolios equally weigh all of the strategies in a given class: *Value*, *Size*, *Seasonality*, *Reversal*, *Momentum*, and *Low-Risk*, and the *Total* portfolio equally weighs all the 53 strategies considered in this study. *Panels A* and *B* of the table focus on the strategies formed of the country and industry indices, respectively. The asterisks ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10

The Role of Academic Publications on Subsequent Performance of Index-Level Anomalies

	Countries						Industries					
	Equally-weighted portfolios			Value-weighted portfolios			Equally-weighted portfolios			Value-weighted portfolios		
	Date 1	Date 2	Date 3	Date 1	Date 2	Date 3	Date 1	Date 2	Date 3	Date 1	Date 2	Date 3
Pane A: Univariate Models												
α	0.63***	0.59***	0.62***	0.44***	0.41***	0.46***	0.62***	0.55***	0.57***	0.56***	0.46***	0.49***
	(11.46)	*(12.50)*	*(13.79)*	*(8.09)*	*(9.48)*	*(10.43)*	*(13.90)*	*(14.37)*	*(15.41)*	*(11.71)*	*(12.23)*	*(12.49)*
β_{PUB}	-0.17***	-0.17**	-0.22***	-0.16**	-0.19***	-0.30***	-0.15***	-0.05	-0.10**	-0.27***	-0.20***	-0.25***
	(-2.72)	*(-2.53)*	*(-3.63)*	*(-2.36)*	*(-2.70)*	*(-4.56)*	*(-3.13)*	*(-0.98)*	*(-2.10)*	*(-4.73)*	*(-3.37)*	*(-4.42)*
Pane B: Multivariate Models												
α	0.59***	0.61***	0.59***	0.38***	0.43***	0.39***	0.60***	0.58***	0.56***	0.53***	0.50***	0.48***
	(10.65)	*(13.27)*	*(11.87)*	*(6.91)*	*(9.34)*	*(8.70)*	*(13.54)*	*(15.91)*	*(14.48)*	*(10.97)*	*(12.42)*	*(12.05)*
β_{PUB}	-0.02	-0.10	-0.03	0.00	-0.23***	-0.04	-0.04	0.02	0.09	-0.12*	-0.13*	-0.04
	(-0.28)	*(-1.33)*	*(-0.36)*	*(0.06)*	*(-2.83)*	*(-0.58)*	*(-0.70)*	*(0.31)*	*(1.49)*	*(-1.83)*	*(-1.89)*	*(-0.58)*
β_{M}	-0.26***	-0.21***	-0.25***	-0.30***	-0.17**	-0.27***	-0.18***	-0.21***	-0.23***	-0.26***	-0.25***	-0.30***
	(-3.68)	*(-2.95)*	*(-3.82)*	*(-3.80)*	*(-2.05)*	*(-3.71)*	*(-3.36)*	*(-3.80)*	*(-4.59)*	*(-3.95)*	*(-3.65)*	*(-4.86)*
β_{MKT}	0.03***	0.03***	0.03***	0.03***	0.02***	0.03***	-0.45	-0.45	-0.46	-1.97***	-1.99***	-1.97***
	(4.24)	*(4.22)*	*(4.24)*	*(3.33)*	*(3.28)*	*(3.33)*	*(-0.91)*	*(-0.90)*	*(-0.91)*	*(-3.13)*	*(-3.16)*	*(-3.13)*
β_{LIQ}	0.06***	0.06***	0.06***	0.13***	0.13***	0.13***	4.75***	4.73***	4.73***	10.87***	10.87***	10.85***
	(7.80)	*(7.81)*	*(7.80)*	*(15.75)*	*(15.80)*	*(15.76)*	*(8.76)*	*(8.74)*	*(8.74)*	*(15.89)*	*(15.89)*	*(15.86)*
β_{IVOL}	0.01	0.01	0.01	0.03***	0.03***	0.03***	2.98***	2.99***	3.01***	4.20***	4.25***	4.22***
	(1.09)	*(1.11)*	*(1.09)*	*(4.27)*	*(4.31)*	*(4.26)*	*(5.65)*	*(5.67)*	*(5.70)*	*(6.31)*	*(6.38)*	*(6.34)*

Note. The table reports the results of panel regressions following equations (6) and (7), which examine the role of academic publications in shaping the index-level anomaly returns. The dependent variables are monthly excess returns on the equally- or value-weighted long-short anomaly portfolios of countries (*Panel A*) or industries (*Panel B*). The independent variables are as follows. *PUB* is the dummy variable taking a value of one following the publication date and zero before the publication date; *M* is the dummy variable taking the value of one in the years 2005–2018, or zero otherwise; *MKT* is the excess return on the market portfolios; *IML* and *RMS* are long-short value-weighted portfolios going long (short) for 30% of the indices with the lowest (highest) liquidity and the highest (lowest) idiosyncratic volatility, respectively. *PUB* is obtained using three different approaches: as the publication of the first anomaly in a particular class at the individual equity level (*Date 1*), as the actual publication date of each individual equity-level anomaly (*Date 2*), and as the publication date of the first index-level anomaly in a given class (*Date 3*). β_{PUB}, β_{M}, β_{MKT}, β_{IML}, are β_{RMS} are the regression coefficients corresponding with the variables *PUB*, *M*, *MKT*, *IML*, and *RMS*, respectively. α represents the average abnormal return (expressed in percentage). The numbers in parentheses are *t*-statistics and the asterisks ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively.