Recency Bias and the Cross-Section of International Stock Returns*

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Abstract

Investors often focus on recent information only, underestimating the relevance of data from the distant past. In consequence, the ordering of historical returns reliably predicts future stock performance in the cross-section. Using data from 49 countries, we comprehensively examine this anomaly within international markets. The average return differential between the high and low deciles of global stocks sorted on chronological return ordering equals 0.91% per month. The effect is distinctly robust among the biggest companies but exhibits substantial international heterogeneity. The mispricing prevails in countries characterized by high individualism and shareholder protection. Furthermore, it is concentrated following down markets and periods of excessive volatility.

Keywords: chronological return ordering, recency bias, behavioral finance, the cross-section of stock returns, asset pricing, return predictability, international markets.

JEL Classification: G11, G12, G14, G15.

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1. Introduction

The recency effect is a memory phenomenon in which the most recently presented facts or impressions are learned or remembered better than earlier material.[1] This cognitive bias inclines individuals to give greater importance to recent events over observations from the distant past (Anderson, 1965; Murdock, 1962; Slovic & Lichtenstein, 1972). Among many diverse domains, historical information ordering also matters in financial markets.[2] It influences how investors trade, choose securities, and react to corporate events.[3] Most essentially, the recency bias may also affect how they form expectations about the future distribution of stock returns.[4] Therefore, it may lead to a predictable price behavior: the order of past returns affects future stock performance (Mohrschladt, 2021). In this article, we perform the first comprehensive global investigation of the return ordering anomaly across 49 countries.

From an asset-pricing angle, the recency effect implies that investors overemphasize recent returns at the cost of distant ones.[5] If the recent returns were comparably high, investors' return expectations would be biased upwards. These distorted predictions may eventually lead to share overvaluation. The emerging mispricing is finally corrected by arbitrage forces, thus driving the prices down again. On the other hand, if recent payoffs were relatively low, then the behaviorally provoked supply may move stocks below their intrinsic value. Likewise, when arbitrageurs step in, the underpricing is corrected, and the prices rebound. To capture this pattern, Mohrschladt (2021) calculates the chronological return ordering (*CRO*) variable and scrutinizes its importance for the cross-section of stock returns. The *CRO* measure links historical payoffs with the time that has passed since they were recorded. The results from the U.S. market demonstrate a robust relationship between *CRO* and future equity returns.

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[1] The definition based on the APA Dictionary of Psychology (https://dictionary.apa.org/recency-effect).

[2] For further discussion and experimental evidence, see Baucells, Weber, and Welfens (2011), Hogarth and Einhorn (1992), and Tuttle, Coller, and Burton (1997). The psychological roots of this phenomenon are associated with the memory day effect (Brown, Neath, & Chater, 2007), representativeness (Kahneman & Tversky, 1972), the law of small numbers (Rabin, 2002), and experience-based learning (Hertwig et al., 2004).

[3] Empirical studies demonstrated impact of the recency effect on mutual fund choice (Bailey, Kumar, & Ng, 2011; Barber, Huang, & Odean, 2016), price reception (Bhootra & Hur, 2013), reactions to earning announcements (Hartzmark & Shue, 2018), trading patterns, (Nofsinger & Varma, 2013), or evaluation of accounting evidence by auditors. (Tubbs, Messier, & Knechel, 1990).

[4] Several recent works document that investors form their return expectations by extrapolating the recent stock performance: see, e.g., Bacchetta, Mertens, and van Wincoop (2009), Amromin and Sharpe (2013), Greenwood and Shleifer (2014), and Kuchler and Zafar (2019), and Da, Huang, and Jin (2021).

[5] The works of Adam, Marcet, and Beutel (2017); Casella and Gulen (2018); Greenwood and Shleifer (2014); Nagel and Xu (2019) demonstrate survey data that supports this view.

Motivated by the considerations above, we comprehensively investigate the *CRO* effect in international stock markets. We analyze data on more than 77 thousand companies from 49 countries for the years 1990–2020. We aim to ascertain whether the recency bias affects stock return around the world.

Our results demonstrate that the ordering of historical returns robustly predicts the cross-section of stock returns in international markets. Companies with relatively low recent returns and high distant ones visibly outperform their counterparts with comparably high recent returns and low distant ones. The average return differential between the value-weighted deciles of global stocks with high and low *CRO* values equals 0.91% per month. This abnormal performance cannot be attributed to common risk factors. In a nutshell, the *CRO* effect is a powerful asset pricing anomaly that holds worldwide.

Notably, unlike most equity anomalies (Hou, Xue, & Zhang, 2020; Hollstein, 2020), the *CRO* effect survives in different firm size environments. It is not driven by some dusty corner of the stock market populated by microcaps, but it remains solid and significant even in the largest companies. For example, the average spread portfolio return in the group of big global firms amounts to 0.95% per month. The similar values for small and micro-stocks are 0.75% and 0.38%, respectively. To sum up, the *CRO* variable effectively predicts returns even among the largest and most liquid stocks, thus paving the way for successful practical implementations.

Further cross-sectional regressions and meticulous bivariate sorts confirm the robustness of the *CRO* effect. It cannot be explained by a battery of established return predictors. The anomaly is not subsumed by the size, value, momentum, liquidity, beta, idiosyncratic risk, short-term reversal, maximum daily return, skewness, profitability, or asset growth effects. Moreover, the long-short *CRO* strategies continue to deliver significant alphas even when the portfolios are reconstructed only once in six months. Lastly, the phenomenon does not depend on any particular industry.

Notably, the historical return ordering effect comes with an intriguing caveat. While the phenomenon is powerful in developed countries, its magnitude is visibly weaker in emerging ones. Only the biggest and most liquid firms in emerging markets exhibit the *CRO* anomaly. Hence, to understand the sources of these international differences, we turn to country-level tests.

Ample amounts of research document that various country characteristics determine the heterogeneity of stock mispricing in international markets. Examples include market development, arbitrage constraints, or national culture.[6] The essential behavioral mechanism driving the *CRO* effect qualitatively resembles other equity anomalies. To discover the sources of international variation in the historical return ordering effect, we test a broad battery of potential predictors from several different domains: cultural traits, market development, informational efficiency, limits to arbitrage, and shareholder protection.

Overall, the *CRO* anomaly can be detected in most markets around the world. Taking the equal-weighted portfolios as an example, we find that the top *CRO* quintile of stocks has historically outperformed the bottom quintile in 84% of countries. Furthermore, the difference is significant at the 5% level in 59% of them. Nonetheless, the magnitude of the anomaly is uneven, prevailing in some countries and being visibly weaker—or even completely missing—in others.

Having scrutinized a range of possible sources of this heterogeneity, we show that two variables play a critical role: individualism and investor protection. The tertile of countries with the highest individualism score of Hofstede (2001) displays the monthly *CRO* long-short strategy returns higher by 0.26%–0.40% (depending on the measurement approach) than the most collectivistic countries. Our findings in this regard match abundant theoretical and empirical evidence arguing that the level of individualism affects return expectations, distorts probability assessment, and, thus, drives mispricing (Chui, Titman, & Wei, 2020; Cheon & Lee, 2018; Dou, Truong, & Veeraraghavan, 2016; Hollstein & Sejdiu, 2020). Analogously, the *CRO* spread portfolios in the tertile markets with the highest anti-self-dealing index (Djanko et al., 2008) outperform their low investor protection counterparts by 0.27%–0.45% per month. The effect of shareholder protection emphasizes the role of individual investors, who exhibit stronger extrapolative thinking (Da, Huang, & Jin, 2021) and are more prone to behavioral biases, hence, contributing to mispricing (Collins, Gong, & Hribar, 2003; Kaniel et al., 2012).

Last, we are also interested in the dynamics of the CRO effect through time. The asset pricing literature documents that factor premia reveal a remarkable time-series variation (Ilmanen et al., 2021; Jacobs, 2015). These fluctuations may result from diverse economic mechanisms, such as time-varying risk aversion, macroeconomic exposure, changes in sentiment, or limits to arbitrage. In particular, a number of studies demonstrated how the market state and volatility shapes the dynamics of major anomalies and global factor premia (e.g., Gutierrez and Hameed [2006]; Huang [2006]; Ilmanen et al. [2019]; Jacobs

[6] See, e.g., for market development: Jacobs (2016), Titman, Wei, and Xie (2013), Watanabe et al. (2013); for national culture: Cheon and Lee (2018), Chui, Titman, and Wei (2010), Docherty and Hurst (2018), Hollstein and Sejdiu (2020).

[2015]; Wang and Xu [2015]). Hence, we appeal to various economic theories and sources to capture what drives the changes in the magnitude of the *CRO* anomaly.

We examine the role of 16 candidate variables from several different areas: investor sentiment, barriers to arbitrage, economic conditions, risk, and uncertainty. We demonstrate that market crashes augment the global *CRO*-driven mispricing. The anomaly is particularly pronounced following extreme volatility and significant down markets. The pattern is robust to different measurement methods (e.g., implied vs. historical volatility, alternative estimation periods) and market segments (global, developed, and emerging markets). Outside these difficult periods, the profits on global *CRO* portfolios hardly differ from zero.

The remainder of the study proceeds as follows. Section 2 summarizes the data and variables. Section 3 presents the global evidence on the *CRO* effect. Section 4 explores the sources of international heterogeneity in the examined anomaly. Section 5 discusses the time-series variation in the recency bias-driven mispricing. Finally, Section 6 concludes the study.

2. Data and Variables

This section reviews the data and variables examined in our research. First, we describe our sample preparation process. Second, we discuss how our principal variable – *CRO* – is calculated. Eventually, we outline the control variables used in this study.

2.1. Data Sources and Sample Preparation

The study relies on stock-level data from 49 markets around the world. The dataset includes 23 developed markets and 26 emerging ones, and the complete list is provided in Table 1.[7] Following the standard approach in international asset pricing studies (e.g., Cakici and Zaremba [2021a]; Chui, Titman, and Wei [2010]; Griffin, Kelly, and Nardari [2010]; Griffin, Hirschey, and Kelly [2011]; Hou et al. [2011]; Jacobs [2016]; Jacobs and Müller [2020]), we obtain the market and accounting data from Datastream. The principal study period for returns runs from January 1990 to December 2020, though for some individual markets—especially emerging ones—the research period starts later due to data unavailability (detail in Table 1).[8] Importantly, to compute some control variables requiring historical information, such as asset growth or co-skewness, we also utilize earlier data dating back to December 1987. Our total company universe covers 77,010 firms,

[7] All our references to the developed and emerging markets follow the MSCI classification (https://www.msci.com/market-classification).

[8] Our starting date roughly matches other typical international studies, such as Fama and French (2012, 2017), and is associated with data availability and quality. Notably, Wordscope added numerous companies in the late 1980s, but their historical data was not automatically backfilled (Hou et al., 2011).

containing 51,413 stocks from developed and 25,597 from emerging markets. The precise quantity of companies per month is not constant through time, and, as depicted in Figure A1 in the Internet Appendix, it systematically increases as the global financial markets mature. Table 1 displays our sample's elementary statistical properties, providing a breakdown into individual countries.

[Insert Table 1 here]

As in Hollstein (2020) and Lee (2011), we consider both active and dead stocks to avoid survivorship bias. Furthermore, we use Datastream Worldscope datatypes to mitigate any issues associated with look-ahead bias. Finally, we download data with five decimal places to avoid potential inaccuracies associated with foreign exchange conversions.

Although Datastream is a popular database, its data quality tends to be uneven. It typically requires certain adjustments and filtering to eliminate possible errors (for discussion, see, e.g., Cakici and Zaremba [2020], Hanauer [2020], Ince and Porter [2006], Tobek and Hronec [2018], or Ulbricht and Weiner [2005]). Hence, we apply a battery of static and dynamic filters from asset pricing literature. To begin with, our sample includes only common stocks. We discard other securities such as warrants, American depositary receipts, convertible bonds, closed-end funds, and investment and or unit trusts (Campbell et al., 2010; Griffin, Kelly, & Nardari, 2010; Ince & Porter, 2006; Karolyi et al., 2012). Second, within particular markets, we concentrate only on companies located in their domestic countries with their securities listed therein (Griffin, Kelly, & Nardari, 2010; Ince & Porter, 2006). Third, we discard stocks quoted in different currencies than those linked with their country of origin (Griffin, Kelly, & Nardari, 2010). Fourth, we remove companies with their ISIN codes inconsistent with their associated countries (Annaert et al., 2013). Finally, we base our calculations on primary quotations only (Fong et al., 2017); for firms with multiple listed securities, we focus on the most liquid and biggest one available (Schmidt et al., 2019).

Our dynamic screens, in turn, mainly concentrate on eliminating erroneous returns that may result from incorrect dealing with different corporate actions, such as share splits or consolidations (Griffin, Kelly, & Nardari, 2010; Griffin, Hirschey, & Kelly, 2011; Ince & Porter, 2006; Jacobs, 2016; Schmidt et al., 2019). We delete all monthly returns greater than 500% and daily values exceeding 100% (Chui, Titman, & Wei, 2010; De Groot et al., 2012; van der Hart et al., 2005; Rouwenhorst, 1999).[9] Moreover, we discard any zero returns at the end of the return time series (Hanauer, 2020; Ince & Porter, 2006). This filter is associated with the Datastream tendency to report stale prices following a delisting. Furthermore, as in Cakici and Zaremba (2021b), we require all stocks to have their book

[9] We also experiment with alternative thresholds between 100% and 500% for both daily and monthly returns, as well as restrictions on minimum (negative) returns. All of this has no measurable impact on our findings.

value of equity available for the last six months. Finally, we remove companies with low stock prices to deal with the microstructure problems associated with penny stocks.[10] Specifically, we drop 10% of securities with the lowest price at the beginning of each month. Notably, we do not impose any limitations on the minimum firm size (Zaremba & Maydybura, 2019) or liquidity (Griffin, Hirschey, & Kelly, 2011), as we control for these issues in dedicated tests.

To cope with the issues related to exchange rate risks, we closely follow Fama and French (2012, 2017) and express all the market data in U.S. dollars. Being Consistent with this framework, we proxy the risk-free rate with the one-month U.S. T-bill rate.

2.2. Chronological Return Ordering

To calculate our principal return-predicting variable, chronological return ordering (*CRO*), we closely follow Mohrschladt (2021). The variable is designed to reflect whether relatively high returns have been recorded in either the more distant or recent past. To capture this, the *CRO* measure relies on the correlation between the historical stock returns and the number of days that have passed since the return realization. As in Mohrschladt (2021), we employ a monthly estimation period; so the *CRO* for stock i at day t is computed as the Pearson's product-moment pairwise correlation coefficient between daily returns and the corresponding number of days (d) remaining until the end of the month t:

$$CRO_{i,t} = cor(r_{i,t-d}, d). \tag{1}$$

The interpretation of *CRO* is intuitive and straightforward. *CRO* measures the return correlations with time distance. Hence, low *CRO* numbers indicate comparably high recent returns relative to those in the distant past. To put it differently, a low *CRO* score means that the returns are increasing over time (within the estimation window). On the other hand, high *CRO* values indicate comparably low recent returns and high returns in the distant past. In other words, the returns are decreasing over time.

Following our theoretical reasoning, low *CRO* values should imply overvaluation because investors, who extrapolate recent performance, tend to overestimate the expected returns. In consequence, the low *CRO* scores signal low future returns. Conversely, high *CRO* values indicate undervaluation induced by investors overemphasizing recent low returns, thus, undershooting the expected returns. As a result, the high *CRO* scores should be associated with high future returns.

[10] The specific limits of the minimum stock price limits differ across finance literature. Therefore, we check a number of other percentage (5%, 20%) or absolute (USD 0.5, USD 5) threshold, as well as no restrictions at all. Our results remain qualitatively intact.

In our baseline approach, we use the monthly formation window. This period is commonly employed in many equity anomalies that rely on variables derived from past returns (e.g., Bali, Cakici, & Whitelaw, 2011; Chiang, Kirby, & Nie, 2021; Cosemans & Frehen, 2021; DeLisle et al., 2021). It is also frequently reported in various print and online financial media. Nonetheless, to verify the robustness of our findings, we relax this assumption and experiment with estimation periods from 3 to 36 months—using both daily and monthly data frequency. The details of these tests are discussed in Section 3.2.

2.3. Control Variables

To assure that *CRO* provides incremental and independent information about future returns, our tests incorporate a battery of control variables from asset pricing literature. The firm size (*SIZE*) is proxied by the logarithm of the company's market value at the end of month *t*-1 (Banz, 1981). The book-to-market ratio (*BM*) is calculated as the six-month lagged book value of equity divided by the current market capitalization (Rosenberg, Reid, & Lanstein, 1985). The short-term reversal (*REV*) and momentum (*MOM*) reflect capture stock's past performance and are calculated as the return in month *t* and months *t*-12 to *t*-2—respectively (Jegadeesh, 1990; Jegadeesh & Titman, 1993; Lehmann, 1990).

Stock market beta (*BETA*) (Sharpe 1964) and idiosyncratic risk (*IVOL*) (Ang et al., 2006; Bali & Cakici, 2008) are estimated from the capital asset pricing model (CAPM). The market excess return (*MKT*) in this model is calculated as the value-weighted return on all the stocks in the local country stock market. Firm illiquidity (*ILLIQ*) is captured by the Amihud (2002) measure, reflecting the average ratio of absolute daily returns to daily dollar trading volume. The co-skewness (*SKEW*) is computed as a regression on a squared local market return, closely following Harvey and Siddique (2002). Importantly, *BETA*, *IVOL*, *ILLIQ*, and *SKEW* are all calculated using 12 months of daily data.[11]

The *MAX* variable of Bali, Cakici, and Whitelaw (2011) captures the maximum daily return over the previous month. The asset growth (*AG*) is calculated as in Cooper et al. (2008), i.e., as the annual logarithmic change in the book value of total assets lagged by six months, that is, through months *t*-19 to *t*-7. Finally, the firm profitability (*PROF*) is represented by operating profitability (Ball et al., 2015; Fama & French, 1996), which expresses the EBIT ratio to book value of equity—both lagged by six months.

Table A1 in the Internet Appendix reports the basic statistical properties of the variables used in this study, and Table A2 displays pairs-wise correlation coefficients. Notably,

[11] For robustness, we also experiment with deriving the variables for different estimation periods up to five years. We also consider alternative methodological approaches, such as computing *BETA* as in Frazzini and Pedersen (2013), or deriving *IVOL* from extended factor models, as in Ang et al. (2006) or Bali and Cakici (2008). All these have no visible effect on our overall conclusions.

CRO does not exhibit a visible relationship with any of the other control variables. The highest absolute coefficient is recorded for *BETA* and amounts to only 0.033 in the global sample.

3. Global Empirical Findings

This section contains the investigations of the *CRO* effect in global stocks. First, we report portfolios from single sorts followed by additional robustness checks. Subsequently, we supplement this analysis with bivariate sorts and cross-sectional regressions.

3.1. Univariate Sorts

We start our analysis by examining whether *CRO* predicts the cross-section of future returns in the international setting. We begin with univariate portfolio sorts. To this end, we rank all the stocks in our sample on CRO and sort them into deciles every month. Subsequently, we form equal- and value-weighed portfolios. All the portfolios are rebalanced monthly. We also explore long-short zero-investment strategies that buy (sell) the decile of stocks with the highest (lowest) value of *CRO*. These differential portfolios represent an acid test for a potential cross-sectional pattern in returns.

To account for multidimensional return structure, we test the portfolio returns with the six-factor asset pricing model (Fama & French, 2018):

$$R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{WML} WML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_t, \quad (2)$$

where R_t is the month-t excess return on an evaluated portfolio, and MKT_t, SMB_t, HML_t, WML_t, RMW_t, and CMA_t are monthly returns on factor portfolios: market (*MKT*), small-minus-big (*SMB*), high-minus-low (*HML*), winners-minus-losers (*WML*), robust-minus-weak (*RMW*), and conservative-minus-aggressive (*CMA*). β are estimated portfolio exposures, and the subscripts indicate the relevant risk factors. α represents the abnormal return (so-called "alpha"), and ε_t is the error term. Model (3) nests several other frequently employed asset pricing models, such as the CAPM, the four-factor model of Carhart (1997), or the three- and five-factor models of Fama and French (1992, 1993, 2015). To assure consistency with the tested portfolios, we calculate the factor returns based on Datastream data, always using the same equity universe as the tested strategies (e.g., we use developed market factors for developed market strategies). The precise methods of factor return calculations are summarized in Table A3 of the Internet Appendix. Furthermore, Table A4 and Figure A2 therein provide a basic overview of factor performance and statistical properties.

Table 2 reports the returns on portfolios from one-way sorts on *CRO*. We present the findings for three different equity universes: 1) the United States (Panel A); 2) global

sample of all countries, excluding the US (Panel B); and 3) total global sample (Panel C). The results in Panel A match the findings of Mohrschladt (2021), who examines the same geographical sample. The high *CRO* stocks visibly outperform the low CRO stocks. The differential return amounts to 1.30% (0.79%) for equal-weighted (value-weighted) portfolios and remains highly significant even after accounting for the six-factor model exposure. Furthermore, the cross-sectional return pattern does not appear to be driven by small firms, as the average firm size is comparable across all the decile portfolios.

[Insert Table 2 here]

The results for other international markets (Panel B) are overall consistent. The top *CRO* stocks still outperform the bottom *CRO* stocks, surviving the application of the six-factor model (2). Interestingly, while the average differential returns on the value-weighted portfolios exhibit qualitatively similar size as in the U.S. – 0.91% per month – the payofss on the equal-weighted portfolios are visibly lower. The monthly average amounts to 0.36%. Finally, the average returns on the equal-weighted (value-weighted) spread portfolios in the combined global sample equal 0.63% (0.91%) per month. To sum up, our initial check confirms that the *CRO* effect is not a solely U.S. phenomenon; it drives the returns on international stocks—as well.

Supplementary to the performance measures in Table 2, we also calculate the average characteristics of the examined decile portfolios. This exercise serves as an initial test of whether the anomalous returns on the single-sorted portfolios do not stem from an association between CRO and other return predictors. For brevity, we summarize these results in Table A5 in the Internet Appendix.

The decile characteristics do not exhibit any apparent linear or monotonic pattern. In other words, the considered variables are not visibly related to *CRO*. In particular, *CRO* is not associated with firm value or liquidity, so the extreme deciles are not populated by small and illiquid firms. Likewise, stocks with high or low *CRO* scores are not associated with elevated idiosyncratic or systematic volatility. To sum up, we find no suggestion that the abnormal returns on the decile portfolios may compensate for some other established type of risk or behavioral mispricing.

3.2. Additional Robustness Checks

To assure the validity of our conclusions from univariate sorts in Table 2, we run several additional robustness checks. Specifically, we are primarily interested in whether the anomaly-based strategy survives real-life conditions and practical implementation challenges. Therefore, we consider several subsample analyses and alternative assumptions.

The role of firm size. The majority of equity anomalies suffer from microcap bias; they are driven primarily by the smallest firms in the market (Hou, Xue, & Zhang, 2020;

Hollstein, 2020). Outside this microcap universe, numerous anomalies can hardly be confirmed. To investigate whether this problem concerns the *CRO* effect, we replicate the global portfolio sorts in big, small, and micro firms. Following the definition in Fama and French (2008), the big stocks comprise the largest companies accounting for 90% of the total market capitalization. The small firms represent the subsequent 7% of the market capitalization. Finally, the microcaps are the tiniest companies responsible for 3% of the aggregate market value.

The results of this exercise are brevity in Table 3. Supplementary, Figure A3 in the Internet Appendix illustrates the performance of the CRO strategies in different size environments through time.

[Insert Table 3 here]

Our findings reveal that small or micro firms do not drive the *CRO* anomaly. Unlike many other anomalies, it is actually *stronger* in big companies than in smaller ones. Taking the value-weighted portfolios as an example, the differential returns for big, small, and micro firms amount to 0.95%, 0.75%, and 0.38%—respectively. The stronger recency bias among big companies matches the findings of Da, Huang, and Jin (2021), who argue that extrapolative beliefs are typically stronger for large stocks. This feature emphasizes a potential practical value of the CRO-based strategy, as it could be implemented in the biggest and most liquid firms.

The *CRO* effect across industries. We are also interested in whether any particular industry drives the chronological anomaly. Therefore, we replicate our global one-way sorts in 11 industries classified by Datastream: basic materials, consumer discretionary, consumer staples, energy, financials, healthcare, industrials, real estate, technology, telecommunication, and utilities. The results, as is reported in Table A6 in the Internet Appendix, corroborate that the *CRO* anomaly does not depend on any particular industry. The cross-sectional pattern is solid and robust across different industry profiles.

Alternative estimation periods. Mohrschladt (2021) demonstrated that the CRO anomaly in the U.S. survives for a range of different estimation windows. Moreover, Greenwood and Shleifer (2014) document, who examine survey expectations of future stock performance using past returns, indicate that investors respond non-linearly to the history of returns. They argue that investors put the most weight on the returns from the most recent quarter (e.g., American Association of Individual Investors data) or one year (e.g., the Gallup survey of investor optimism).

To verify what lookback windows are relevant in international markets, we replicate our global analysis from Table 2 for different formation periods. First, we check three-, six-, and twelve-month periods of daily returns. Second, we consider monthly return measurement intervals instead of daily ones and examine one, two, and three years of monthly

returns. Finally, we also check the impact of dropping the last day's return from our monthly estimation period.

The outcomes of these tests are displayed in Table A7 in the Internet Appendix. The *CRO* anomaly works well for the three months of daily returns. It is also relatively strong for the 12-month period, which, initially, was closely scrutinized by Mohrschladt (2021)—especially for value-weighted portfolios. Analogously, the *CRO* effect survives, removing the most recent return from the estimation period. Nevertheless, we cannot confirm the other formation windows' anomaly. In particular, it disappears for long-run estimation periods, comprising two to three years of monthly returns. In this regard, our findings are similar to Greenwood and Shleifer (2014), who conclude that investors put more weight past three months and one year rather than on earlier historical data.

Extended holding periods. Short-lived trading signals tend to be challenging to implement in practice. The reason is that they typically require high portfolio turnover, which may be costly from a trading perspective (Novy-Marx & Velikov, 2016). Hence, we examine the performance of the global portfolios from sorts on *CRO* with three- and six-month holding periods. As the results in Table A8 in the Internet Appendix demonstrate, the strategy profits become lower in this setting; however, the anomaly persists. The long-short *CRO* portfolios continue to deliver significant alphas, even when the portfolios are reconstructed only once in six months.

Developed vs. emerging markets. A popular narrative suggests that emerging markets are less efficient and, therefore, are prone to more substantial equity anomalies. Interestingly, while early studies argue that inefficiencies should be more extensive in emerging markets (e.g., Bekaert & Harvey 2002; Bhattacharya et al., 2000), more recent evidence demonstrates an inverse relationship instead: the anomalies are stronger in developed markets than in emerging ones (Eisdorfer, Goyal, & Zhdanov, 2017; Jacobs, 2016; Titman, Wei, & Xie, 2013; Watanabe et al., 2013). But what about the *CRO* anomaly? Does it perform equally in developed and emerging countries? The gravity of this question lies in also its practical consequences. To what extent could chronological ordering be translated into efficient quantitative strategies in different types of markets?

To answer these questions, we reproduce our decile portfolio analysis from one-way sorts on CRO in developed and emerging markets (see Table 1 for detailed classification). Table 4 displays the results of this experiment.[12]

[Insert Table 4 here]

[12] For cumulative profits in developed and emerging markets over time, see Table A4 in the Internet Appendix.

The *CRO* effect is powerful and robust in the developed markets (Table 4, Panel A). The average return on an equal-weighted (value-weighted) spread portfolio equals 1.12% (1.00%) and is highly significant even after accounting for the exposure to factors of the model (2). Nonetheless, the picture of the emerging markets (Table 3, Panel B) differs dramatically. In a nutshell, no chronological return ordering anomaly can be observed. Neither average returns nor alphas on the long-short portfolios produce any significant profits. For the equal-weighted portfolios, the mean returns and alphas are even slightly negative—though insignificant.

To further explore the absence of the *CRO* anomaly in emerging markets, we conduct an additional test. Emerging markets are typically populated with smaller and less liquid companies. As Table 1 indicates, an average emerging market company is three times smaller than a developed market one. Importantly, the small and illiquid firms are more prone to exhibit stale and untradeable prices, which may distort the *CRO* signal measurement. Hence, we apply the portfolio sorts to different firm size categories in emerging markets.

To obtain a comprehensive image, we employ three distinct sets of breakpoints to differentiate between big, small, and micro stocks. First, we closely follow the approach in Table 3, i.e., we classify the big, small, and micro firms as those representing 90%, 7%, and 3% of total market capitalization, respectively. Second, we apply the same method but calculate the breakpoints based on the developed market's sample. Subsequently, we apply these breakpoints to the emerging markets. Finally, the third is identical to the first, but we discard all firms with capitalization below USD 300 million. The merit behind the last two methods is to make the size classification more aligned with the developed markets. As we have already noted, the firms in emerging markets are typically smaller than in developed ones, so even the big companies may have a size corresponding with small or micro subsets in mature markets.

Table 5 summarizes the results of this analysis. The *CRO* effect cannot be detected in micro and small firms, nor in most of the equal-weighted portfolios, regardless of the size classification methods. Nonetheless, in the big firm segment, the value-weighted portfolios exhibit a familiar overperformance of high-*CRO* stocks. When using the standard size breakpoints (derived from emerging markets (Table 5, Panel A), the long-short *CRO* strategies yield a mean differential return of 0.61% and the associated six-factor model alpha 0.75%. Importantly, these "big emerging market firms" may still contain relatively small companies. Hence, when we employ the developed market size breakpoints (Table 5, Panel B), which impose a higher threshold for big firms, the *CRO* effect becomes even stronger. The mean return on the spread portfolio and the associated alpha amount to 0.76% and 0.97% per month, respectively, both statistically significant. Finally, the performance of the *CRO* strategy in the sample excluding firms below USD 300 million

(Table 5, Panel C) appears qualitatively similar, with the average return (alpha) equalling 0.63% (0.81%).

[Insert Table 5 here]

Overall, the abovementioned numbers are lower and less significant than in developed markets, suggesting that the *CRO* anomaly is relatively weak in emerging markets. Nonetheless, it still does exist. The recency bias continues to affect asset pricing in emerging markets, although it is limited to the biggest and most liquid companies. The small and micro firms, on the other hand, display no similar pattern in returns.

To sum up, though the chronological return ordering effect is reasonably robust to many considerations, it is not equally strong in different markets. Its magnitude varies remarkably across international markets and is visibly lower in emerging markets than in developed ones. We will explore the sources of this heterogeneity in Section 4.

3.3. Bivariate Sorts

So far, our evidence demonstrates the strong *CRO* effect in the global setting, which exhibits, however, considerable cross-sectional variation across markets. A possible reason may be that the *CRO* anomaly is driven by some particular group of firms that share common features. Firm size or liquidity, which tends to be lower in emerging markets, may serve as an example. To explore this possibility, we now turn to bivariate portfolio sorts. This exercise also helps to ascertain that *CRO* provides incremental information about future returns that is not already captured by some other well-known return predictive variables.

To create the bivariate portfolios, each month, we independently sort stocks into deciles based on *CRO* and one of the control variables outlined in Section 2.3. The intersection of the two sorts forms 100 portfolios. Subsequently, within each control decile, we calculate the average returns on the portfolios with a similar level of CRO. This allows us to produce deciles with dispersion in CRO but with a consistent level of the control variable. Furthermore, we also calculate the difference in returns between the top and bottom *CRO* decile. This allows us to investigate how widespread the *CRO* anomaly is, and whether it is not driven by some other established equity anomaly.

Table 6 reports the performance of the two-way sorted portfolios. Panels A and B focus on equal-weighted and value-weighted portfolios—respectively. A quick overview confirms that the *CRO* effect is not driven by any of the 11 stock characteristics considered. For the equal-weighted portfolios (Table 6, Panel A), the average return spread between the high and low *CRO* deciles range from 0.67% to 0.91%. The corresponding six-factor alphas vary between 0.75% and 1.02%, all significantly departing from zero at the 1% level.

[Insert Table 6 here]

The average differential returns for the value-weighted portfolios (Table 6, Panel B) are slightly higher than the equal-weighted ones: they vary from 0.68% to 1.06%, and the corresponding alphas are between 0.78% and 1.28%. Again, all the values are statistically significant. To sum up, none of the control variables is able to explain the CRO effect.

Comparing the results bivariate sorts with the univariate sorts in Table 2, Panel C, the average abnormal returns on the conditional and unconditional strategies are comparable. The control variables have a limited impact on the magnitude of the CRO profits. This is consistent with the observations in Table A2 in the Internet Appendix, showing that *CRO* does not exhibit a substantial correlation with other control variables.

3.4. Cross-Sectional Regressions

Bivariate sorts are a powerful tool examining the role of different characteristics, which do not impose any functional form between *CRO* and control variables. However, considering more than one or two control characteristics jointly may be hardly feasible. Furthermore, aggregating stocks into portfolios may lead to information loss. Therefore, we continue with cross-sectional regressions in the style of Fama and MacBeth (1973).

To this end, each month, we estimate the following regression equation:

$$R_{i,t+1} = \gamma_0 + \gamma_{CRO} CRO_{i,t} + \sum_{j=1}^{n} \gamma_K K_{i,t}^{j} + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,t+1}$ is the return on the stock i in month t+1, CRO represents the chronological return ordering in month t, and $K_{i,t}^{j}$ is the vector of additional control variables listed in Section 2.3. We apply the regressions for the full global sample and some other subsamples that we explored in our earlier tests: big, small, and micro firms, as well as developed and emerging markets.

Table 7 shows the average slope coefficients of the cross-sectional regressions. We present both multivariate test results that incorporate all the control variables and univariate tests accounting for *CRO* only. Importantly, in unreported analyses, we also explore different specifications, considering alternative sets of control variables. This robustness check has no measurable influence on our overall findings.

[Insert Table 7 here]

The cross-sectional regressions confirm the predictive abilities of the *CRO* over future returns in international markets. In the total global sample (column [1]), the slope coefficients in univariate tests are positive and significant at the 1% level. Even when we account for all 11 control variables that are used in this study, the CRO effect remains

solid and significant. Notably, Harvey et al. (2016) argue that to account for growing "zoo," a more stringent significance hurdle should be employed. The recorded t-statistics of 5.65 in the multivariate tests easily exceeds the 3.0 t-statistic threshold that is advocated by Harvey et al. (2016). Furthermore, the Bonferroni adjustment, a conservative approach of accounting for multiple testing framework (see, e.g., Chordia et al. [2020], Müller and Schmickler [2020]), implies that the level of t-statistic marking 1%-significance in our case equals 3.34. Our results also pass this cut-off point.

Regressions [2] – [4], as is seen in Table 7, report the results for different firm size environments. In line with our earlier observations, the *CRO* anomaly is strong in all different market segments, not being driven by any "obscure market corner" of microcaps. Finally, columns [5] and [6] compare the role of chronological return ordering in both developed and emerging markets. As in Table 4, we find that the entire anomaly is driven purely by the developed markets. While in this class of countries, the return predictability is evident; in emerging markets, the *CRO* coefficients are insignificant. In other words, the *CRO* plays no vital role in the cross-section of returns in the less developed markets. Let us now take a closer look at the potential sources of these international differences in the magnitude of the *CRO*-related mispricing.

4. Heterogeneity in the International Return Ordering Effect

Our examinations, thus far, reveal a considerable difference in the magnitude of the *CRO* anomaly between developed and emerging markets. To explore this, we begin by testing this effect in individual countries. Next, we explore the potential sources of the international variation in the anomaly.

4.1. Country-Level Evidence

To investigate the chronological return ordering for individual stock markets, we perform country-level portfolio sorts. Each month for each market, we sort countries into quintiles based on *CRO*. The use of quintiles instead of deciles is dictated by a smaller number of stocks in single-country samples than in international ones. Subsequently, we form zero-investment long-short portfolios that buy (sell) high (low) *CRO* quintile and evaluate them with the six-factor model (2). Table 8 summarizes the results of these tests.

[Insert Table 8 here]

The chronological return ordering anomaly is widespread across numerous markets. Table 8 corroborates that the effect is neither U.S.-specific, nor driven by any particular country. It prevails internationally: 84% (86%) of the markets display positive return differences between high and low CRO equal-weighted (value-weighted) quintiles. The average

spread portfolio returns equal 0.57% and 0.60% for the equal- and value-weighed strategies—respectively. Comparing with the aggregate global results from Tables 2 and 4, the long-short portfolio returns are relatively lower, but this corresponds with the narrower spread between the high and low *CRO* subsets as we move from the deciles to quintiles.

59% of the equal-weighted and 43% of the value-weighted long-short strategies display positive returns significant at the 5% level (t-statistics > 1.96). If we assume the higher hurdle for t-statistics of 3, as advocated by Harvey et al. (2016), the analogous numbers decrease to 37% and 22%—respectively.

Interestingly, the overview of the performance of country-level CRO strategies uncovers remarkable variation across markets. On the one hand, as we already notice, the chronological ordering anomaly is generally more substantial in developed markets (Table 8, Panel A) than in emerging ones (Table 8, Panel B). On the other hand, even within the subset of the developed market, the cross-sectional differences are noteworthy. Let us take a closer look at the equal-weighted strategies. The United States, researched initially by Mohrschladt (2021), produces relatively high profits (1.02% per month) but is not a top performer. The average spread portfolio for Canada is 2.16%, and the associated t-statistic amount to an outstanding 11.54. On the other hand, in Denmark and Spain, the mean differential returns barely differ from zero, equalling 0.09% and 0.02% per month—respectively. Finally, in the United Kingdom, the average returns even fall below zero, totaling -0.43% per month.[13]

4.2. What Determines the Cross-Country Variation in the Return Ordering Anomaly?

Although our results, thus far, confirm the essential role of chronological return ordering on stock mispricing worldwide, they also reveal a substantial cross-country heterogeneity in its magnitude. What drives these differences across countries? Are they linked to cultural traits, market efficiency, and development, or maybe trading frictions?

[13] In an additional unreported analysis, we verify that the outlying behavior of the UK market is entirely driven by the microcaps in this country. The atypical behavior of the smallest companies in this country has been also recorded for other anomalies (e.g., Amihud et al. [2015], Cakici and Zaremba [2020a], Lee et al. [2011]), and is linked to microstructure issues. In a specific quote-driven segment of the British market, the closing prices represent midpoints between bid and ask prices—rather than actual transaction prices (Amihud et al., 2015). This mechanism is unique to the UK and does not affect any other country in our sample. To ensure that the UK specificity does not impact materially our results, we reproduce all our baseline tests, such as those in Tables 2 to 7, with the UK excluded from the sample. Furthermore, we also replicate the calculation limiting the UK sample to the stocks listed in the SETS segment of the British market, which is dedicated to larger and more liquid firms. In all these tests, our major findings remain unaffected. The results of these tests are available upon request.

4.2.1. Testing Method

To resolve the puzzle that is indicated above, we broadly follow the research methodology in Chui, Titman, and Wei (2010), who originally examine the international variation in momentum profits. Using the Fama-MacBeth (1973) procedure, we estimate monthly cross-sectional regressions of the *CRO* spread portfolios on an array of different market characteristics from international asset pricing literature:

$$CRO_{j,t+1} = \delta_0 + \delta_1 F_j + \delta_2 M_{j,t} + \varepsilon_{j,t}. \tag{4}$$

where $CRO_{j,t+1}$ represents the return on a spread portfolio buying (selling) the quintile of stocks with the highest (lowest) *CRO* variable in country j in month t+1. We use both equal- and value-weighted portfolios. F_j represents the vector of time-invariant country characteristics (for example, national cultures). On the other hand, $M_{j,t}$ denotes the time-varying market features (for example, liquidity or stock synchronicity). Finally, δ_0, δ_1, and δ_2 are the estimated regression coefficients, and $\varepsilon_{j,t}$ indicates the disturbance term.

Our regressions include a battery of various country characteristics (see Section 4.2.2). We begin with running univariate tests that examine the importance of individual return predictors. Then, we carry on with multivariate regressions within different categories of characteristics. Moreover, it would also be of interest to incorporate all different variables in Eq. (4), rather than considering them in groups, so we estimate a *comprehensive* model. To deal with the limited number of degrees of freedom, we apply the framework of Chui et al. (2010) and incorporate only the predictors that proved significant in the first steps. To be specific, we employ only these variables that surpass the 5% significance threshold on all earlier tests, i.e., equal- and value-weighted univariate and group regressions.

4.2.2. Market Characteristics

To dig into the potential determinants of the CRO-driven mispricing across countries, we check a comprehensive set of country and market characteristics. We source the predictors from extant literature and group them into five categories: national culture, market development, informational efficiency, limits to arbitrage, and investor protection. Below, we provide a brief overview of these variables, while the detailed sources, explanation, and descriptive statistics are presented in Tables A9 and A10 in the Internet Appendix.

To begin with, many studies document that stock mispricing hangs on different cultural traits (Hofstede, 2001; Hofstede, Hofstede, & Minkov, 2005). A seminal paper by Chui, Titman, and Wei (2010) indicates that individualism is linked with overconfidence and self-attribution biases. Hence, it has been demonstrated to amplify various behavioral anomalies (Chui, Titman, & Wei, 2020; Cheon & Lee, 2018; Dou, Truong, & Veeraraghavan, 2016; Hollstein & Sejdiu, 2020). Notably, one of the most affected anomalies is

momentum (Chui, Titman, & Wei, 2010), which—similarly to our recency effect—is sometimes explained with extrapolative models (Barberis & Shleifer, 2003; Barberis et al., 2018). Furthermore, abundant psychological literature (Phillips & Wright, 1977; Wright et al., 1978; Wright & Phillip, 1980; Lau & Ranyard, 1999) associates the level of collectivism and individualism with probabilistic thinking in the society Hollstein and Sejdiu (2020) links this phenomenon with distortions of future return expectations, that may cause anomalous returns.

The second cultural dimension considered is masculinity. It expressed the values of competitiveness, achievement, and drive to win, which may provoke risk-taking, self-attribution, and overconfidence biases. Analogously to individualism, it materially influences trading patterns (Anderson et al., 2011; Barber & Odean, 2001; Tan, Cheong, & Zurbruegg, 2019) and stock mispricing (Galariotis & Karagiannis, 2020).

Uncertainty avoidance, in turn, may affect investors' willingness to engage in risk-taking activities, which always include some level of uncertainty. On the other hand, it may also make investors excessively sensitive to extreme returns, laying grounds for deepened stock mispricing (Dou, Truong, & Veeraraghavan, 2016; Maher & Parikh, 2011; Galariotis & Karagiannis, 2020). Finally, long-term orientation in the national culture may make investors less sensitive to short-term price fluctuations, which shape the *CRO* anomaly. Consistently, Docherty and Hurst (2018) show that myopic investors overemphasize the recent price changes, amplifying the momentum profits in short-term-oriented societies. Following Azevedo and Müller (2020) and Hollstein & Sejdiu (2020), we consider all six of Hofstede's cultural traits in our tests: power distance (*POWER*), individualism (*INDIV*), masculinity (*MASC*), uncertainty avoidance (*UNC*), long-term orientation (*LTOR*), and indulgence (*INDUL*). Notably, certain cultural traits are typically associated with economic growth (see Alesina and Giuliano [2015] for a comprehensive review). For example, developed countries tend to be more individualistic. Consequently, the international differences in cultural dimensions may explain the differences in the *CRO* anomaly between developed and emerging markets.

The second category of characteristics concerns market development. As we have already noted, the evidence on the impact of market development is mixed. Although the common narrative suggests that the anomalies should prevail in less developed markets, a recent comprehensive study by Jacobs (2016) leads to opposite conclusions. While our preliminary tests in Tables 4 and 5 pointed to market development's critical role, the phenomenon may be driven by other market characteristics that partly overlap with market development. Without looking far, individualism may serve as an example. In this study, we use three different proxies for market development: 1) a developed market indicator (*DEV*) of Azevedo and Müller (2020); 2) the measure of the importance of the stock market for the economy (*MKT*) by Watanabe et al. (2013); and 3) the measure of financial openness (*OPEN*) by Chinn and Ito (2006).

The third group of variables encompasses indicators of market efficiency. In informationally efficient markets, new information is more quickly incorporated in the prices, and potential inefficiencies are swiftly eliminated. Consequently, any substantial mispricing is less likely to arise. We employ for measures of market efficiency from finance literature: 1) future earnings response coefficient (*FERC*) originating from Collins et al. (1994) and Durnev et al. (2003); 2) stock return synchronicity (*SYNCH*) by Morck, Yeung, and Yu (2000); and 3) the delay measure (*DELAY*) introduced by Hou and Moskowitz (2005).

The fourth set of *CRO* return predictors relates to limits to arbitrage. If the *CRO* anomaly manifests irrational mispricing, it should be more evident in countries with stronger trading frictions. This behavior complies with the concept of limits to arbitrage, which discourages sophisticated investors from eliminating an anomaly (Shleifer & Vishny, 1997). In line with this argument, ample research demonstrates that diverse proxies of limits to arbitrage; such as short-sale limitations, idiosyncratic risk, trading costs, or illiquidity (Chordia, Roll, & Subrahmanyam, 2008; Chu, Hirschleifer, & Ma, 2020; Fan, Opsal, and Yu, 2015; Lam & Wei, 2011; McLean 2010; Sadka & Scherbina, 2007; Stambaugh, Yu, & Yuan, 2012); influence the degree of mispricing. Following these arguments, we account for five different measures of limits to arbitrage, that generally build on Lam and Wei (2011) and Watanabe et al. (2013): 1) illiquidity (*AMIH*) measured with the Amihud's (2002) ratio; 2) stock turnover (*TV*); 3) short-sale availability indicator (*SHORT*) from Bris, Goetzmann, and Zhu (2007) and McLean, Pontiff, and Watanabe (2009); 4) idiosyncratic risk (*IRISK*); and 5) closely related return dispersion (*DISP*).

The final category of characteristics refers to shareholder protection. This feature may influence the CRO effect in a number of ways. First, it may be indirectly related to mispricing, as it could be viewed as an implicit arbitrage limitation (Barberis & Thaler, 2003; Hollstein & Sejdiu 2020; Watanabe et al., 2013). Furthermore, less constrained board members and directors may augment the uncertainty of stock valuations. Moreover, Lin, Massa, and Zhang (2014) argue that corporate governance influences stock price informativeness and Gonenc and Ursu (2018) show that it may facilitate the occurrence of mispricing.

On the other hand, empirical evidence on the influence of shareholder protection on the magnitude of mispricing is inconclusive. Dong (2019) and Fan et al. (2015), who comprehensively examine multiple anomalies worldwide, find that the correlation between mispricing and investor protection is mixed and depends on a particular anomaly. Formidable investor protection helps attract more unsophisticated investors (Giannetti & Koskinen, 2010). In consequence, the position of individual investors is especially strong in markets with solid shareholder protection. Importantly, Da, Huang, and Jin (2021) argue that extrapolative beliefs are stronger among non-professionals. Hence, the level of shareholder protection may be associated with a stronger recency bias in a market. Moreover—from a broader perspective—unsophisticated individual investors tend to be more prone to

behavioral biases and contribute to mispricing (Collins, Gong, & Hribar, 2003; Kaniel et al., 2012). Since the two forces outlined above—associated with limits to arbitrage and behavior of individual investors—will determine the overall impact of shareholder protection on the *CRO* effect. To account for these aspects, we incorporate two investor protection metrics developed by Djanko et al. (2008): anti-director rights index (*AD*) and anti-self-dealing index (*AS*).

4.2.3. Primary Results

Table 9 reports the results of the regression of local *CRO* strategy profits on different country characteristics. Panels A and B present the outcomes for equal-weighted and value-weighted *CRO* spread portfolios, respectively, and the two sets of results are generally similar and consistent. Let us focus first on the univariate regressions in column (1). The results of these tests match many of our earlier theoretical assumptions. To begin with cultural traits, for equal-weighted portfolios, the *CRO*-driven mispricing is more substantial in countries characterized by, e.g., high individualism, indulgence, low uncertainty avoidance, and short-term orientation. This complies with our reasoning that the chronological return ordering effect may be augmented when the national culture correlates with self-attribution bias and overconfidence. When investors focus on short-term performance, they tend to be overconfident and sensitive to extreme returns. Notably, the measures of national culture are partly correlated. In consequence, the group regressions (column 2) and the cross-checks with the value-weighted portfolios (Table 9, Panel B) confirm that the most crucial role is played by individualism (*IND*). This cultural trait remains significant at the 5% level in univariate and group regressions for both equal-weighted and value-weighted portfolios.

[Insert Table 9 here]

Turning now to market development measures, the univariate tests corroborate the relevance of this category of country characteristics. For equal-weighted portfolios, all three measures considered, *DEV*, *MKT*, and *OPEN*, display positive and significant coefficients. This matches our earlier observations that the magnitude of the effect of chronological return ordering goes hand in hand with market development. Its role, however, is less evident for value-weighted portfolios—especially in the group regressions.

The two following categories of variables, concerning market efficiency and limits to arbitrage, lead to somewhat mixed and not entirely consistent findings. No single variable is significant for both equal-weighted and value-weighted portfolios.

Finally, the investor protection indicators appear to play a role in the occurrence of the *CRO* anomaly. The phenomenon is particularly vivid for *AS*, which proves significant for univariate and multivariate tests of equal- and value-weighted strategies. The positive influence of *AS* emphasizes the links between shareholder protection and extrapolative

beliefs of individual investors. As demonstrated by Da, Huang, and Jin (2021), extrapolative thinking is stronger among non-professionals. Stronger investor protection may attract retail investors, who are typically considered less sophisticated and more prone to behavioral biases than institutional players (Keim & Madhavan, 1995; Schmeling, 2007; Chang & Wei, 2011).

To conclude, many of the variables that are partly significant in univariate or multivariate tests shed some light on the underlying drivers of the cross-sectional variations in international *CRO* returns. However, not all of them are significant at the 5% level across different test specifications. Two particular variables, *INDIV* and *AS*, matter in all the methodological variations for both weighting schemes (equal- and value-weighted) in both univariate and multivariate tests. The last column (7) of Table 9 presents comprehensive tests involving these two variables. Notably, both features remain significant, providing independent information about the future regardless of the portfolio-weighting scheme. To sum up, the chronological ordering anomaly is particularly pronounced in individualistic cultures and markets that are characterized by high investor protection.

Of particular note is that both investor protection and individualism are closely associated with capital market development. Abundant research has demonstrated that stronger investor protection facilitates equity issuance, financial development, and access to finance (Pagano & Volpin, 2006; Deakin, Sarkar, & Siems, 2018; La Porta, Lopez-de-Silanes, & Shleifer, 2013). As a result, it encourages efficient investment, higher valuations, and leads to larger and healthier equity markets (La Porta et al., 2002; La Porta, Lopez-de-Silanes, & Shleifer, 2013; McLean, Zhang, & Zhao, 2012). Also, within our sample, the cross-sectional correlation between *AS* and *MKT* variables, representing the market development, equals 0.56. In consequence, these two variables cast light on why we observe a much stronger *CRO* anomaly in developed markets than in emerging ones.

Similarly, individualism encourages risk-taking, supporting financial market development and economic growth through multiple channels (Ball, 2001; Dutta & Mukherjee, 2015). Hence, individualism encourages bigger and more developed markets for risky assets, such as venture capital or equities (Dutta & Mukherjee, 2015; Gantenbein, Kind, & Volonté; 2019). This link also resonates in our sample. The average *INDIV* value for developed markets is 65, while for the emerging ones, it equals only 33.

Summing up, both the *INDIV* and *AS* variables are associated with market development. Therefore, their influence helps to understand why the magnitude of the *CRO* anomaly differs so much in the developed and emerging markets (vide Table 4).

4.2.4. Further Tests

To further scrutinize the role of these two variables, we supplement our examinations with several additional analyses. To start with, we perform several robustness checks of

our principal results from Table 9. First, we replace the continuous explanatory variables with dummy variables in the spirit of Hollstein and Sejdiu (2020). Second, following the reasoning of Brennan, Chordia, & Subrahmanyam (1998), we substitute the raw returns as dependent variables with risk-adjusted returns from the six-factor model (2). Third, we control for the market development by considering *INDIV* and *AS* jointly with *DEV*.

For brevity, we report the results of these examinations in Table A11 in the Internet Appendix. None of these three robustness checks affects our findings measurably; *INDIV* and *AS* remain reliable predictors of *CRO* returns across countries. Notably, the last tests (Table A11, Panel C) suggest that *INDIV* and *AS* subsume the importance of market development. When these characteristics are considered jointly with *DEV*, the last variable no longer plays any relevant role. Intuitively, as discussed in Section 4.2.1, the developed markets usually provide better investor protection and are characterized by a more individualistic culture. Consequently, once we control these two characteristics, the difference in *CRO* strategy performance between developed and emerging markets can no longer be confirmed. In a nutshell, the role of *INDIV* and *AS* explains why we observe the different magnitudes of the CRO anomaly in developed and emerging markets, as demonstrated in Table 4.

Finally, to better visualize the heterogeneity in the magnitude of the *CRO* anomaly in countries with different degrees of investor protection and individualism, we perform country-level sorts. Each month, we sort all the markets into tertiles based on their *INDIV* and *AS* scores. Next, we analyze the average performance of country-specific *CRO* spread portfolios presented in Table 8 in different classes of individualism and investor protection.

The results of this exercise, as is displayed in Table 10, Panel A; substantiate our earlier conclusions from the cross-sectional regressions. Average returns and alphas on the *CRO* strategies in countries with high individualism and anti-self-dealing index are visibly greater than in other markets. For equal-weighted portfolios, the top *INDIV* tertile outperforms the bottom tertile by 0.40% per month. For the sorts on *AS*, the analogous difference also equals 0.40%. The outperformance is significant at the 1% level and robust to the value-based weighting scheme and controlling for the six-factor model (2) exposure.

[Insert Table 10 here]

To provide a broader picture, Figure A5 in the Internet Appendix illustrates the relative outperformance of the high *INDIV* and *AS* countries through time. A quick overview reveals that the pattern is stable through time and not specific to any particular subperiod.

In an unreported analysis, we check that the cross-sectional correlation between *INDIV* and *AS* is very low, amounting to 0.002. Therefore, we expect that the information contents of these two variables do not overlap, and their predictive powers over the CRO anomaly are independent of each other. Consistently with this, both of them are significant in the joint regression in Table 9. Nevertheless, to verify it further, we perform an additional exercise: conditional double sorting.

Whereas Panel A of Table 10 concentrates on unconditional rankings, Panel B considers conditional two-way sorts. In this approach, in order to examine the effect of one variable (*INDIV* or *AS*), we initially sort markets on the other variable (*AS* or *INDIV*, respectively) into tertiles. Then, within each tertile of the control variables, we sort markets into subtertiles of the primary variable, producing 3×3=9 portfolios from bivariate dependent sorts. Finally, we calculate the average subtertile returns across the tertiles of the primary variable. This procedure allows us to disentangle the roles *INDIV* and *AS* and extract the incremental effect of one variable after controlling for the other.

The results of this exercise, demonstrated in Table 10, Panel B, confirm that both *INDIV* and *AS* provide unique and independent information about cross-country differences in the *CRO* anomaly profits. Top *INDIV* markets display higher *CRO* returns than low *INDIV* markets; even after controlling for *AS*, and vice versa, *AS* retains its predictive power—even after accounting for *INDIV*. The results are significant and robust to different weighting schemes and after applying the six-factor model (2).

5. Does the Return Ordering Effect Vary over Time?

Our considerations have, so far, concentrated on the unconditional effect of the chronological return ordering. Hence, we have not explored the time-variation in the occurrence of this anomaly. A growing body of research advocates the dynamic effects in asset pricing anomalies, and the conditional pricing effects of the *CRO* have, thus far, not been scrutinized. For that reason, we now extend our earlier discussions with the examination of the drivers of potential variation in the *CRO* anomaly through time.

Figure 1 displays the cumulative returns on the global decile spread portfolios formed on *CRO*, which were tested in Table 2, Panel C. The strategies exhibit relatively stable performance, but still, some fluctuations can be recorded. For instance, following substantial payoffs in the years1990-2002, no clear pattern emerges in the period 2003-2008. This is followed by another, a more extended bull period for the *CRO* anomaly, and the curve flattens again in the most recent years. To ascertain the sources of these fluctuations, we now carry on with more detailed scrutiny.

5.1. Drivers of the Dynamics in the Return Ordering Anomaly

Following the approach in Ilmanen et al. (2021), we pursue a broad-ranging search for potential economic drivers of the *CRO* anomaly variation. The considered variables draw inspiration from diverse asset pricing theories and associate the global *CRO*-driven mispricing with an array of various economics shocks, news, and variables. We provide their exhaustive description and calculation methods, data sources, and statistical properties in Tables A12 and A13 in the Internet Appendix. The section below contains a summary of the economic reasoning for their inclusion.

As it was already noticed, the behavioral perspective on stock market anomalies builds on two principal pillars: investors irrationality (or limited rationality), which allows mispricing to emerge; and limits to arbitrage, that prevent sophisticated investors from quickly capitalizing on market inefficiencies - thus - eliminating them (Barberis & Thaler, 2003). This view produces a testable implication that the anomalies should be stronger when arbitrage is more costly (Jacobs, 2015). Therefore, we start with several proxies of limits to arbitrage.

Finance literature typically associates market volatility with funding conditions (Brunnermeier & Pedersen, 2009; Gromb & Vayanos, 2002). This phenomenon may be driven by forced premature closing of leveraged or short positions, problems with raising capital (Gromb & Vayanos, 2010; Shleifer & Vishny, 1997), or high risk aversion and so-called "flights to safety" (Baele et al., 2020; Vayanos, 2004). Furthermore, extreme volatility adversely affects liquidity. As a result, anomalies that depend on liquidity provisions tend to be affected (Nagel, 2012). Lastly, institutional investors tend to suffer from fund outflows during excessive volatility periods, which lead to forced leverage reductions (Ang, Gorovyy, & van Inwegen, 2011; Ben-David, Franzoni, & Moussawi, 2012). Motivated by this reasoning, we account for three different proxies for volatility. Besides the total volatility measured with the standard deviation of global market returns, we also use implied volatility captured by the CBOE VIX Volatility index (e.g., Durand, Lim, & Zumwalt [2011]; Peltomäki & Äijö [2015]; Jacobs [2015]). Finally, total volatility tends to be correlated with aggregate idiosyncratic volatility, which influences arbitrageurs' diversification abilities (Akbas et al., 2016; Pontiff, 2016). Hence, as in Jacobs (2015), we consider the average global idiosyncratic risk—as well.

Market spreads and interest rates form another contributor to arbitrage costs. To account for this, we scrutinize the relevance of three factors: a) U.S. T-Bill yield; b) TED spread, that is, the LIBOR Eurodollar rate minus the T-Bill rate; and c) credit spread, calculated as the 10-year BAA corporate bond yield minus the 10-year Treasury bond yield. The interest rate levels explicitly influence the costs of financing activities. Moreover, the TED spread, which is also typically used as a proxy for funding liquidity (Ang, Gorovyy, & Verstegen, 2011; Asness, Moskowitz, and Pedersen 2013; Brunnermeier & Pedersen,

2009; Moskowitz, Ooi, and Pedersen 2013), commonly widens during "flights to quality" or "flights to safety" (Brunnermeier, Nagel, & Pedersen, 2008). Parallel arguments hold for corporate spreads (Akbas et al., 2013; Engelberg et al., 2009).

The measures linked with interest rates are closely linked with funding liquidity. Nevertheless, trading liquidity may also matter for arbitrage activity. For example, Mashruwala, Rajgopal, and Shevlin (2006) demonstrate that trading costs constitute a significant barrier for arbitrageurs. To capture the role of time-varying trading liquidity, we follow Lam and Wei (2011) and proxy it with the average Amihud (2002) illiquidity ratio.

The second pillar of behavioral perspective on stock market anomalies is investors' irrationality. In line with this view, the magnitude of mispricing tends to be affected by investor sentiment (Baker, Wang, & Wurgler, 2008; Jacobs, 2015; Stambaugh, Yu, & Yuan, 2012, 2014). Notably, the sentiment also relates to liquidity, which implicitly influences transaction costs (Kumari, 2019; Liu, 2015). To account for the role of investor sentiment, we use the index of Baker and Wurgler (2006).

The magnitude of behavioral biases tends to be affected by past market returns. For example, Cooper, Gutierrez, and Hameed (2006) and Huang (2006) claim that bull markets augment investor overconfidence and self-attribution biases—reinforcing equity mispricing. On the flip side, severe market crashes typically coincide with abnormal volatility and illiquidity, restricting arbitrage opportunities and amplifying potential mispricing. Empirical evidence is ambiguous, with some models positing that anomaly returns decrease following significant disasters, tail events, and downside risk (Gabaix, 2012; Lanfear, Lioui, & Siebert, 2019; Lettau, Maggiori, & Weber, 2014; Tsai & Wachter, 2015). To control the role of the market state, we account for both short-term (six months) and long-term (60 months) global market returns. As in Ilmanen et al. (2021), we also include a tail risk dummy variable indicating the fifth percentile of the lowest market returns.

Following Ilmanen et al. (2021), we also reflect on a couple of essential macroeconomic variables. There has been much research scrutinizing and modeling the effect of economic shocks and the state of the business cycle (for review of theories and models, see Daniel and Titman [2012], Ilmanen et al. [2019], Kim and Na [2016]). The impact can be direct or indirect, e.g., via the influence of sentiment (Sibley, Xing, & Zhang, 2012). To consider these issues, we include the global GDP growth and inflation rates in our testing framework. In addition to that, we also control for the term spread, which partly mirrors expectations of future output and growth (Favero et al., 2012; Rudebusch & Wu, 2008).

Eventually, we investigate the impact of global economic policy and geopolitical uncertainty (Baker, Bloom, & Davis, 2016; Caldara & Iacoviello, 2018; Davis, 2016). Heightened factors may affect both investor sentiment and barriers to argbitrage. The existing

evidence on the direction and magnitude of the impact of uncertainty on stock mispricing is ambivalent (see, e.g., Brogaard and Detzel [2015] or Gu et al. [2020]).

5.2. Regression Analysis

To scrutinize the importance of the variables described in Section 5.1, we use the method of Ilmanen et al. (2021) and run predictive regressions. We regress contemporaneous returns on global decile spread portfolios from sorts on CRO (identically as reported in Table 2) on the economic variables lagged by one period. This lag aims to ensure that the variables reflect the most recent economic news available to market participants. Therefore, the estimated regressions coefficient represents predictive relationships.

For the sake of conciseness, in the baseline tests, we examine the aggregate global portfolios formed out of stocks from 49 countries. Nonetheless, in additional robustness checks, we broaden our investigations to the subsets of both developed and emerging markets. Finally, since we examine a battery of various return predictors (see Table A12 in the Internet Appendix), we apply the Bonferroni correction to account for a multiple hypothesis framework. Given the 16 variables considered, the 5% significance level implies a t-statistic threshold of 2.96.

Table 11 presents the outcomes of our predictive regressions. Importantly, we apply this to both equal-weighted and value-weighted long-short decile portfolios formed on CRO. Furthermore, we run both univariate regressions (Table 11, Panel A) and multivariate regressions (Table 11, Panel B). In the second method, we extend the equation with the six factors from model (2).

[Insert Table 11 here]

Several variables turn out to play an essential role in shaping the CRO anomaly returns. First, the CRO profits are more substantial during periods of elevated market volatility. Positive and significant coefficients can be observed for both historical and implied volatility measures. This observation complies with the reasoning that high volatility tends to impede arbitrage activity.

The same argument may explain the partial significance of the TED and credit spreads. The coefficients on these two variables are also positive and exhibit relatively t-statistics. This supports the view that the mispricing may be augmented by challenges to arbitrage activities driven by limited funding liquidity. In this case, however, the evidence is weaker as the t-statistics do not go past the 5%-significance hurdle in all specifications.

Next, we observe the detrimental impact of past short-term returns. The coefficients of regressions are negative across all test specifications. This indicates that the CRO anomaly is stronger (weaker) following recent market downsides (upsides). In other words, the

CRO spread portfolios perform particularly well following short-term bear markets, and yields lower returns following recent global bull markets.

Finally, the positive and significant coefficients on the tail risk dummy lead to similar conclusions. The *CRO* strategy profits are powerful in periods of low global equity returns. Extreme market states tend to augment the *CRO*-linked mispricing.

Overall, the findings in Table 11 suggest that the chronological return anomaly is particularly pronounced in challenging market conditions: during high volatility states, following market crashes, severe bear markets, and during tight funding environments. This is consistent with the behavioral view on market anomalies, asserting that they should be the strongest during periods when arbitrage activities are limited. Importantly, this observation has some practical implications – both positive and negative – for the potential CRO-based trading strategies. On the positive side, it may potentially offer a partial hedge against market crashes, as it overperforms during the most challenging market conditions. On the other hand, however, practical benefitting from the CRO effect may be challenging, as the profits predominantly source from periods when trading may be comparably tricky and costly.

5.3. Supplementary Tests

Two variables in Table 11 seem particularly strong and convincing: past short-term return and volatility. Hence, we take a closer look at them and supplement their examinations with several robustness checks.

First, we relax the assumptions regarding the estimation windows. To be specific, for both variables, we examine a range of different formation periods, ranging from one to 12 months. Second, whereas our baseline approach focused on the global *CRO* effect, we replicate the tests for the subsamples of developed and emerging markets. For the sake of brevity, in Figure A6 in the Internet Appendix, we illustrate just the *t*-statistics associated with coefficients from these regressions. Overall, the impact of market volatility and past returns is robust to alternative estimation periods and consideration of developed and emerging markets. Admittedly, we observe some variation in the statistical significance among different tests; for example, the past market return effect appears weaker in emerging markets than in developed ones. Nevertheless, overall, their effect on *CRO*-related mispricing is robust across the vast majority of tested specifications.

Finally, to better visualize the impact of past global market return and volatility on CRO profits, we calculate the global CRO zero-investment (long-short) strategy performance within the periods of high and low volatility and market returns. In this exercise, we sort monthly CRO strategy returns based on past volatility and stock market returns. Specifically, we group them into two halves using the median of market volatility (*volatile* vs. *stable* market states) and short-term (six-month) return (*Bull* vs. *bear* markets).

Subsequently, we calculate the average portfolio returns and the six-factor model alphas in different subperiods and calculate differences between the two periods. The results of this analysis are summarized in Table 12.

[Insert Table 12 here]

Table 12, Panel A, concentrates on the role of market volatility. The mean *CRO* spread portfolio performance is very strong during the *volatile* market. The six-factor model alphas amount to 1.25% and 1.77% monthly for equal- and value-weighted strategies—respectively. On the other hand, during stable markets, the *CRO* profits do not depart from zero. The mean abnormal returns equal only 0.09% and 0.33% per month.

Table 12, Panel B - in turn - concentrates on the performance in bull and bear markets. Again, similarly as in the case of volatility, the premium materializes only following low (below-median) market returns. The average *CRO* returns following bear markets amount to 1.34% and 1.76% for equal-weighted and value-weighted strategies. In contrast, the performance following bull markets may be disappointing. The *CRO* anomaly returns and alphas do not differ significantly from zero, neither in equal-weighting nor in the value-weighting framework.

To conclude, the global CRO anomaly's profit is realized almost solely after harsh, crash-like market conditions. Following periods of elevated volatility and low past returns, they are high and significant. However, during other market states, i.e., stable periods of low volatility and bull markets, the anomaly is insignificant and cannot be confirmed.

6. Concluding Remarks

The recency effect asserts that investors overweight recent facts while underweighting or ignoring those from distant paths. This phenomenon may distort an investor's expectations of future asset prices, thus causing predictable return patterns in the stock market. This study investigates the role of the recency effect in the cross-section of international stock returns. Building on Mohrschladt (2021), we examine the return predictability by chronological return ordering in 49 stock markets around the world.

The results show that companies with comparably low recent returns and high distant ones significantly outperform their counterparts with relatively high recent returns and low distant ones. Globally, an equal-weighted (value-weighted) decile of top *CRO* stocks outperforms the bottom *CRO* decile by 0.63% (0.91%) per month; the effect remains strong after controlling for common asset pricing factors.

Crucially, unlike many other anomalies, the *CRO* effect is not concentrated in microcaps. The cross-sectional pattern in returns is powerful and significant in both small and big firms as well. The average returns on long-short *CRO* strategies are actually higher for

the largest stocks than for smaller ones. This observation is essential in terms of implementability—the anomaly does not originate from some dusty corner of the markets but works well among the biggest and most liquid companies in the global equity universe.

Further cross-sectional regressions and bivariate sorts demonstrate the robustness of the *CRO* anomaly. It cannot be explained by a battery of other variables, such as beta, illiquidity, reversal, momentum, idiosyncratic volatility, or skewness. The *CRO* does not display a measurable relationship with any of these and other control variables. Furthermore, it does not depend on any particular industry, and survives even if portfolios are reconstructed only once in six months.

Notably, the magnitude *CRO* anomaly differs across countries, and the effect is particularly strong in developed markets. This pattern can be partly attributed to the difference in firm sizes, as emerging markets are typically home to smaller companies. In addition, a careful analysis of country characteristics from domains—cultural traits, market development, informational efficiency, limits to arbitrage, and shareholder protection—allows for a better understanding of the cross-country variation sources. The *CRO* effect is more pronounced in countries with individualistic national cultures and strong shareholder protection. The monthly differences in *CRO* spread portfolio returns between tertiles of high and low countries sorted by these characteristics amount to about 0.40% per month.

Finally, our further analyses uncover that the global *CRO* effect fluctuates over time. The dynamics are primarily driven by the global market state and volatility. The anomaly is especially strong following significant market crashes. The spread portfolio returns are both high and robust in volatile periods and after significant down markets. On the other hand, in stable times, the *CRO* strategy profits hardly differ from zero.

Our study has direct practical implications. Given the prevalence of the recency anomaly in big stocks, it could be directly translated into quantitative trading strategies with several favorable characteristics. The *CRO* effect remains powerful, even in the biggest and most liquid stock market companies, without sacrificing profitability. Furthermore, its robustness in developed markets alleviates potential implementation barriers and reliance on small and demanding markets. Finally, the superior performance following market crashes allows the production of sizeable profits, even in the volatile and challenging market environment.

Future studies on the historical return ordering could be extended to different asset classes. The recency effect works in many different domains, and it is not limited to any particular type of securities. Therefore, its underlying mechanism may equally affect commodities, cryptocurrencies, or corporate bonds. From the perspective of the return ordering anomaly, however, these asset classes remain an unchartered territory.

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Table 1. Research Sample

The table presents the statistical properties of the sample: the average monthly stock returns (μ), their standard deviation (Vol), skewness ($Skew$), and kurtosis ($Kurt$). First, for all the statistics, we compute value-weighted cross-sectional means; second, we calculate the time-series averages of monthly values. N is the average monthly number of stocks in the sample. MV denotes the average company market capitalization. Start and End refer to the beginning and ending months of the study period. Panels A and B report the results for developed and emerging markets, respectively; Panel C displays aggregate international statistics. μ and Vol are expressed in percentage, and MV is expressed in USD million.

	μ	Vol	Skew	Kurt	N	MV	Start	End
				Panel A: Developed markets				
Australia	0.70	14.32	1.60	18.99	861.52	798.84	Jan 1990	Dec 2020
Austria	0.40	7.67	0.34	5.64	64.96	1131.04	Jan 1990	Dec 2020
Belgium	0.48	7.16	0.37	7.03	96.51	1961.46	Jan 1990	Dec 2020
Canada	0.63	15.58	1.78	20.32	1087.95	819.82	Jan 1990	Dec 2020
Denmark	1.08	9.91	0.77	9.42	144.18	1586.50	Jan 2000	Dec 2020
Finland	0.80	8.96	0.61	6.58	94.29	1596.74	Jan 1990	Dec 2020
France	0.59	9.96	1.15	14.37	562.16	2337.32	Jan 1990	Dec 2020
Germany	0.53	10.26	0.62	9.79	906.92	2276.11	Jan 1990	Dec 2020
Hong Kong	0.94	14.13	1.90	20.55	736.71	1418.88	Jan 1990	Dec 2020
Ireland	0.35	10.41	0.09	4.85	32.46	1979.59	Jan 1990	Dec 2020
Israel	0.69	10.52	0.92	12.82	256.40	518.05	Jan 2000	Dec 2020
Italy	0.36	9.08	1.07	11.33	204.01	2192.77	Jan 1990	Dec 2020
Japan	0.06	10.84	3.00	49.01	2750.56	1357.14	Jan 1990	Dec 2020
Netherlands	0.64	8.54	0.39	7.98	115.44	4695.96	Jan 1990	Dec 2020
New Zealand	0.81	8.03	0.27	6.71	72.26	466.87	Jan 1990	Dec 2020
Norway	0.69	12.23	0.78	8.74	134.01	965.98	Jan 1990	Dec 2020
Portugal	0.30	8.85	0.51	5.08	47.54	1070.79	Jan 1990	Dec 2020
Singapore	0.62	9.64	1.17	13.88	303.25	780.96	Jan 1990	Dec 2020
Spain	0.49	8.85	0.75	8.54	122.69	3620.56	Jan 1990	Dec 2020
Sweden	0.85	11.92	1.16	13.10	258.68	1096.06	Jan 1990	Dec 2020
Switzerland	0.74	7.42	0.48	7.91	182.06	4315.88	Jan 1990	Dec 2020
United Kingdom	0.45	12.17	1.17	18.92	1125.86	1915.19	Jan 1990	Dec 2020
United States	0.75	11.94	1.28	20.43	3130.49	4241.92	Jan 1990	Dec 2020
				Panel B: Emerging markets				
Argentina	0.60	10.53	0.66	4.30	58.21	682.79	Jan 1996	Dec 2020
Brazil	0.81	10.89	0.36	4.66	88.88	1471.35	Jan 1997	Dec 2020
Chile	0.47	7.78	0.35	5.08	122.50	989.34	Jan 1993	Dec 2020
China	0.89	10.27	1.24	11.61	1446.03	1251.10	Jan 1996	Dec 2020
Colombia	0.98	5.80	0.31	3.67	39.08	2682.35	Jan 2005	Dec 2020
Czechia	1.10	13.63	0.07	3.72	21.68	1818.13	Jan 1999	Dec 2020
Egypt	0.17	12.40	1.22	9.50	147.50	369.95	Jan 2006	Dec 2020
Greece	0.43	11.99	0.89	8.36	161.21	338.77	Jan 1990	Dec 2020
Hungary	0.74	9.83	0.42	5.12	31.32	770.14	Jan 2000	Dec 2020
India	0.94	14.06	1.43	12.01	1213.87	545.65	Jan 1993	Dec 2020
Indonesia	0.91	14.03	1.44	12.17	230.82	653.86	Jan 1993	Dec 2020
Malaysia	0.53	10.62	1.58	16.42	524.63	447.08	Jan 1990	Dec 2020
Mexico	0.74	8.94	0.38	5.17	95.62	2262.57	Jan 1995	Dec 2020
Pakistan	0.71	11.80	1.19	9.50	174.38	161.77	Jan 1995	Dec 2020
Peru	1.11	9.26	0.32	3.87	92.93	472.74	Jan 2002	Dec 2020
Philippines	0.37	12.18	1.24	10.27	153.82	646.75	Jan 1994	Dec 2020
Poland	0.71	13.29	1.38	15.06	280.72	439.91	Jan 2000	Dec 2020
Qatar	0.72	7.43	0.74	5.69	37.23	3333.50	Jan 2007	Dec 2020

Russia	1.01	12.01	1.33	11.57	141.31	5016.93	Jan 2005	Dec 2020
Saudi Arabia	0.52	9.12	1.05	9.54	130.82	3003.58	Jan 2007	Dec 2020
South Africa	0.57	10.13	0.45	7.29	221.10	1251.67	Jan 1990	Dec 2020
South Korea	0.62	14.32	2.24	24.94	923.98	567.19	Jan 1990	Dec 2020
Taiwan	0.54	11.03	1.53	13.67	1005.14	687.20	Jan 1995	Dec 2020
Thailand	0.70	12.24	1.50	14.42	358.03	465.66	Jan 1992	Dec 2020
Turkey	0.73	13.70	2.20	20.02	276.86	751.00	Jan 2006	Dec 2020
UAE	0.23	9.55	0.79	6.13	84.71	1982.76	Jan 2006	Dec 2020
Panel C: Aggregate statistics								
Developed	0.60	11.46	1.41	21.46	13161.70	2108.35	Jan 1990	Dec 2020
Emerging	0.75	11.25	1.27	12.07	6765.77	738.69	Jan 1990	Dec 2020
Global	0.63	11.42	1.38	19.60	19927.47	1665.00	Jan 1990	Dec 2020

Table 2. Univariate Portfolio Sorts

The table reports the monthly returns on equal-weighted and value-weighted decile portfolios from one-way sorts on chronological return ordering (*CRO*). *High* and *Low* indicate the deciles with the highest and lowest *CRO* values, respectively; *High-Low* represents a long-short strategy buying (selling) the *High* (*Low*) portfolio. $\overline{R}$ is the average monthly excess return, and α denotes the alpha from the six-factor model of Fama and French (2018). $\overline{R}$ and α are reported in percentages. The numbers in parentheses are corresponding *t*-statistics adjusted for heteroskedasticity and autocorrelation using the Newey-West (1987) method. PanelA presents the results for the United States, Panel B for the global sample excluding the United States, and Panel C for the entire global sample. The average number of firms in a single decile portfolio in Panels A, B, and C amounts to 313, 1701, and 2014—respectively. The sample encompasses 49 countries and the study period runs from January 1990 to December 2020.

	Equal-weighted portfolios				Value-weighted portfolios			
	R	t-stat$_R$	α	t-stat$_\alpha$	R	t-stat$_R$	α	t-stat$_\alpha$
				Panel A: The United States				
Low	0.37	*(1.43)*	-0.72	*(-7.25)*	0.27	*(1.14)*	-0.54	*(-4.43)*
2	0.67	*(2.46)*	-0.45	*(-5.55)*	0.49	*(2.02)*	-0.34	*(-3.04)*
3	0.79	*(2.98)*	-0.30	*(-4.65)*	0.78	*(3.28)*	-0.01	*(-0.08)*
4	0.90	*(3.34)*	-0.25	*(-3.94)*	0.69	*(2.86)*	-0.13	*(-1.45)*
5	1.05	*(3.94)*	-0.08	*(-1.32)*	0.77	*(3.19)*	0.01	*(0.09)*
6	1.09	*(4.02)*	-0.04	*(-0.64)*	0.86	*(3.56)*	0.16	*(1.97)*
7	1.19	*(4.36)*	0.06	*(0.98)*	0.69	*(2.69)*	-0.07	*(-0.65)*
8	1.34	*(4.91)*	0.21	*(3.12)*	0.97	*(4.00)*	0.30	*(3.37)*
9	1.41	*(5.14)*	0.32	*(4.32)*	0.93	*(3.80)*	0.19	*(1.90)*
High	1.67	*(5.92)*	0.56	*(5.86)*	1.06	*(4.27)*	0.36	*(2.91)*
High-Low	1.30	*(8.57)*	1.28	*(8.10)*	0.79	*(4.25)*	0.90	*(4.60)*
				Panel B: Global sample excluding the United States				
Low	0.50	*(1.97)*	-0.17	*(-1.46)*	-0.12	*(-0.45)*	-0.71	*(-5.14)*
2	0.45	*(1.75)*	-0.24	*(-2.36)*	-0.02	*(-0.07)*	-0.60	*(-5.60)*
3	0.49	*(1.90)*	-0.17	*(-1.90)*	0.12	*(0.47)*	-0.38	*(-4.29)*
4	0.59	*(2.32)*	-0.03	*(-0.38)*	0.23	*(0.90)*	-0.18	*(-2.11)*
5	0.60	*(2.36)*	-0.03	*(-0.39)*	0.30	*(1.17)*	-0.14	*(-1.54)*
6	0.67	*(2.61)*	0.05	*(0.65)*	0.36	*(1.37)*	-0.05	*(-0.53)*
7	0.79	*(3.01)*	0.18	*(2.17)*	0.45	*(1.66)*	0.04	*(0.42)*
8	0.85	*(3.21)*	0.27	*(2.89)*	0.53	*(1.97)*	0.12	*(1.09)*
9	0.83	*(3.07)*	0.25	*(2.29)*	0.66	*(2.43)*	0.24	*(2.08)*
High	0.86	*(2.92)*	0.31	*(2.17)*	0.80	*(2.79)*	0.31	*(2.18)*
High-Low	0.36	*(1.94)*	0.48	*(2.40)*	0.91	*(4.37)*	1.02	*(4.56)*
				Panel C: Global sample				
Low	0.47	*(1.93)*	-0.25	*(-2.62)*	0.04	*(0.17)*	-0.59	*(-5.16)*
2	0.51	*(2.08)*	-0.22	*(-2.89)*	0.08	*(0.36)*	-0.53	*(-6.10)*
3	0.61	*(2.48)*	-0.11	*(-1.66)*	0.29	*(1.29)*	-0.23	*(-3.37)*
4	0.68	*(2.81)*	-0.01	*(-0.13)*	0.42	*(1.75)*	-0.05	*(-0.76)*
5	0.77	*(3.19)*	0.09	*(1.56)*	0.47	*(1.99)*	-0.03	*(-0.52)*
6	0.85	*(3.50)*	0.19	*(3.21)*	0.55	*(2.26)*	0.16	*(2.60)*
7	0.95	*(3.84)*	0.31	*(4.99)*	0.54	*(2.18)*	0.17	*(2.67)*
8	1.02	*(4.08)*	0.38	*(5.66)*	0.65	*(2.68)*	0.27	*(3.70)*
9	1.05	*(4.11)*	0.43	*(5.39)*	0.79	*(3.22)*	0.41	*(4.30)*
High	1.10	*(3.96)*	0.52	*(4.32)*	0.95	*(3.72)*	0.53	*(4.47)*
High-Low	0.63	*(3.68)*	0.77	*(4.18)*	0.91	*(4.89)*	1.13	*(5.62)*

Table 3. The CRO Anomaly Among Big, Small, and Microcap Companies

The table reports the monthly returns on equal-weighted and value-weighted decile portfolios from one-way sorts on chronological return ordering (*CRO*). *High* and *Low* indicate the deciles with the highest and lowest CRO values, respectively, and *High-Low* represents a long-short strategy buying (selling) the *High* (*Low*) portfolio. $\overline{R}$ is the average monthly excess return, and α denotes the alpha from the six-factor model of Fama and French (2018). $\overline{R}$ and α are reported in percentages. The numbers in parentheses are corresponding *t*-statistics that are adjusted for heteroskedasticity and autocorrelation using the Newey-West (1987) method. The table also presents the average firm market value ($\overline{MV}$)—expressed in USD billion. The global sample for this analysis encompasses 49 countries and the study period runs from January 1990 to December 2020. The tests are implemented in three distinct size environments: *Big firms* (Panel A) are the largest companies, they account for 90% of the total global market capitalization; *Small firms* (Panel B) represent the subsequent 7% of the global market value; *Micro firms* (Panel C) are the smallest companies that account for the remaining 3% of the market capitalization. The average number of firms in a single decile portfolio in Panels A, B, and C amounts to 374, 406, and 1234—respectively.

	Equal-Weighted Portfolios				Value-Weighted Portfolios				$\overline{MV}$
	$\overline{R}$	t-stat$_R$	α	t-stat$_\alpha$	$\overline{R}$	t-stat$_R$	α	t-stat$_\alpha$	
				Panel A: Big firms					
Low	0.07	*(0.28)*	-0.59	*(-5.32)*	-0.02	*(-0.10)*	-0.66	*(-5.53)*	7.11
2	0.21	*(0.83)*	-0.46	*(-5.64)*	0.05	*(0.20)*	-0.58	*(-6.60)*	7.85
3	0.29	*(1.16)*	-0.32	*(-4.56)*	0.30	*(1.28)*	-0.22	*(-3.11)*	8.03
4	0.37	*(1.51)*	-0.20	*(-3.54)*	0.40	*(1.68)*	-0.10	*(-1.72)*	8.21
5	0.45	*(1.82)*	-0.13	*(-2.43)*	0.49	*(2.03)*	0.04	*(0.78)*	8.26
6	0.55	*(2.15)*	0.03	*(0.49)*	0.47	*(1.90)*	0.03	*(0.56)*	8.36
7	0.66	*(2.58)*	0.15	*(2.60)*	0.54	*(2.13)*	0.16	*(2.20)*	8.41
8	0.74	*(2.84)*	0.25	*(3.36)*	0.66	*(2.70)*	0.37	*(4.84)*	8.37
9	0.79	*(3.02)*	0.29	*(3.15)*	0.78	*(3.14)*	0.38	*(4.12)*	8.25
High	0.99	*(3.58)*	0.48	*(3.69)*	0.93	*(3.64)*	0.55	*(4.60)*	7.85
High-Low	0.92	*(4.75)*	1.07	*(5.15)*	0.95	*(4.92)*	1.21	*(5.82)*	
				Panel B: Small firms					
Low	0.26	*(0.99)*	-0.41	*(-3.33)*	0.21	*(0.80)*	-0.46	*(-3.75)*	0.57
2	0.39	*(1.50)*	-0.24	*(-2.49)*	0.36	*(1.42)*	-0.25	*(-2.60)*	0.57
3	0.54	*(2.09)*	-0.06	*(-0.67)*	0.52	*(2.01)*	-0.07	*(-0.78)*	0.57
4	0.57	*(2.22)*	-0.03	*(-0.44)*	0.54	*(2.11)*	-0.05	*(-0.71)*	0.57
5	0.52	*(2.04)*	-0.06	*(-0.92)*	0.51	*(1.99)*	-0.06	*(-1.00)*	0.57
6	0.60	*(2.36)*	0.04	*(0.62)*	0.59	*(2.30)*	0.02	*(0.42)*	0.57
7	0.62	*(2.38)*	0.09	*(1.40)*	0.59	*(2.29)*	0.06	*(1.02)*	0.57
8	0.69	*(2.60)*	0.17	*(2.00)*	0.68	*(2.56)*	0.16	*(1.85)*	0.57
9	0.84	*(3.01)*	0.32	*(2.64)*	0.84	*(3.01)*	0.32	*(2.66)*	0.57
High	0.96	*(3.14)*	0.41	*(2.51)*	0.95	*(3.13)*	0.40	*(2.44)*	0.57
High-Low	0.70	*(2.99)*	0.82	*(3.26)*	0.75	*(3.21)*	0.86	*(3.46)*	
				Panel C: Micro firms					
Low	0.70	*(2.84)*	-0.05	*(-0.50)*	0.57	*(2.28)*	-0.17	*(-1.62)*	0.09
2	0.69	*(2.82)*	-0.09	*(-0.94)*	0.61	*(2.49)*	-0.11	*(-1.23)*	0.09
3	0.74	*(2.96)*	-0.06	*(-0.71)*	0.65	*(2.60)*	-0.11	*(-1.45)*	0.08
4	0.82	*(3.35)*	0.05	*(0.53)*	0.67	*(2.75)*	-0.06	*(-0.85)*	0.08
5	0.98	*(3.96)*	0.21	*(2.36)*	0.77	*(3.13)*	0.04	*(0.59)*	0.08
6	1.06	*(4.30)*	0.30	*(3.41)*	0.81	*(3.32)*	0.09	*(1.30)*	0.08
7	1.15	*(4.54)*	0.38	*(4.26)*	0.87	*(3.53)*	0.17	*(2.42)*	0.08
8	1.23	*(4.86)*	0.49	*(5.30)*	0.93	*(3.72)*	0.26	*(3.29)*	0.08
9	1.23	*(4.72)*	0.50	*(5.05)*	0.92	*(3.55)*	0.24	*(2.66)*	0.09
High	1.16	*(4.14)*	0.52	*(4.01)*	0.95	*(3.37)*	0.36	*(2.80)*	0.09
High-Low	0.45	*(2.85)*	0.58	*(3.42)*	0.38	*(2.12)*	0.54	*(2.80)*	

Table 4. Portfolio Sorts in Developed and Emerging Markets

The table reports the monthly returns on equal-weighted and value-weighted decile portfolios from one-way sorts on chronological return ordering (*CRO*). *High* and *Low* indicate the deciles with the highest and lowest *CRO* values, respectively; *High-Low* represents a long-short strategy buying (selling) the *High* (*Low*) portfolio. $\overline{R}$ is the average monthly excess return, and α denotes the alpha from the six-factor model of Fama and French (2018). $\overline{R}$ and α are reported in percentages. The numbers in parentheses are corresponding *t*-statistics adjusted for heteroskedasticity and autocorrelation using the Newey-West (1987) method. The table also presents the average firm market value ($\overline{MV}$) expressed in USD billion. This analysis's total sample encompasses 49 countries and the study period runs from January 1990 to December 2020. Panel A shows the results for 23 developed markets and Panel B for 26 emerging markets, as is classified in Table 1. The average number of stocks in a decile portfolio in Panels A and B equals 1325 and 691–respectively.

	Equal-weighted portfolios				Value-weighted portfolios				$\overline{\text{MV}}$
	$\bar{R}$	t-stat$_R$	α	t-stat$_\alpha$	$\bar{R}$	t-stat$_R$	α	t-stat$_\alpha$	
				Panel A: Developed markets					
Low	0.16	*(0.64)*	-0.51	*(-5.48)*	-0.02	*(-0.10)*	-0.68	*(-6.13)*	1.80
2	0.32	*(1.31)*	-0.34	*(-4.47)*	0.12	*(0.51)*	-0.49	*(-5.64)*	2.00
3	0.46	*(1.91)*	-0.17	*(-2.62)*	0.27	*(1.19)*	-0.29	*(-4.21)*	2.03
4	0.56	*(2.31)*	-0.05	*(-0.78)*	0.44	*(1.83)*	-0.05	*(-0.75)*	2.08
5	0.66	*(2.73)*	0.05	*(0.92)*	0.53	*(2.23)*	0.02	*(0.28)*	2.07
6	0.80	*(3.30)*	0.22	*(3.91)*	0.48	*(1.99)*	0.04	*(0.67)*	2.08
7	0.94	*(3.76)*	0.37	*(6.18)*	0.60	*(2.40)*	0.24	*(3.36)*	2.17
8	1.05	*(4.18)*	0.48	*(7.13)*	0.67	*(2.77)*	0.25	*(3.66)*	2.19
9	1.13	*(4.46)*	0.56	*(7.05)*	0.86	*(3.48)*	0.45	*(4.95)*	2.30
High	1.28	*(4.90)*	0.73	*(7.21)*	0.98	*(3.91)*	0.54	*(5.03)*	2.32
High-Low	1.12	*(7.26)*	1.24	*(7.60)*	1.00	*(5.55)*	1.21	*(6.41)*	
				Panel B: Emerging markets					
Low	1.09	*(3.33)*	0.23	*(1.24)*	0.33	*(1.02)*	-0.15	*(-0.79)*	0.75
2	1.04	*(3.26)*	0.22	*(1.42)*	0.43	*(1.33)*	-0.06	*(-0.36)*	0.79
3	0.98	*(3.12)*	0.21	*(1.37)*	0.29	*(0.93)*	-0.17	*(-1.23)*	0.77
4	0.96	*(3.02)*	0.19	*(1.38)*	0.32	*(1.03)*	-0.01	*(-0.05)*	0.77
5	1.02	*(3.36)*	0.24	*(2.18)*	0.51	*(1.69)*	0.16	*(1.29)*	0.76
6	0.90	*(3.01)*	0.03	*(0.26)*	0.39	*(1.29)*	-0.06	*(-0.50)*	0.77
7	0.93	*(3.08)*	0.01	*(0.06)*	0.37	*(1.21)*	0.00	*(0.00)*	0.77
8	0.77	*(2.37)*	-0.23	*(-1.72)*	0.56	*(1.68)*	-0.10	*(-0.61)*	0.77
9	0.83	*(2.38)*	-0.19	*(-1.05)*	0.40	*(1.24)*	-0.11	*(-0.74)*	0.78
High	0.72	*(1.89)*	-0.25	*(-1.03)*	0.69	*(1.92)*	0.31	*(1.42)*	0.75
High-Low	-0.37	*(-1.12)*	-0.48	*(-1.31)*	0.36	*(1.14)*	0.46	*(1.32)*	

Table 5. Portfolio Sorts in Emerging Markets: The Role of Firm Size

The table reports the monthly returns on equal- and value-weighted decile portfolios from one-way sorts on chronological return ordering (*CRO*) formed within emerging markets. *High* and *Low* indicate the deciles with the highest and lowest *CRO* values, respectively; *H-L* represents a long-short strategy buying (selling) the *High* (*Low*) portfolio. $\overline{R}$ is the average monthly excess return, and α denotes the alpha from the six-factor model of Fama and French (2018). All returns and alphas are reported as percentages, and the numbers in parentheses are Newey-West (1987) adjusted *t*-statistics. The total sample in this analysis encompasses 26 emerging markets and the study period runs from January 1990 to December 2020. The tests reported in Panel A are implemented in four distinct size environments: *All firms* refers to all companies in the sample; *Big firms* are the largest companies, they account for 90% of the total global market capitalization; *Small firms* represent the subsequent 7% of the global market value; *Micro firms* are the smallest companies that account for the remaining 3% of the market capitalization. The breakpoints to differentiate between Big, Small, and Micro firms in Panel B are calculated using the same procedure based on the developed market sample and subsequently applied to emerging market equities. Finally, the classification in Panel C follows the same procedure as in Panel A, but the firms with capitalization below USD 300 million are excluded from the sample.

	Panel A: Emerging market breakpoints				Panel B: Developed market breakpoints				Panel C: Firms <USD 300 million excluded			
	All	Micro	Small	Big	All	Micro	Small	Big	All	Micro	Small	Big
					Equal-weighted portfolios							
Low	1.09	1.33	1.37	0.41	1.09	1.41	0.52	0.13	0.44	0.86	0.43	0.27
2	1.04	1.27	1.12	0.43	1.04	1.18	0.63	0.27	0.46	1.11	0.59	0.31
3	0.98	1.20	0.93	0.49	0.98	1.11	0.69	0.52	0.72	0.69	0.75	0.55
4	0.96	1.31	1.13	0.49	0.96	1.21	0.70	0.39	0.67	0.59	1.17	0.42
5	1.02	1.38	0.88	0.46	1.02	1.12	0.45	0.52	0.59	0.69	0.37	0.57
6	0.90	1.22	0.77	0.53	0.90	1.09	0.50	0.59	0.62	0.93	0.45	0.58
7	0.93	1.24	0.73	0.36	0.93	1.07	0.41	0.58	0.56	0.68	0.44	0.51
8	0.77	1.49	0.64	0.33	0.77	1.12	0.39	0.28	0.41	0.69	0.62	0.40
9	0.83	1.16	0.72	0.36	0.83	1.02	0.39	0.50	0.53	0.29	0.54	0.49
High	0.72	0.98	0.45	0.68	0.72	0.78	0.63	0.70	0.69	0.50	0.73	0.70
H-L $\overline{R}$	-0.37	-0.35	-0.92	0.28	-0.37	-0.62	0.12	0.57	0.24	-0.35	0.29	0.42
	(-1.12)	*(-1.06)*	*(-2.34)*	*(0.85)*	*(-1.12)*	*(-1.87)*	*(0.34)*	*(1.84)*	*(0.77)*	*(-0.86)*	*(0.76)*	*(1.37)*
H-L α	-0.48	-0.51	-1.03	0.24	-0.48	-0.71	-0.06	0.78	0.23	-0.37	0.19	0.47
	(-1.31)	*(-1.40)*	*(-2.38)*	*(0.67)*	*(-1.31)*	*(-1.92)*	*(-0.15)*	*(2.29)*	*(0.66)*	*(-0.81)*	*(0.44)*	*(1.38)*
					Value-weighted portfolios							
Low	0.33	1.21	1.22	0.22	0.33	1.31	0.52	0.08	0.25	0.82	0.41	0.23
2	0.43	1.17	1.12	0.32	0.43	1.03	0.67	0.20	0.30	1.11	0.61	0.25
3	0.29	1.01	0.89	0.25	0.29	0.81	0.63	0.24	0.38	0.70	0.74	0.25
4	0.32	0.99	1.07	0.29	0.32	1.08	0.71	0.27	0.34	0.58	1.19	0.24
5	0.51	1.16	0.87	0.19	0.51	0.80	0.50	0.24	0.32	0.70	0.35	0.23
6	0.39	0.84	0.78	0.51	0.39	0.75	0.48	0.45	0.48	0.93	0.46	0.47
7	0.37	0.84	0.67	0.39	0.37	0.66	0.43	0.52	0.44	0.68	0.45	0.50
8	0.56	1.02	0.64	0.38	0.56	0.75	0.39	0.38	0.35	0.69	0.61	0.37
9	0.40	0.78	0.63	0.33	0.40	0.63	0.41	0.32	0.42	0.29	0.51	0.33
High	0.69	0.63	0.50	0.82	0.69	0.41	0.69	0.84	0.85	0.50	0.73	0.86
H-L $\overline{R}$	0.36	-0.58	-0.73	0.61	0.36	-0.90	0.17	0.76	0.60	-0.32	0.32	0.63
	(1.14)	*(-1.64)*	*(-1.87)*	*(1.87)*	*(1.14)*	*(-2.51)*	*(0.48)*	*(2.34)*	*(1.87)*	*(-0.79)*	*(0.83)*	*(1.96)*
H-L α	0.46	-0.57	-0.83	0.76	0.46	-0.86	-0.02	0.97	0.75	-0.34	0.23	0.81
	(1.32)	*(-1.46)*	*(-1.95)*	*(2.13)*	*(1.32)*	*(-2.18)*	*(-0.05)*	*(2.72)*	*(2.13)*	*(-0.74)*	*(0.54)*	*(2.30)*

Table 6. Bivariate Portfolios Sorts

This table summarizes the performance of portfolios from two-way independent sorts on chronological return ordering (*CRO*) and additional variables: firm size (*SIZE*), book-to-market ratio (*BM*), momentum (*MOM*), illiquidity (*ILLIQ*), stock market beta (*BETA*), idiosyncratic volatility (*IVOL*), short-term reversal (*REV*), maximum daily return (*MAX*), co-skewness (*SKEW*), operating profitability (*PROF*), and asset growth (*AG*). The intersection of independent sorts into deciles on the control variables and *CRO* forms 10×10=100 bivariate portfolios. This table presents average monthly returns across the ten control deciles to produce decile portfolios with dispersion in *CRO* but with a consistent level of the control variable. All portfolios are rebalanced monthly. *Low CRO* and *High CRO* denote the deciles with the lowest and highest *CRO* values, respectively. *High-Low* $\bar{R}$ indicates the difference in average monthly returns between the *High CRO* and *Low CRO* portfolios, and *High-Low* α is the corresponding alpha obtained from the model of Fama and French (2018). The values in parentheses are corresponding *t*-statistics adjusted for heteroskedasticity and autocorrelation using the Newey-West (1987) method. The tests are implemented within a global sample encompassing 49 countries. The study period runs from January 1990 to December 2020. Panels A and B report the results for equal-weighted and value-weighted portfolios—respectively.

	Control variables										
	SIZE	BM	MOM	ILLIQ	BETA	IVOL	REV	MAX	SKEW	PROF	AG
	Panel A: Equal-weighted portfolios										
Low CRO	0.47	0.47	0.43	0.29	0.45	0.42	0.39	0.47	0.44	0.29	0.32
2	0.51	0.50	0.49	0.51	0.49	0.47	0.48	0.48	0.48	0.50	0.51
3	0.60	0.59	0.59	0.63	0.59	0.59	0.60	0.58	0.58	0.63	0.63
4	0.66	0.66	0.66	0.71	0.66	0.66	0.66	0.64	0.66	0.71	0.70
5	0.77	0.76	0.76	0.77	0.76	0.76	0.78	0.76	0.76	0.78	0.78
6	0.84	0.83	0.84	0.85	0.84	0.83	0.86	0.84	0.84	0.86	0.86
7	0.94	0.93	0.95	0.95	0.95	0.94	0.96	0.94	0.95	0.96	0.95
8	1.01	1.01	1.02	0.99	1.03	1.02	1.02	1.02	1.02	1.00	1.01
9	1.07	1.07	1.07	1.08	1.07	1.07	1.05	1.08	1.06	1.08	1.10
High CRO	1.14	1.16	1.15	1.21	1.15	1.17	1.08	1.22	1.15	1.20	1.20
High-Low $\bar{R}$	0.67	0.69	0.71	0.91	0.70	0.74	0.68	0.75	0.71	0.91	0.89
	(4.06)	*(4.12)*	*(4.50)*	*(5.18)*	*(4.58)*	*(4.38)*	*(4.23)*	*(4.45)*	*(4.22)*	*(4.58)*	*(4.58)*
High-Low α	0.75	0.79	0.81	1.00	0.81	0.84	0.77	0.85	0.82	1.02	0.99
	(3.54)	*(3.70)*	*(3.85)*	*(4.40)*	*(4.07)*	*(3.81)*	*(3.79)*	*(3.82)*	*(3.85)*	*(4.08)*	*(4.09)*
	Panel B: Value-weighted portfolios										
Low CRO	0.42	0.24	0.05	0.11	0.15	-0.04	0.05	0.08	-0.01	0.02	0.10
2	0.47	0.30	0.12	0.30	0.22	0.12	0.08	0.11	0.14	0.13	0.16
3	0.57	0.41	0.23	0.44	0.33	0.33	0.26	0.31	0.28	0.34	0.38
4	0.65	0.54	0.34	0.58	0.44	0.46	0.44	0.40	0.46	0.43	0.49
5	0.74	0.59	0.41	0.58	0.50	0.49	0.48	0.42	0.43	0.49	0.58
6	0.81	0.68	0.47	0.66	0.52	0.52	0.55	0.54	0.54	0.52	0.61
7	0.89	0.71	0.50	0.77	0.59	0.60	0.64	0.57	0.58	0.59	0.60
8	0.97	0.82	0.58	0.83	0.69	0.66	0.76	0.72	0.70	0.67	0.75
9	1.02	0.93	0.70	0.88	0.79	0.75	0.85	0.74	0.81	0.74	0.85
High CRO	1.09	1.12	0.91	1.08	0.88	1.02	1.06	1.05	1.04	1.00	1.07
High-Low $\bar{R}$	0.68	0.89	0.86	0.97	0.73	1.06	1.00	0.97	1.05	0.98	0.97
	(4.18)	*(4.86)*	*(4.74)*	*(5.96)*	*(5.28)*	*(4.83)*	*(5.61)*	*(4.96)*	*(5.61)*	*(4.73)*	*(5.31)*
High-Low α	0.78	1.03	1.00	1.02	0.82	1.25	1.12	1.10	1.28	1.17	1.11
	(3.74)	*(4.08)*	*(3.83)*	*(4.74)*	*(4.29)*	*(4.08)*	*(4.62)*	*(4.10)*	*(5.07)*	*(4.08)*	*(4.55)*

Table 7. Cross-Sectional Regressions

The table reports the average slope coefficients from the cross-sectional regressions in the style of Fama and MacBeth (1979) based on the following equation:

$$R_{i,t+1} = \gamma_0 + \gamma_{CRO} CRO_{i,t} + \sum_{j=1}^{n} \gamma_K K_{i,t}^{j} + \varepsilon_{i,t},$$

where $R_{i,t+1}$ is the return on the company i in month t+1, *CRO* represents the chronological return ordering in month t, and $K_{i,t}^{j}$ is the vector of additional control variables: firm size (*SIZE*), book-to-market ratio (*BM*), momentum (*MOM*), illiquidity (*ILLIQ*), stock market beta (*BETA*), idiosyncratic volatility (*IVOL*), short-term reversal (*REV*), maximum daily return (*MAX*), co-skewness (*SKEW*), operating profitability (*PROF*), and asset growth (AG). γ_0, γ_{CRO}, and γ_K are estimated monthly regression parameters and $\varepsilon_{i,t}$ is the error term. We run both univariate tests, excluding all the control variables and multivariate tests including them. $\overline{R^2}$ denotes the average cross-sectional coefficient of determination. The numbers in parentheses are t-statistics adjusted with the Newey-West (1987) method. The study period runs from January 1990 to December 2020. The tests are implemented in the entire global sample encompassing all firms in 49 markets (*All markets*), as well as in several subsamples. *Big firms* are the largest companies accounting for 90% of the total global market capitalization; *Small firms* represent the subsequent 7% of the global market value, and *Micro firms* are the smallest companies accounting for the remaining 3% of the market capitalization. *Developed* and *Emerging* refer to the 23 developed markets and 26 emerging markets—as classified in Table 1.

	(1) All Firms	(2) Big firms	(3) Small firms	(4) Micro firms	(5) Developed	(6) Emerging
			Univariate tests			
CRO	0.255	0.235	0.313	0.430	0.354	-0.103
	(4.61)	*(4.07)*	*(5.19)*	*(5.60)*	*(7.24)*	*(-0.91)*
	0.006	0.008	0.005	0.006	0.006	0.017
			Multivariate tests			
CRO	0.269	0.238	0.371	0.480	0.368	0.005
	(5.65)	*(4.95)*	*(7.02)*	*(7.33)*	*(9.40)*	*(0.05)*
MV	-0.168	-0.060	-0.095	-0.385	-0.142	-0.305
	(-3.23)	*(-1.44)*	*(-3.29)*	*(-5.32)*	*(-2.96)*	*(-3.08)*
BM	0.179	0.161	0.225	0.223	0.166	0.326
	(5.99)	*(4.62)*	*(3.83)*	*(2.75)*	*(5.16)*	*(4.50)*
MOM	0.350	0.329	0.565	0.550	0.359	0.423
	(5.94)	*(5.69)*	*(7.71)*	*(5.70)*	*(6.15)*	*(4.57)*
BETA	-0.101	-0.073	-0.071	-0.067	-0.079	-0.080
	(-1.49)	*(-1.11)*	*(-0.88)*	*(-0.76)*	*(-1.03)*	*(-0.98)*
REV	-0.039	0.040	0.020	-0.594	-0.106	0.100
	(-0.55)	*(0.56)*	*(0.23)*	*(-5.37)*	*(-1.60)*	*(0.95)*
IVOL	0.117	-0.007	0.148	0.378	0.085	-0.116
	(1.45)	*(-0.10)*	*(1.55)*	*(3.22)*	*(0.99)*	*(-1.02)*
SKEW	-0.009	-0.005	-0.042	-0.076	-0.012	-0.013
	(-0.35)	*(-0.19)*	*(-0.97)*	*(-1.40)*	*(-0.41)*	*(-0.24)*
PROF	-0.006	-0.013	0.039	0.047	-0.018	0.100
	(-0.57)	*(-1.28)*	*(1.10)*	*(0.87)*	*(-1.37)*	*(2.62)*
AG	-0.060	-0.046	-0.092	-0.104	-0.067	-0.086
	(-5.32)	*(-3.39)*	*(-2.83)*	*(-1.88)*	*(-5.55)*	*(-1.88)*
ILLIQ	0.022	-0.011	-0.029	-0.098	0.014	0.151
	(0.96)	*(-0.74)*	*(-0.69)*	*(-1.59)*	*(0.72)*	*(1.65)*
MAX	-0.174	-0.132	-0.346	-0.279	-0.151	-0.097
	(-4.55)	*(-3.29)*	*(-5.85)*	*(-3.47)*	*(-4.30)*	*(-0.95)*
$\overline{R^2}$	0.055	0.065	0.061	0.067	0.060	0.115

Table 8. Country-Level Univariate Sorts on Chronological Return Ordering

The table reports the monthly differential returns on equal-weighted and value-weighted portfolios formed on chronological return ordering (*CRO*). Each month, the long-short strategies buy (sell) a quintile of stocks with the highest (lowest) *CRO*. $\overline{R}$ denotes the mean monthly return, and α is the alpha from Fama and French's six-factor model (2018). The numbers in parentheses are corresponding *t*-statistics adjusted for heteroskedasticity and autocorrelation using the Newey-West (1987) method. The sample encompasses 49 countries, and Panels A and B report the results for the 23 developed and 26 emerging markets—respectively. $\overline{R}$ and α are presented in percentage. Panel C shows summary statistics for the entire sample: the average $\overline{R}$ and α across countries; the proportion of countries with a positive value; and the proportion of countries with a *t*-statistic exceeding a certain threshold (1.96, 3.00). The study period runs from January 1990 to December 2020.

	Equal-Weighted Portfolios				Value-Weighted Portfolios			
	$\bar{R}$	t-stat$_R$	α	t-stat$_\alpha$	$\bar{R}$	t-stat$_R$	α	t-stat$_\alpha$
Panel A: Developed Markets								
Australia	1.56	(9.22)	1.50	(7.80)	0.82	(4.06)	0.78	(3.36)
Austria	0.64	(2.77)	0.63	(2.63)	0.55	(1.81)	0.50	(1.56)
Belgium	0.67	(3.65)	0.77	(3.96)	0.73	(2.63)	0.87	(2.98)
Canada	2.16	(11.54)	2.21	(11.16)	1.12	(5.00)	1.20	(4.95)
Denmark	0.09	(0.44)	-0.10	(-0.42)	0.02	(0.04)	-0.04	(-0.10)
Finland	1.01	(4.51)	1.00	(4.29)	0.83	(2.07)	0.75	(1.81)
France	0.82	(5.62)	0.56	(3.62)	0.66	(3.13)	0.45	(1.95)
Germany	0.66	(4.36)	0.48	(2.92)	0.05	(0.21)	0.00	(-0.02)
Greece	0.92	(3.00)	0.96	(2.97)	0.51	(1.23)	0.61	(1.37)
Hong Kong	0.50	(2.59)	0.48	(2.35)	0.68	(2.49)	0.87	(2.97)
Ireland	1.22	(3.13)	1.31	(3.25)	1.43	(2.88)	1.46	(2.84)
Israel	0.59	(2.63)	0.47	(1.87)	1.34	(3.73)	1.15	(2.88)
Italy	0.59	(3.57)	0.49	(2.83)	0.78	(3.24)	0.73	(2.88)
Japan	0.86	(6.28)	0.79	(5.41)	0.74	(3.85)	0.83	(4.08)
Netherlands	0.31	(1.70)	0.42	(2.20)	0.70	(2.61)	0.94	(3.29)
New Zealand	1.24	(4.66)	1.16	(4.02)	0.93	(3.11)	0.79	(2.49)
Norway	1.23	(5.10)	1.23	(4.93)	0.70	(2.40)	0.79	(2.58)
Portugal	0.72	(2.03)	0.53	(1.45)	0.23	(0.60)	0.38	(0.94)
Singapore	1.62	(8.78)	1.55	(8.38)	0.71	(3.23)	0.60	(2.60)
Spain	0.02	(0.07)	0.01	(0.04)	-0.33	(-1.10)	-0.16	(-0.52)
Sweden	1.03	(5.26)	0.97	(4.70)	0.88	(2.67)	0.95	(2.85)
Switzerland	0.65	(4.45)	0.56	(3.64)	0.28	(1.14)	0.22	(0.86)
United Kingdom	-0.43	(-3.88)	-0.41	(-3.32)	0.65	(3.14)	0.90	(3.92)
United States	1.02	(8.18)	1.02	(7.86)	0.60	(3.70)	0.69	(4.09)
Panel B: Emerging Markets								
Argentina	0.39	(1.01)	0.53	(1.37)	0.90	(1.76)	0.90	(1.73)
Brazil	0.81	(2.18)	0.98	(2.49)	0.46	(0.80)	0.80	(1.32)
Chile	-0.21	(-0.95)	-0.20	(-0.82)	0.23	(0.64)	0.84	(2.25)
China	0.05	(0.23)	0.03	(0.15)	0.10	(0.31)	0.34	(1.10)
Colombia	0.14	(0.42)	0.19	(0.56)	0.27	(0.63)	0.18	(0.40)
Czechia	-0.25	(-0.59)	-0.20	(-0.45)	-0.47	(-0.80)	-0.11	(-0.18)
Egypt	-0.94	(-1.76)	-0.14	(-0.24)	-0.49	(-0.93)	0.10	(0.18)
Hungary	1.03	(1.66)	1.36	(2.14)	1.32	(2.47)	1.64	(2.99)
India	0.51	(2.21)	0.36	(1.53)	0.94	(2.83)	0.69	(2.00)
Indonesia	0.94	(3.28)	0.62	(2.10)	0.59	(1.71)	0.69	(1.88)
Malaysia	0.98	(5.26)	0.78	(4.08)	1.11	(4.85)	0.87	(3.69)
Mexico	0.38	(1.41)	0.44	(1.56)	0.95	(2.96)	1.09	(3.31)
Pakistan	-0.27	(-0.86)	-0.05	(-0.15)	-0.11	(-0.27)	0.01	(0.02)

Peru	0.28	(0.98)	0.55	(1.74)	0.21	(0.53)	0.23	(0.51)
Philippines	1.00	(2.76)	0.89	(2.40)	0.78	(1.96)	1.16	(2.90)
Poland	0.61	(2.21)	0.85	(2.95)	0.44	(1.25)	0.59	(1.61)
Qatar	0.04	(0.12)	-0.04	(-0.10)	0.32	(0.65)	0.30	(0.58)
Russia	0.67	(1.42)	0.79	(1.64)	0.73	(1.22)	1.08	(1.79)
South Africa	0.94	(4.85)	1.08	(4.98)	0.57	(1.94)	0.95	(2.95)
Saudi Arabia	-0.25	(-0.71)	-0.24	(-0.68)	0.47	(1.40)	0.33	(0.97)
South Korea	0.56	(2.21)	0.65	(2.57)	0.58	(1.59)	0.64	(1.72)
Taiwan	-0.21	(-0.94)	-0.11	(-0.46)	-0.09	(-0.30)	0.04	(0.13)
Thailand	0.73	(2.77)	0.63	(2.35)	0.44	(1.30)	0.28	(0.82)
Turkey	-0.31	(-1.24)	-0.32	(-1.25)	-0.25	(-0.40)	-0.39	(-0.65)
UAE	0.44	(0.99)	0.65	(1.32)	-0.04	(-0.05)	-0.12	(-0.14)
Panel C: Summary Statistics								
Average	0.57		0.59		0.52		0.60	
% positive	84%		80%		86%		88%	
% t-stat > 1.96	59%		57%		43%		45%	
% t-stat > 3.00	37%		31%		22%		16%	

Table 9. Country-Level Drivers of the Chronological Return Ordering Effect

The table presents the average slope coefficients of cross-sectional regressions of monthly differential returns on single-country portfolios formed on chronological return ordering (*CRO*). The dependent variable is the return on the zero-investment strategies that assume buying (selling) a quintile of stocks with the highest (lowest) *CRO*. The strategies are implemented in each of the 49 individual stock markets in our sample and rebalanced monthly. The explanatory variables encompass five categories: 1) cultural traits: power distance (*POWER*), individualism (*INDIV*), masculinity (*MASC*), uncertainty avoidance (*UNC*), long-term orientation (*LTOR*), and indulgence (*INDUL*); 2) market development: the developed market dummy (*DEV*), the importance of the stock market for the economy (*MKT*), and financial openness (*OPEN*); 3) informational efficiency: future earnings response coefficient (*FERC*), stock return synchronicity (*SYNCH*), and delay measure (*DELAY*); 4) limits to arbitrage: Amihud's illiquidity ratio (*AMIH*), turnover ratio (*TV*), short sale permission (*SHORT*), idiosyncratic risk (*IRISK*), and return dispersion (*DISP*); 5) investor protection: anti-director rights index (*AD*), and anti-self-dealing index (*AS*). A detailed explanation of the variables is provided in Table A9 in the Internet Appendix. The leftmost column (1) presents the coefficients of univariate regressions; columns (2) to (6) report the coefficients from multivariate regressions that run within different categories of independent variables; eventually, the rightmost column (7) displays the coefficients from the comprehensive model. The numbers in parentheses are corresponding *t*-statistics adjusted for heteroskedasticity and autocorrelation using the Newey-West (1987) method. *#Obs.* denotes the number of country-month observations, and $\overline{R^2}$ is the average cross-sectional adjusted R^2 coefficient. The study period runs from January 1990 to December 2020. All coefficients are multiplied by 1,000. Panels A and B display the results for the equal-weighted and value-weighted portfolios—respectively. The bold font indicates the variables with coefficients significant at the 5% level across all the specifications and weighting schemes.

Panel A: Equal-weighted portfolios

	(1) Univariate tests	(2) Cultural traits	(3) Market development	(4) Informational efficiency	(5) Limits to arbitrage	(6) Investor protection	(7) Comprehensive test
POWER	-0.03 (-1.89)	0.03 (1.25)					
INDIV	**0.06 (3.68)**	**0.05 (2.14)**					**0.06 (3.27)**
MASC	0.01 (0.50)	0.01 (0.69)					
UNCER	-0.06 (-3.36)	-0.05 (-2.40)					
LTOR	-0.03 (-2.01)	-0.02 (-1.00)					
INDUL	0.07 (2.81)	0.05 (1.52)					
DEV	2.36 (2.29)		-0.45 (-0.32)				
MKT	0.08 (4.00)		0.06 (2.88)				
OPEN	1.18 (3.72)		0.68 (1.55)				
FERC	-0.94 (-1.05)			-0.76 (-0.71)			
SYNCH	-1.54 (-1.41)			-1.74 (-1.55)			
DELAY	-1.47 (-1.04)			-0.59 (-0.37)			
AMIH	3.85 (0.28)				-1.04 (-0.13)		
TV	6.65 (1.49)				3.14 (0.74)		
SHORT	2.12 (1.76)				1.94 (1.49)		
IRISK	3.08 (1.89)				2.75 (1.45)		
DISP	39.03 (2.32)				27.07 (1.44)		
AD	0.77 (2.07)					-0.04 (-0.08)	
AS	**5.52 (2.88)**					**5.89 (2.70)**	**5.54 (2.91)**
$\overline{R^2}$		0.0088	0.0233	0.0155	0.0508	0.0091	0.0107
#Obs.		14964	13992	13257	13704	14412	14412

Panel B: Value-weighted portfolios

	(1) Univariate tests	(2) Cultural traits	(3) Market development	(4) Informational efficiency	(5) Limits to arbitrage	(6) Investor protection	(7) Comprehensive test
POWER	-0.02 (-0.80)	0.07 (2.35)					
INDIV	**0.05 (2.51)**	**0.06 (2.09)**					**0.05 (2.39)**
MASC	0.03 (1.21)	0.03 (1.34)					
UNCER	-0.05 (-2.29)	-0.04 (-1.92)					
LTOR	-0.03 (-1.48)	0.00 (-0.15)					
INDUL	0.08 (2.82)	0.07 (1.87)					
DEV	1.63 (1.18)		-0.28 (-0.15)				
MKT	0.06 (2.03)		0.04 (1.39)				
OPEN	0.94 (2.03)		0.73 (1.20)				
FERC	-0.66 (-0.45)			-1.41 (-0.99)			
SYNCH	-3.10 (-2.82)			-3.27 (-2.92)			
DELAY	-0.73 (-0.41)			2.36 (0.88)			
AMIH	-8.53 (-0.59)				-14.80 (-1.37)		
TV	-4.91 (-0.89)				-6.38 (-1.05)		
SHORT	3.81 (2.76)				4.49 (3.02)		
IRISK	3.61 (1.99)				6.61 (3.04)		
DISP	19.27 (0.97)				1.40 (0.06)		
AD	0.79 (1.55)					-0.20 (-0.32)	
AS	**6.04 (2.64)**					**6.68 (2.37)**	**6.22 (2.71)**
$\overline{R^2}$		0.0060	0.0229	0.0190	0.0457	0.0005	0.0033
#Obs.		14964	13992	13257	13704	14412	14412

Table 10. Individualism, Investor Protection, and the Performance of Chronological Return Ordering Strategies

The table reports the performance of strategies formed based on chronological return ordering (*CRO*) sorted on market characteristics. The long-short country-specific strategies are rebalanced monthly and assume buying (selling) a quintile of stocks with the highest (lowest) *CRO*. Panel A reports the unconditional sorts. In this framework, we group the countries into tertiles (*High*, *Mid*, *Low*) based on the individualism score (*INDIV*) of Hofstede (2001) and anti-self-dealing index (*AS*). *H-L* represents the *High* minus *Low* differential return. Panel B reports the conditional sorts. In this approach, we calculate average *High*, *Mid*, and *Low* tertile returns on one variable after controlling for the other variable through two-way dependent sorts into 3×3=9 portfolios. $\overline{R}$ denotes the mean monthly return, and α is the alpha from the six-factor model of Fama and French (2018). The subscripts *EW* and *VW* denote equal-weighted and value-weighted country-specific CRO strategies—respectively. $\overline{R}$ and α are presented in percentage. The values in parentheses are corresponding *t*-statistics adjusted for heteroskedasticity and autocorrelation using the Newey-West (1987) method. The sample encompasses 49 countries and the study period runs from January 1990 to December 2020.

	Sorts on INDIV					Sorts on AS				
	Low	Mid	High	H-L	t-*stat*	Low	Mid	High	H-L	t-stat
					Panel A: Unconditional sorts					
$\bar{R}_{EW}$	0.45	0.63	0.85	0.40	*(4.15)*	0.52	0.53	0.92	0.40	*(3.86)*
α_{EW}	0.47	0.54	0.85	0.38	*(4.10)*	0.47	0.48	0.92	0.45	*(3.78)*
$\bar{R}_{VW}$	0.42	0.55	0.75	0.33	*(2.37)*	0.42	0.46	0.82	0.40	*(3.19)*
α_{VW}	0.43	0.49	0.78	0.36	*(2.83)*	0.39	0.45	0.84	0.45	*(2.88)*
					Panel B: Conditional sorts					
$\bar{R}_{EW}$	0.52	0.62	0.83	0.31	*(3.15)*	0.59	0.51	0.85	0.27	*(2.70)*
α_{EW}	0.55	0.51	0.81	0.26	*(2.74)*	0.54	0.49	0.83	0.29	*(2.56)*
$\bar{R}_{VW}$	0.39	0.62	0.68	0.28	*(2.00)*	0.49	0.39	0.82	0.33	*(2.77)*
α_{VW}	0.40	0.56	0.69	0.29	*(1.99)*	0.46	0.38	0.81	0.36	*(2.24)*

Table 11. Time-Series Variation in the Global Chronological Return Ordering Effect

The table presents the slope coefficients of time-series regressions of global chronological return ordering (CRO) strategies on various economic measures. The long-short *CRO* strategies buy (sell) an equal-weighted or value-weighted decile of stocks with the highest (lowest) *CRO* value. The portfolios are formed within the pooled global sample encompassing 49 countries. The monthly returns are regressed on lagged values of different economic variables. Their detailed explanation is provided in Table A12 in the Internet Appendix. All the predictors are lagged by one period to capture the announcement lag, hence, reflecting the news associated with the variable and its contemporaneous impact on the *CRO* anomaly. The regressions in Panel A do not include any control variables. In contrast, the regression equations in Panel B incorporate six global factors from the model of Fama and French (2018): market excess return (MKT), small minus big (SMB), high minus low (HML), robust minus weak (RMW), conservative minus aggressive (CMA), and winners minus losers (WML). The values in parentheses are corresponding *t*-statistics adjusted for heteroskedasticity and autocorrelation using the Newey-West (1987) method. The bold font indicates coefficients that pass statistical significance at the 5% level after the Bonferroni correction for multiple hypotheses. The study period runs from January 1990 to December 2020.

	Panel A: No control variables		Panel B: Control variables included	
	Equal-weighted portfolios	Value-weighted portfolios	Equal-weighted portfolios	Value-weighted portfolios
Market volatility	**0.016 (4.06)**	**0.014 (3.46)**	**0.015 (4.21)**	**0.016 (3.75)**
Implied volatility	**0.022 (3.04)**	**0.022 (3.68)**	0.021 (2.88)	**0.021 (3.64)**
Idiosyncratic risk	-0.263 (-1.98)	-0.152 (-1.15)	-0.180 (-1.38)	-0.090 (-0.73)
TED spread	1.232 (1.85)	1.601 (2.95)	1.404 (2.62)	**1.711 (3.97)**
Treasury bill yield	0.034 (0.39)	0.083 (0.96)	0.100 (1.21)	0.145 (1.61)
Credit spread	**0.927 (3.48)**	**0.819 (3.29)**	0.734 (2.44)	0.688 (2.66)
Illiquidity	0.352 (1.64)	0.049 (0.20)	0.158 (0.72)	-0.130 (-0.55)
Baker-Wurgler index	-0.004 (-1.27)	-0.001 (-0.49)	-0.002 (-0.70)	0.001 (0.36)
Short-term market return	**-0.380 (-3.20)**	**-0.380 (-3.72)**	**-0.357 (-3.18)**	**-0.355 (-3.81)**
Long-term market return	-0.418 (-1.94)	-0.176 (-0.74)	-0.262 (-1.15)	-0.093 (-0.37)
Tail risk	**0.032 (3.34)**	**0.036 (6.91)**	0.027 (2.60)	**0.032 (5.36)**
GDP growth	-0.032 (-1.20)	-0.003 (-0.19)	-0.014 (-0.48)	0.010 (0.42)
Inflation rate	0.089 (0.37)	0.199 (1.04)	0.237 (1.28)	0.348 (1.60)
Term spread	0.235 (1.20)	0.100 (0.47)	0.149 (0.75)	0.055 (0.26)
Economic uncertainty	0.000 (0.24)	0.000 (0.35)	0.000 (-0.32)	0.000 (-0.33)
Geopolitical risk	0.000 (0.74)	0.000 (-0.70)	0.000 (0.25)	0.000 (-1.29)

Table 12. Global Chronological Return Ordering Anomaly in Different Market States

The table reports the performance of the long-short chronological return ordering (*CRO*) strategies during periods of high and low past volatility (Panel A) and short-term market returns (Panel B)—as defined in Table A11 in the Internet Appendix. The *CRO* strategies buy (sell) an equal-weighted or value-weighted portfolio of stocks with the highest (lowest) *CRO* score. The portfolios are formed within the pooled global sample encompassing 49 countries. The monthly returns are grouped into halves based on the median of past volatility and short-term past return on the market portfolio. *High* (*Low*) represent the periods of above-median (below-median) volatility and past market returns, and *High-Low* indicate the difference between the *High* and *Low* market states. $\overline{R}$ denotes the mean monthly return, and α is the alpha from the six-factor model of Fama and French (2018). The values in parentheses are corresponding *t*-statistics adjusted for heteroskedasticity and autocorrelation using the Newey-West (1987) method. The significance for the High-Low portfolios is calculated using a dummy-regressions model, as seen in Cooper, Gutierrez, and Hameed (2004). The study period runs from January 1990 to December 2020.

	Equal-weighted portfolios		Value-weighted portfolios	
	$\bar{R}$	α	$\bar{R}$	α
Panel A: Volatile vs. stable markets				
High market volatility	1.07 (3.99)	1.25 (3.97)	1.37 (4.54)	1.77 (4.70)
Low market volatility	0.12 (0.59)	0.09 (0.36)	0.38 (1.80)	0.33 (1.32)
High - Low	0.95 (2.33)	1.17 (2.22)	0.99 (2.50)	1.44 (2.71)
Panel B: Bull vs. bear markets				
High market return	0.13 (0.62)	-0.05 (-0.19)	0.39 (1.73)	0.18 (0.69)
Low market return	1.13 (4.14)	1.34 (3.99)	1.43 (4.97)	1.76 (5.15)
High - Low	-1.00 (-2.89)	-1.38 (-2.90)	-1.04 (-3.00)	-1.58 (-2.86)

Figure 1. Cumulative Performance of Global Chronological Return Ordering Strategies

The figure presents the cumulative returns on equal-weighted and value-weighted global strategies based on chronological return ordering (CRO). Every month, the zero-investment strategy takes a long (short) position in the decile of stocks with the highest (lowest) CRO. The stocks are selected from the global sample comprising 49 markets. The study period runs from January 1990 to December 2020. The returns are cumulated additively and are reported in percentage.