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Enhanced momentum strategies☆

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ABSTRACT

This paper compares the performance of three enhanced momentum strategies proposed in the literature: constant volatility-scaled momentum, constant semi-volatility-scaled momentum, and dynamic-scaled momentum. Using data for individual stocks from the U.S. and across 48 international countries, we find that all three approaches decrease momentum crashes and lead to higher risk-adjusted returns. However, in multiple factor comparison tests, no enhanced momentum strategy emerges as consistently superior. Finally, cross-country analyses relate momentum and the two constant volatility-scaled momentum returns to market dynamics, whereas dynamic-scaled momentum is significantly less affected, suggesting a reduced sensitivity to time-varying investor overconfidence.

1. Introduction

The evidence for momentum is pervasive: stocks with the highest returns over the past six to twelve months tend to outperform in the subsequent period (Jegadeesh and Titman, 1993; 2001). Within the U.S. equity market, a long-short momentum factor generated an average raw return of 0.60% (Fama-French three-factor model (FF3FM) alpha of 0.88%) per month between January 1930 and December 2017. However, besides its high profitability, momentum occasionally experiences large drawdowns. For instance, the momentum factor for the U.S. equity market exhibited a drawdown of -49.01% in 1932, and in 2009 the momentum factors in both the U.S. and international (non-U.S.) equity markets experienced substantial losses.

Grundy and Martin (2001) explain the risks of momentum by time-varying factor exposures. For instance, after bear markets, the market betas of loser stocks tend to be higher than those of winner stocks. When the market rebounds after a bear market, the overall negative market sensitivity of the winner-minus-loser strategy generates negative strategy returns during the market up-movement. Asem and Tian (2010) investigate the effect of market dynamics on momentum returns in stock markets and document that there are higher momentum returns when markets continue in the same state than when they transition to a different state. Market transitions occur when market up-movements (down-movements) follow a bear (bull) market and are associated with low momentum returns, picking up the occurrence of momentum crashes.

Volatility-scaling aims at managing these crashes. The idea is based on the empirical observation that returns are relatively low when volatility is high, named the leverage effect, and that factor-return volatility is positively autocorrelated in the short term.[1] Three volatility-scaled strategies have been proposed and investigated for the U.S. equity market. Barroso and Santa-Clara (2015) study momentum strategies that are deflated by their

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[1] See, among others, Bekaert and Wu (2000) for asymmetry in the risk to return relation and Engle (1982), Bollerslev (1987) for volatility autocorrelation. Wang and Yan (2021) find that for momentum in the U.S., the performance improvement from volatility-scaling stems mainly from the leverage effect.

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past realized volatility and scaled to a constant target volatility level. Realized volatility is calculated from past daily momentum returns and serves as a proxy for future volatility. Relatedly, Wang and Yan (2021) test factors scaled by semi-volatility (downside risk) to distinguish down- from up-movements. Daniel and Moskowitz (2016) extend the constant-volatility scaling approach by additionally taking the predicted momentum return into account. This paper compares these three enhanced momentum strategies—constant volatility-scaled momentum (cMOM), constant semi-volatility-scaled momentum (sMOM), and dynamic-scaled momentum (dMOM)—for a long sample of U.S. and a broad sample of non-U.S. stocks using a uniform data set and methodology.

Our main findings can be summarized as follows. First, we show that all enhanced strategies substantially increase Sharpe ratios by using a long sample of U.S. stocks from 1930 to 2017 and a broad sample of stocks from 48 international markets from 1990 to 2017. Furthermore, skewness, kurtosis, and maximum drawdowns decrease in magnitude compared to standard momentum (MOM) so that their return distributions become more Gaussian. Comparing the individual enhanced strategies within the two samples, we find similar improvements for Sharpe ratios and t-statistics (both roughly double compared to MOM) across all three strategies, while returns during bear-up months are highest for dynamic-scaled momentum (dMOM).

Second, mean-variance spanning and ex-post maximum Sharpe ratio (cf., Barillas et al., 2019) tests show that all enhanced momentum strategies significantly increase the maximum Sharpe ratio as compared to a factor opportunity set that already includes momentum. In pairwise tests for both the U.S. and the non-U.S. sample, the augmented model with constant volatility-scaled momentum (cMOM) significantly outperforms the one augmented with constant semi-volatility-scaled momentum (sMOM). However, the model augmented with cMOM outperforms the model augmented with dMOM only for the non-U.S., but not for the U.S. sample.

Third, cross-country panel regressions document that the market continuation dummy has the highest significance in explaining differences in momentum returns *across countries*. This finding is consistent with the evidence provided in Asem and Tian (2010) and Hanauer (2014) that momentum returns *across time* are higher in market continuations for the U.S. and Japan, respectively. The result is also consistent with behavioral explanations of momentum, i.e., time-varying overconfidence drives momentum returns (Daniel et al., 1998). While cMOM and sMOM are similarly affected by the market continuation dummy as MOM, we document a weaker impact on dMOM, suggesting a reduced sensitivity to time-varying investor overconfidence. We also document that MOM, cMOM, and sMOM are more related to market continuations in bear markets than in bull markets. This behavior is consistent with the option-like behavior of momentum in bear markets (Daniel and Moskowitz, 2016), i.e., expected momentum returns are low in bear markets when market volatility is high and the market rebounds. When splitting our sample into two sub-periods from 01/1990 to 12/2003 and from 01/2004 to 12/2017, we identify a significant effect of individualism on momentum returns only for the first, but not for the second subperiod. Thus, the results in Chui et al. (2010) do not hold out-of-sample, while the effect of the market continuation dummy on all momentum strategies is robust across both sub-periods. In addition, the panel regressions indicate that all momentum strategies are positively affected by firm-specific return variation (i.e., a negative coefficient on R^2), although to a lesser degree. Based on Hou et al. (2013) and Kelly (2014), this finding appears to be consistent with noise trader-based interpretations of this variable.

Fourth, enhanced momentum strategies should be at least as implementable as MOM as their break-even costs (i.e., transaction costs that theoretically would render the strategies insignificant) are higher than the ones for MOM. Furthermore, all momentum strategies generate their performance mainly during non-January months.

This paper contributes to the literature in at least three aspects. First, we align our research with the ongoing debate about whether volatility-managed investment strategies yield higher Sharpe ratios than non-managed strategies. Moreira and Muir (2017) highlight the advantage for mean-variance investors when scaling different equity long-short strategies by realized variance. However, Cederburg et al. (2020) examine 103 equity factors and find that volatility-management generates statistically significant Sharpe ratio improvements for only 8 out of 103 factors. Importantly, the authors show that the 8 equity factors all relate to momentum strategies. Similarly, Barroso and Detzel (2021) investigate whether limits-to-arbitrage explain the abnormal returns of volatility-managed equity factors scaled by their prior-month variance as in Moreira and Muir (2017). They find that volatility-managed factors besides the market factor are generally not profitable after accounting for transaction costs. However, the momentum factor becomes profitable after transaction costs when scaling it by its realized volatility.

Second, we add to the replication literature with an extensive replication of momentum strategies. According to Hou et al. (2020), replication provides a contribution when extending existing studies out-of-sample. In this regard, the majority of asset pricing studies are based solely on U.S. market data. Karolyi (2016) argues that this implicitly creates a "home bias" for the U.S. market. Harvey (2017) furthers the replication argument by stating that many published results would not hold in the future because of unreported tests, testing of multiple hypotheses, and data snooping. Harvey et al. (2016) link data-snooping concerns with the pressure and incentive to publish, which generates a publication bias, and propose higher t-statistic hurdles. Since we are conducting a comparison study that tests already published enhanced momentum strategies for both the U.S. and international markets, affirmative results for both samples alleviate concerns that previously documented patterns are due to chance or data snooping.

Third, we contribute to the literature investigating the drivers of cross-country differences in anomaly returns (cf., among others, Titman et al., 2013; Watanabe et al., 2013; Stambaugh et al., 2015; Jacobs, 2016). Chui et al. (2010) show that momentum is persistent worldwide except for Asia, and propose cross-country differences in individualism as an explanation, while Docherty and Hurst (2018) document that momentum is stronger in more myopic countries. We add to this literature by extensively investigating the source of the four momentum strategies starting in 1990. We employ the comprehensive country-level predictor set from Jacobs (2016) as well as behavioral predictors from Chui et al. (2010) and Asem and Tian (2010), comprising proxies for investor overconfidence, limits-to-arbitrage, information uncertainty and differences of opinion, and market efficiency. To the best of our knowledge, our study is the first that tests the explanatory power of a market continuation dummy, among other predictors, across countries and for both momentum and enhanced momentum strategies. The market continuation dummy proxies time-varying overconfidence in line with the overreaction hypothesis (Daniel et al., 1998).

Our paper is also related to studies that propose alternative momentum definitions to avoid the risks of momentum. Grundy and Martin (2001) show that adjusting the momentum strategy for the dynamic ex-post market and size factor exposures substantially reduces the volatility of the strategy without a loss in return. Similar to Grundy and Martin (2001), Gutierrez and Prinsky (2007) use firm-specific returns relative to the Fama-French three-factor model during the formation period. They find that this firm-specific momentum - also called residual or idiosyncratic momentum - experiences no long-term reversals. In addition, Blitz et al. (2011) document that idiosyncratic momentum exhibits only half of the volatility of standard momentum without any significant decrease in returns. Furthermore, Blitz et al. (2020) show that commonly-used asset pricing factors, including momentum, cannot explain idiosyncratic momentum both in the U.S. and internationally and Haesen et al. (2017) find that residualizing stock returns also increases the performance of momentum spillovers from equities to corporate bonds.

The rest of the paper is structured as follows: Section 2 describes the data, factor construction, enhanced momentum strategies, and research methodologies. Section 3 presents our empirical results for the implemented strategies, mean-variance spanning tests, maximum ex-post Sharpe ratio tests, cross-country panel regressions, break-even transaction cost analyses, and the January effect. We provide our conclusions in Section 4.

2. Data and methodology

2.1. Data

The data analyzed in this paper is collected from various sources. We use a sample consisting of 66,905 stocks for 49 equity markets from January 1926 to December 2017. We differentiate into U.S. and non-U.S. (international) equity data with respect to differences in the sample period availability. Both monthly and daily returns are measured in USD. The U.S. data comes from the Center for Research on Security Prices (CRSP) and covers January 1926 to December 2017. International data is collected from Refinitiv for the sample period January 1987 to December 2017, and the country selection follows the Morgan Stanley Capital International (MSCI) Developed and Emerging Markets Indices. We include all countries classified either as developed or emerging markets at some point during the sample period. More precisely, the countries are only part of the actual sample in those years in which they are part of the MSCI Developed and Emerging Markets Indices. Next to the U.S., the following countries are included: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Morocco, the Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Qatar, Russia, Singapore, South Africa, (Republic of) South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, the United Kingdom (U.K.), and the United Arab Emirates.

Our U.S. sample includes all common equity stocks traded on NYSE, NYSE MKT (formerly: AMEX), or NASDAQ within the CRSP universe. We exclude all stocks with a CRSP share code (SHRCD) different than 10 or 11. If available, we use Fama-French factors from Kenneth French's website[2] and the monthly updated value factor (HML_d) from AQR[3] for the long sample, which leaves us with constructing MOM and the enhanced momentum strategies. The non-U.S. sample comprises market data from Datastream and accounting data from Worldscope. We process data through static and dynamic screens to ensure data quality. As the first step, we identify stocks by Refinitiv Datastream's constituent lists. We use Worldscope lists, research lists, and, to eliminate survivorship bias, dead lists. Following Ince and Porter (2006), Griffin et al. (2010), and Schmidt et al. (2017), we apply generic as well as country-specific static screens to eliminate non-common equity stocks. In addition, we apply dynamic screens for stock return and price data as recommended in the literature. Appendix A.1 describes the static and dynamic screens in detail. The emerging market data is restricted to start only in July 1994. For both the U.S. and non-U.S., analyst data is gathered from the Institutional Brokers' Estimate System (I/B/E/S).

We require stocks to have a valid market capitalization for June y and December $y-1$ and a positive book equity value for December $y-1$ to be regarded for the market, size, and value portfolios within the non-U.S. sample. For both the U.S. and the non-U.S. sample, we calculate MOM, constant volatility-scaled momentum, constant semi-volatility-scaled momentum, and dynamic-scaled momentum and therefore additionally require valid stock returns from months $t-12$ to $t-2$.

Finally, a country is only part of the final sample in those months for which at least 30 stock-month observations are available after filters.[4] For the construction of dMOM, 24 months of return data for the value-weighted market index are used to calculate the bear market indicator. We require an additional 24 months for both momentum returns and the bear-market indicator to calibrate Eq. (7). Eventually, our momentum strategy sample starts in January 1930 (January 1990) for the U.S. (non-U.S.). We end up with a total of 8,550,324 firm-month observations. Table 1 shows the descriptive statistics for the stocks in the final sample.

2.2. Factor construction

Our approach for constructing the factor portfolios follows Fama and French (1993, 2012). We calculate the portfolio breakpoints for each country separately to ensure that country effects do not drive our results. The market factor, RMRF, consists of value-weighted returns of all available (and valid) securities less the risk-free rate. Since we measure returns in USD, we calculate excess returns based on the one-month U.S. Treasury bill rate. The size and value factors are constructed by independent double sorts and six value-weighted portfolios. For every end-of-June of year y, we assign stocks among two size-sorted and three book-to-market sorted portfolios based on their market capitalization and book-to-market ratio, respectively. Market capitalization is from end-of-June in year y and the book-to-market ratio is calculated with book value and market capitalization from the fiscal year end in year $y-1$. For the U.S. sample, the size breakpoints are based on the NYSE median market capitalization and stocks are classified as big or small, indicated by B and S. For the non-U.S. sample, we follow Fama and French (2012, 2017) and define size breakpoints so that the largest (smallest) stocks cover 90% (10%) of a country's market capitalization. Subsequently, stocks are independently sorted into three portfolios (Growth, Neutral, and Value, indicated by G, N, and V) based on the country-specific 70% and 30% percentile breakpoints of book-to-market ratios. The breakpoints on book-to-market are calculated from NYSE (big) stocks only for the U.S. (non-U.S.) sample. For the resulting six portfolios (BV, BN, BG, SV, SN, and SG), we calculate monthly value-weighted returns and construct the size (SMB) and value (HML) factor as zero-investment long-short portfolios from July y to end-of-June $y+1$,

$$\begin{aligned} SMB &= (SV+SN+SG)/3-(BV+BN+BG)/3, \\ HML &= (BV+SV)/2-(BG+SG)/2. \end{aligned} \tag{1}$$

Analogous to the value factor, we categorize stocks based on the 70% and 30% percentiles of the past 12–2 month cumulative returns as Winner, Neutral, and Loser (W, N, and L) stocks to

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[3] https://www.aqr.com/Insights/Datasets.

[4] Following Jacobs (2016), we thereby ensure that the six size-momentum portfolios contain at least five stocks on average. As a consequence, some countries (such as India, Hong Kong, and Spain) are excluded from the sample for certain months. Jordan, Sri Lanka, Slovakia, and Venezuela are excluded from the whole sample.

Table 1
Descriptive statistics.
The table presents summary statistics for the 49 countries of our CRSP, Datastream, and Worldscope sample. Column 2 states the market affiliation according to MSCI, with DM as Developed Markets and EM as Emerging Markets. Columns 3, 4, and 5 report the total, minimum, and maximum number of firms per country, respectively. Column 6 states the average mean size per country-month. Column 7 shows the average total size per country-month, and Column 8 reports these values in percentage of the respective total across countries. Size is measured as market capitalization in million USD. The last two columns report the start and end date of data availability for each country. We require that firms have non-missing values for the following items: market value of equity, book-to-market, current month return, and lagged month market capitalization.

Country	Market	Total no. firms	Min no. firms	Max no. firms	Mean size	Average total size	Average total size in %	Start date	End date
Argentina	EM	89	63	75	451	30,835	0.09	2001-07-01	2017-12-31
Australia	DM	2645	113	1574	762	646,804	1.96	1990-01-01	2017-12-31
Austria	DM	163	45	87	1024	70,348	0.21	1991-07-01	2017-12-31
Belgium	DM	234	80	136	1829	204,069	0.62	1991-07-01	2017-12-31
Brazil	EM	244	77	179	2574	364,046	1.10	2000-07-01	2017-12-31
Canada	DM	3715	223	2183	757	789,063	2.39	1990-01-01	2017-12-31
Chile	EM	242	73	170	918	141,856	0.43	1996-07-01	2017-12-31
China	EM	3036	101	2943	1320	2,573,417	7.78	1999-07-01	2017-12-31
Colombia	EM	73	30	55	2531	117,104	0.35	2005-07-01	2017-12-31
Czech Republic	EM	57	30	48	529	18,235	0.06	2001-07-01	2006-01-31
Denmark	DM	319	124	205	945	144,378	0.44	1993-07-01	2017-12-31
Egypt	EM	157	116	135	400	50,502	0.15	2008-07-01	2017-12-31
Finland	DM	220	44	136	1614	191,458	0.58	1994-07-01	2017-12-31
France	DM	1616	176	793	1896	1,232,386	3.73	1990-01-01	2017-12-31
Germany	DM	1459	271	867	1640	1,033,357	3.13	1990-01-01	2017-12-31
Greece	DM/EM	381	88	282	344	75,558	0.23	1995-07-01	2017-12-31
Hong Kong	DM	1529	76	1348	541	439,253	1.33	1995-07-01	2017-12-31
Hungary	EM	63	30	41	740	25,666	0.08	2003-07-01	2016-12-31
India	EM	3250	277	2499	540	778,699	2.36	1997-07-01	2017-12-31
Indonesia	EM	596	125	474	521	186,989	0.57	1996-07-01	2017-12-31
Ireland	DM	80	30	50	1307	49,043	0.15	1993-07-01	2012-05-31
Israel	DM/EM	497	69	403	481	124,644	0.38	2002-07-01	2017-12-31
Italy	DM	552	160	261	1958	434,512	1.31	1990-01-01	2017-12-31
Japan	DM	5207	1065	3748	1184	3,297,967	9.97	1990-01-01	2017-12-31
Malaysia	EM	1261	202	928	380	239,358	0.72	1994-01-01	2017-12-31
Mexico	EM	192	65	117	1869	195,116	0.59	1997-07-01	2017-12-31
Morocco	EM	76	69	73	818	58,102	0.18	2010-07-01	2017-12-31
Netherlands	DM	250	70	161	2728	279,561	0.85	1990-01-01	2017-12-31
New Zealand	DM	212	50	122	381	39,284	0.12	1999-07-01	2017-12-31
Norway	DM	415	60	180	942	137,922	0.42	1992-07-01	2017-12-31
Pakistan	EM	298	56	251	155	21,701	0.07	1997-07-01	2017-12-31
Peru	EM	128	46	99	550	46,179	0.14	2004-08-01	2017-12-31
Philippines	EM	299	95	231	493	99,193	0.30	1996-07-01	2017-12-31
Poland	EM	680	72	495	406	113,879	0.34	2000-10-01	2017-12-31
Portugal	DM/EM	133	40	92	1086	56,786	0.17	1994-07-01	2017-12-31
Qatar	EM	43	41	43	3714	155,183	0.47	2014-07-01	2017-12-31
Russia	EM	468	163	347	2412	590,562	1.79	2008-07-01	2017-12-31
Singapore	DM	834	48	563	598	212,403	0.64	1990-07-01	2017-12-31
South Africa	EM	746	133	433	1091	276,045	0.83	1995-07-01	2017-12-31
South Korea	EM	2478	109	1930	488	530,532	1.60	1994-01-01	2017-12-31
Spain	DM	318	100	160	3550	474,230	1.43	1992-07-01	2017-12-31
Sweden	DM	861	96	498	1001	305,963	0.93	1992-07-01	2017-12-31
Switzerland	DM	358	108	238	3655	769,711	2.33	1990-01-01	2017-12-31
Taiwan	EM	2097	231	1740	552	588,967	1.78	1998-07-01	2017-12-31
Thailand	EM	790	225	614	389	179,716	0.54	1995-07-01	2017-12-31
Turkey	EM	435	65	349	587	149,831	0.45	1997-07-01	2017-12-31
U.K.	DM	3822	1072	1526	1626	2,011,021	6.08	1990-01-01	2017-12-31
U.S.	DM	23,182	536	6651	1057	4,294,423	37.24	1930-01-01	2017-12-31
United Arab Emirates	EM	105	98	105	2002	200,589	0.61	2014-07-01	2017-12-31

form the MOM factor, where only NYSE (big) stocks are considered for the breakpoint calculation. We then calculate the monthly value-weighted returns for the 2x3 portfolios (BW, BN, BL, SW, SN, SL). MOM is constructed by the long-short portfolio as $MOM = (BW + SW)/2 - (BL + SL)/2$ and—in contrast to SMB and HML—rebalanced every month.[5] Asness and Frazzini (2013) introduce the so-called HML-devil factor (denoted as HML_d). HML_d is comparable to HML but updates the market capitalization for the sorting criteria every month. Thus, stocks are sorted into portfolios based on their monthly updated book-to-market ratio.

2.3. Enhanced momentum strategies

Volatility scaling aims to manage the realized volatility of an investment strategy. For cross-sectional momentum (our benchmark strategy, MOM), realized volatility has been shown to have a positive (negative) correlation with future volatility (returns) and to be relatively high as compared to other factors (cf., Bekaert and Wu, 2000; Barroso and Santa-Clara, 2015; Moreira and Muir, 2017). In this study, we identify two potential channels for Sharpe ratio improvements by volatility scaling: volatility smoothing refers

[5] As stated above, we use the Fama-French factors from Kenneth French's website for the U.S. sample. The MOM factor and enhanced momentum strategies, however, are constructed by ourselves in order to ensure an identical stock universe for construction.

to the overall lowered ex-post volatility, and volatility timing to the heightened strategy returns due to the negative correlation between volatility and returns. We compute the realized total and downside volatility of the momentum strategy to control for volatility.[6]

Importantly, volatility scaling does not directly consider the positive autocorrelation of monthly momentum strategy returns. Thus, one can additionally control for the realized return of the momentum strategy to capture the positive autocorrelation. Combining these insights, forecasted returns and variances (or volatilities) at the strategy level can generate scaling weights that increase the Sharpe ratio of MOM compared to a non-scaled strategy. Technically, as a net-zero investment long-short strategy, MOM can be scaled without assuming leverage costs, and the scaling can be interpreted as having a time-varying weight in the long and short legs. We explicitly distinguish between constant-volatility scaling and dynamic scaling. Constant volatility-scaled momentum (cMOM), as proposed in Barroso and Santa-Clara (2015), adjusts the momentum portfolio to a constant target volatility level. The corresponding scaling weight for momentum in month t is defined as follows:

$$w_{cMOM,t} = \frac{\sigma_{target}}{\hat{\sigma}_t}, \tag{2}$$

where σ_{target} is chosen that the full sample volatilities of momentum and cMOM are identical, and $\hat{\sigma}_t = \mathbb{E}_{t-1}[\sigma_t]$ is the forecasted respective expected volatility.[7] Since the forecasted volatility varies over time, the weights for the constant volatility-scaled momentum portfolio can take values between 0 (for $\hat{\sigma}_t = \infty$) and infinity (for $\hat{\sigma}_t = 0$). Following Barroso and Santa-Clara (2015), we calculate the monthly volatility forecast for month t from past daily returns of momentum in the previous six months (126 trading days),

$$\hat{\sigma}^2_{MOM,t} = 21 \cdot \sum_{j=1}^{126} \frac{R^2_{MOM,d-j,t}}{126}, \tag{3}$$

where $R^2_{MOM,d-j,t}$ is the squared realized daily return of momentum returns summed over the last 126 trading days.[8] The correspondingly weighted momentum strategy is cMOM, where the return in month t is calculated by weighting with the inverse of the realized volatility,

$$R_{cMOM,t} = R_{MOM,t} \cdot w_{cMOM,t}. \tag{4}$$

Constant semi-volatility-scaled momentum (sMOM) is constructed analogously to cMOM, but substitutes $\hat{\sigma}_t$ in Eq. (2) by the semi- or downside volatility of momentum. Specifically, as in Wang and Yan (2021), the monthly downside volatility for month t is calculated using the past 126 trading days:

$$\hat{\sigma}^2_{MOM,t,semi} = 21 \cdot \sum_{j=1}^{126} \frac{R^2_{MOM,d-j,t} I_{[R_{MOM,d-j}<0]}}{126}. \tag{5}$$

The return of sMOM is the momentum return in month t weighted with the inverse of the realized downside volatility, scaled with a static scalar to the full sample volatility of momentum. Dynamic-scaled momentum (dMOM) enhances the constant volatility-scaled momentum by additionally incorporating the expected strategy return. In this regard, a mean-variance optimizing investor optimizes momentum as her investment asset according to the dynamic scaling weight that refers to their expected Sharpe ratio.[9] We apply the dynamic approach from Daniel and Moskowitz (2016) and define the dynamic scaling weight for momentum in month t as

$$w_{dMOM,t} = \left(\frac{1}{2\lambda}\right) \cdot \frac{\hat{\mu}_t}{\hat{\sigma}_t^2}, \tag{6}$$

where $\hat{\mu}_t = \mathbb{E}_{t-1}[\mu_t]$ ($\hat{\sigma}_t^2 = \mathbb{E}_{t-1}[\sigma_t^2]$) is the forecasted respective conditional expected return (variance) of momentum, and λ is a static scalar scaling the dynamic strategy to the full sample volatility of momentum. The estimation of $\hat{\mu}_t$ and $\hat{\sigma}_t^2$ can be conducted either *in-sample* or *out-of-sample*. We apply only the *out-of-sample* approach because the *in-sample* estimation suffers from a look-ahead bias. The return of momentum is forecasted with the following time-series regression:

$$R_{MOM,t} = \gamma_0 + \gamma_{int} \cdot I_{Bear,t-1} \cdot \sigma^2_{RMRF,t-1} + \epsilon_t, \tag{7}$$

where $I_{Bear,t-1}$ is a bear-market indicator that equals one if the cumulative past two-year market return is negative (and zero otherwise), $\sigma^2_{RMRF,t-1}$ is the realized variance of RMRF over the past 126 days, γ_{int} is the regression coefficient on the interaction term of the two independent variables, and γ_0 is the regression intercept. The expected return ($\hat{\mu}_t$) is defined as the fitted values from the regression. We estimate Eq. (7) on a monthly updated expanding-window basis.[10] For the variance forecast of the dynamic strategy, we rely on the same approach as for the constant-volatility scaling strategy and use Eq. (3) with a 126-day look-back window for $\hat{\sigma}_t^2$. We eventually derive dMOM as the dynamically weighted momentum strategies with their return in month t given by

$$R_{dMOM,t} = R_{MOM,t} \cdot w_{dMOM,t}. \tag{8}$$

Comparing the constant-volatility and the dynamic strategy, cMOM, and dMOM, the weights differ by $\mathbb{E}_{t-1}[\mu_t] = \hat{\mu}_t$. Hence, the scaling weights of the dynamic strategies can take on negative values when $\hat{\mu}_t < 0$, e.g., (i) in bear market states and (ii) when market volatility is higher as γ_{int} from Eq. (7) is negative for most months. This possibility implies that the dynamic weights might vary more strongly than the constant-volatility scaling weights, capturing the dynamics of momentum returns.

2.4. Methodology

We investigate the performance of the different momentum strategies based on a comprehensive set of methodologies. First, we evaluate the different momentum strategies by mean returns, t-statistics, higher moments (skewness and kurtosis) as well as maximum drawdowns. Second, we compare risk-adjusted strategy returns with respect to the Fama-French three-factor model and conduct pairwise mean-variance spanning tests. Third, we conduct ex-post maximum Sharpe ratio tests of factor models, including different momentum strategies. Lastly, we contrast the profitability of the different momentum strategies with their portfolio turnover to assess their capacity for potential transaction costs. In this section, the testing procedures are presented:

[6] Alternatively, one could use the volatility of individual constituents of the momentum long-short portfolios. However, using volatility at the strategy level is preferable for momentum due to the possibility of volatility timing. Individual volatilities are rather useful to control for realized volatility (volatility smoothing) of time-series momentum strategies (see, e.g., also du Plessis and Hallerbach, 2016, for U.S. industry portfolios). Time-series momentum strategies are scaled upward by volatility (not the inverse, as for cross-sectional momentum) due to the positive relation between volatility and returns.

[7] Doing so, we (i) ensure that the strategy targets a constant risk level over time and (ii) makes the returns of the scaled and unscaled strategy comparable.

[8] For robustness, we also use a one-month look-back window (21 trading days) as used in Moreira and Muir (2017). Our results remain unchanged.

[9] It is, however, an underlying assumption of how investors end up with their return and variances forecasts, respectively how their expectations align for the weight components. Daniel and Moskowitz (2016) mention that investors optimize their objective function *in-sample* and unconditionally, which implies a forward-looking bias. In this regard, we estimate return and variance *out-of-sample*.

[10] In contrast to Daniel and Moskowitz (2016), we estimate an *out-of-sample* regression in an expanding fashion, starting with an initial 24 months for each sample.

Spanning tests To evaluate the strategies' risk-adjusted performance, we calculate spanning alphas for MOM and the three alternative momentum strategies. Therefore, we regress returns of the test asset (e.g., MOM) on returns of the benchmark assets within a linear time-series regression model. The null hypothesis states that the test asset returns are spanned, i.e., that the intercept equals zero. If the null hypothesis is rejected and the intercept is statistically significantly different from zero, the test asset is not spanned by the respective benchmark asset pricing model and extends the efficient portfolio frontier. The intercept quantifies the magnitude of the abnormal return the test asset generates.

Maximum Sharpe ratio tests To quantify the differences in maximum Sharpe ratios for different sets of factors, we apply the methodology from Barillas et al. (2019). In the mean-variance efficient portfolio optimization, the economic significance of factors is quantified by comparing how much an investor could gain from adding a certain factor to her investment opportunity set. We start by calculating the differences between the bias-adjusted maximum squared Sharpe ratios for various pairs of factor models. The maximum squared Sharpe ratio for each model is modified to be unbiased for small samples under joint normality by multiplying it by (T-K-2)/T and subtracting K/T, where T is the number of return observations and K is the number of factors.

However, comparing mean-variance efficient tangency portfolios, as described above, does not provide statistical evidence. Thus, we compute *p*-values for the test of equality of the maximum squared Sharpe ratios, also in a pairwise manner. For nested models (i.e., all of the factors in one model are contained in the other model), we test whether the maximum squared Sharpe ratio for the model with more factors is higher than the maximum squared Sharpe ratio of the model with fewer factors. This becomes equivalent to testing whether the factors in the larger model that are not also in the smaller model have significant alphas when regressed on the smaller model. For example, because the CAPM is nested in the Fama-French three-factor model, one would test whether the CAPM alphas of SMB and HML are zero.[11] For a single excluded factor, the corresponding test is whether the intercept in the regression of the excluded factor on the nested model is significantly different from zero.

Transaction costs As in Grundy and Martin (2001) and Barroso and Santa-Clara (2015), we calculate the round-trip costs that would render the profits of the different momentum strategies insignificant at a certain α-significance level as[12]

$$\text{Round-trip costs}_{\alpha=5\%} = \left(1 - \frac{1.96}{\text{t-stat}_s}\right)\frac{\bar{\mu_s}}{\bar{TO_s}}, \tag{9}$$

where $\bar{\mu_s}$ is the average monthly return, $\bar{TO_s}$ is the average monthly turnover, and t-stat$_s$ is the t-statistic of strategy *s*. Round-trip costs are advantageous since they define an upper bound for the potential transaction costs instead of quantifying them directly. Only the strategy returns, as well as the associated portfolio turnover, are necessary input factors.[13] Moreover, statistical significance can be incorporated within the round-trip costs measure. Holding turnover fixed, round-trip costs with reliance on the α-significance level increase for strategies with higher t-statistics and therefore lead to a higher upper bound.

[11] The statistical test for multiple excluded factors, as in this example, is the application of the (GRS) test in Gibbons et al. (1989).

[12] We choose the *Z*-value of 2.58 for the 1% significance level (instead of 1.96 for the 5% level).

[13] We calculate portfolio turnover as the sum of changes in the securities' weights within assigned long-short factor portfolios. The details of the turnover calculation are presented in Appendix A.2.

Table 2
Summary statistics for momentum strategies.
The table presents the following summary statistics for MOM, cMOM, sMOM, and dMOM: (1) average monthly returns (in %), (2) corresponding t-statistics, (3) annualized Sharpe ratios, (4) skewness, (5) kurtosis, (6) maximum drawdown (in %), defined as the maximum cumulative loss between a peak and a subsequent downturn, (7) average monthly returns (in %) during bear-up market states, and (8) corresponding t-statistics. cMOM is momentum scaled to a constant volatility level by its six-month past volatility. sMOM is momentum scaled to a constant volatility level by its six-month past semi-volatility. dMOM is momentum scaled by its forecasted return relative to its expected variance. The analysis is performed from 01/1930 (01/1990) to 12/2017 for the U.S. (non-U.S.) sample.

	MOM	cMOM	sMOM	dMOM
Panel A: U.S. (01/1930–12/2017)				
Avg. Returns (in %)	0.60	1.10	1.05	1.16
	(4.40)	(8.14)	(7.76)	(8.57)
Sharpe (annualized)	0.47	0.87	0.83	0.91
Skewness	-2.18	-0.32	-0.27	0.10
Kurtosis	21.33	2.33	3.60	7.58
Max. Drawdown (in %)	-69.09	-38.59	-38.27	-40.05
Bear-Up Returns (in %)	-0.39	-0.24	-0.24	-0.09
	(-4.31)	(-3.79)	(-3.77)	(-1.62)
Panel B: Non-U.S. (07/1990–12/2017)				
Avg. Returns (in %)	0.54	1.00	0.96	0.97
	(2.81)	(5.19)	(4.95)	(5.01)
Sharpe (annualized)	0.53	0.98	0.94	0.95
Skewness	-0.91	-0.11	0.16	0.38
Kurtosis	6.93	0.56	0.88	2.20
Max. Drawdown (in %)	-41.36	-25.25	-22.88	-16.98
Bear-Up Returns (in %)	-0.43	-0.30	-0.29	0.02
	(-3.74)	(-3.76)	(-3.96)	(0.25)

3. Empirical results

3.1. Comparison of momentum strategies

In this section, we compare the improvement of enhanced momentum factors as compared to standard momentum, MOM, in global markets. Table 2 depicts the return characteristics for the four momentum strategies.

For the long U.S. sample, the average monthly return of the standard momentum (MOM) factor amounts to 0.60%, with a highly significant t-statistic of 4.40. However, as Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) already show, momentum also has a dark side. The high returns come with a very high kurtosis and negative skewness, implying large drawdowns (fat left tails) such as the maximum drawdown for the momentum factor in 1932 of -69.09%. The returns of the standard momentum factor for the non-U.S. sample show similar features. The average monthly return is 0.54%, with a t-statistic of 2.81. The higher t-statistics for the U.S. sample can be attributed to the larger number of monthly observations, as indicated by similar annualized Sharpe ratios (0.47 vs. 0.53). The momentum returns for the non-U.S. sample also exhibit a high kurtosis and a negative skewness but are more normally distributed compared to their counterparts for the long sample. This result is also reflected in the lower maximum drawdown in 2009 of -41.36%.

Comparing enhanced momentum strategies with MOM, we show that all of them exhibit higher t-statistics and Sharpe ratios (all nearly double compared to MOM). Furthermore, skewness, kurtosis, and maximum drawdowns decrease in magnitude as compared to MOM so that their return distributions become more normally distributed. As MOM crashes typically happen following a bear market and when the contemporaneous market return is positive (cf. Asem and Tian, 2010, “bear-up month”), we also compute the average return (and t-statistic) for these months. We document statistically significant negative mean returns during these

Table 3
Correlation coefficients.
The table reports the time-series averages of the cross-sectional spearman correlation coefficients between the following variables: RMRF (market factor), SMB, HML, HML_d, MOM, cMOM, sMOM, and dMOM. For details regarding variable construction, see Section 2.2. The analysis is performed from 01/1930 (01/1990) to 12/2017 for the U.S. (non-U.S.) sample and depicted within the upper (lower) triangle.

	RMRF	SMB	HML	HML_d	MOM	cMOM	sMOM	dMOM
RMRF		0.27	0.03	0.07	-0.05	-0.03	-0.03	0.01
SMB	0.10		0.01	0.08	-0.04	-0.04	-0.04	-0.02
HML	-0.20	-0.11		0.84	-0.17	-0.15	-0.14	-0.12
HML_d	-0.07	-0.08	0.80		-0.45	-0.41	-0.41	-0.34
MOM	-0.13	0.04	-0.12	-0.53		0.96	0.95	0.84
cMOM	-0.08	0.02	-0.12	-0.53	0.96		1.00	0.94
sMOM	-0.08	0.01	-0.12	-0.52	0.94	0.99		0.95
dMOM	0.07	0.01	-0.17	-0.44	0.68	0.79	0.79	

bear-up states for both samples and all momentum strategies except dMOM. The reason for this exception seems that solely dMOM accounts for the lower expected momentum returns during bear market states, i.e., that it can also take a negative weight in momentum.

To shed light on the co-movement of factor returns, Table 3 shows pairwise factor correlation coefficients for both the U.S. and non-U.S. samples.

MOM and cMOM or sMOM are highly correlated with correlation coefficients above 94%. The correlation between MOM and dMOM is lower, which can be traced back to the larger amendments of the momentum factor by the strategy. Across the enhanced strategies, cMOM and sMOM co-move nearly perfectly with each other (99% and 100% for U.S. and non-U.S., respectively) and less with dMOM (only up to 95%). In addition to the FF3FM factors, we include a monthly updated HML-devil factor (HML_d) in our correlation analysis. The negative correlation between MOM and HML_d as compared to HML is evident for both our U.S. and non-U.S. samples, confirming the results in Asness and Frazzini (2013) and Hanauer (2020). cMOM and sMOM are similarly negatively correlated with HML_d, while dMOM is slightly less negatively correlated. However, all three enhanced momentum strategies are more negatively correlated with HML_d than with HML, which both have a similar mean return. Thus, in non-categorized tests (where only either HML or HML_d is included), we henceforth benchmark our enhanced momentum strategy returns against the FF3FM model where we substitute HML by HML_d, denoted as FF_d.

Figure 1 displays the buy-and-hold returns of momentum and the proposed enhanced strategies for the U.S. sample. All strategies are scaled to the average in-sample volatility of standard momentum for comparability. For the U.S., all strategies increase in returns as compared to MOM, with dMOM as the highest return strategy. dMOM manages to hedge the momentum downturns in 2001 and 2008 and generates stable returns from the 1950s on. All strategies show a similar performance by construction, differing solely by either the numerator or the denominator in the scaling weights. In the non-U.S. sample, cMOM slightly outperforms the other strategies, as shown in Fig. 2.

Next, we analyze the improvement of our enhanced momentum strategies in comparison to MOM by answering the following two questions: How well can enhanced momentum strategies explain standard momentum? And are enhanced momentum strategies able to generate risk-adjusted returns when controlling for MOM? Therefore, we conduct mean-variance spanning tests by varying the benchmark and test assets. In case the spanning alpha is economically meaningful and statistically significant, the test asset is not spanned by the respective benchmark asset pricing model and therefore contains unexplained information. We start by regressing MOM on the FF_d factors and subsequently add single enhanced momentum factors. Following Barillas and Shanken (2017), we consider the FF_d factors as alternative factors when conducting mean-variance tests.

The first row in both panels of Table 4 depicts the results from factor spanning tests of MOM. The FF_d alpha of MOM amounts to 0.88% and 0.97% monthly for the U.S. and non-U.S. samples, respectively. However, when adding enhanced momentum strategies as benchmark assets, the alphas substantially decrease in value (up to 0.04% and -0.04%), remaining only statistically significant with respect to dMOM for both the U.S. and the non-U.S. sample. If MOM was regressed on dMOM standalone, the alpha would be insignificant. This difference stems from the interaction with FF_d factors. As we saw in Table 3, HML_d is most negatively correlated with MOM, followed by cMOM, sMOM, and dMOM. This highly negative correlation makes momentum relatively more attractive when controlling for HML_d than when not.[14]

To get further insights into the relative improvement of enhanced strategies, we employ them as test assets. In the second to the fourth row of each panel, we regress enhanced momentum strategies on the FF_d factors plus MOM in the first column and separately add another enhanced momentum strategy as a benchmark asset in columns 2 to 4. We find that the alphas of all three enhanced strategies with respect to the FF_d factors plus MOM are economically and statistically significant (first column). For the U.S. in Panel A, sMOM is subsumed by cMOM and dMOM, while cMOM and dMOM yield significant spanning alphas when controlling for sMOM, as depicted in the third column. These results are confirmed for the non-U.S. sample in Panel B, with the sole difference that dMOM is subsumed by both cMOM and sMOM. In sum, we conclude that MOM is not subsumed by dMOM and that the volatility-scaled strategies add to the investment opportunity set including MOM

The spanning tests in Table 4 reveal that no enhanced momentum strategy consistently subsumes all other momentum strategies. However, a particular momentum strategy might still span a higher Sharpe ratio than another momentum strategy when added to an existing investment opportunity set, such as the FF3FM or FF_d factors. To test for the statistical significance, we follow Barillas et al. (2019) and conduct pairwise equality tests of

[14] We also investigate if the spanning regression suffer from multicollinearity problems and compute the respective variance inflation factors (VIF). The VIF values typically do not exceed 3. The exceptions are the spanning regressions that include cMOM and sMOM as dependent and independent variables (or the other way around) with VIF values of 5.3 and 5.8 for the long and the broad sample, respectively. However, these values are still below the cut-off value of 7 applied in Green et al. (2017) and Jacobs and Müller (2018). We thank an anonymous reviewer for raising this point.

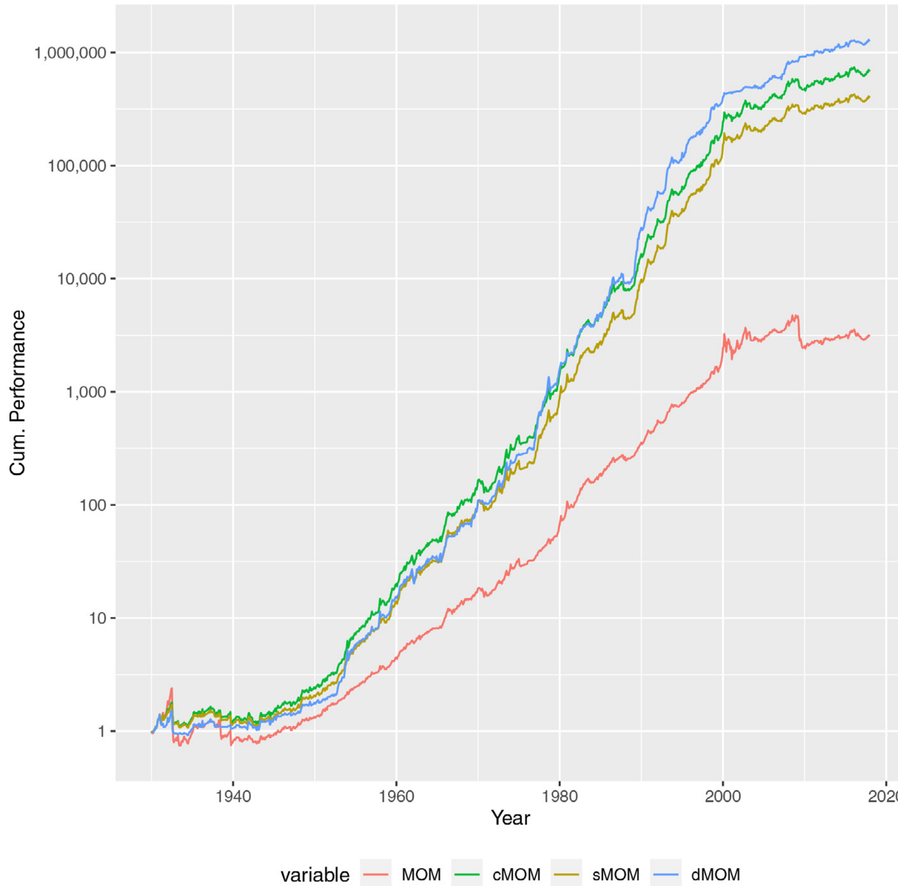

Fig. 1. Cumulative performance of the momentum strategies: U.S.
This figure displays the cumulated performance of a $1 investment in each of the momentum strategies (plus the risk-free rate since all momentum strategies state zero-cost strategies) for the U.S. sample. The following strategies are comprised: MOM, cMOM, sMOM, and dMOM. cMOM is momentum scaled to a constant volatility level by its six-month past volatility. sMOM is momentum scaled to a constant volatility level by its six-month past semi-volatility. dMOM is momentum scaled by its forecasted return relative to its expected variance. For details regarding variable construction, see Section 2.2. The sample period ranges from 01/1930 to 12/2017.

Table 4
Factor spanning tests of momentum strategies.
The table presents alphas and corresponding Newey and West (1987) t-statistics (6 monthly lags) from mean-variance spanning tests for the U.S. and non-U.S. samples. The dependent variables are momentum and the enhanced momentum strategies. The independent variables are the FF_d factors (RMRF (market factor), SMB, and HML_d) as well as MOM, cMOM, sMOM, or dMOM. When MOM is considered the test asset, we omit MOM as an independent variable. The independent factor set for each spanning test is shown above the respective results. For details regarding variable construction, see Section 2.2. The analysis is performed at monthly frequency from 01/1930 (01/1990) to 12/2017 for the U.S. (non-U.S.) sample in Panel A (Panel B).

Panel A: U.S. (01/1930–12/2017)				
Ind. var.	FF_d (+MOM)	FF_d (+MOM)+cMOM	FF_d (+MOM)+sMOM	FF_d (+MOM)+dMOM
MOM	0.88	0.04	0.12	0.35
	(9.34)	(0.69)	(1.89)	(4.78)
cMOM	0.43		0.08	0.05
	(4.97)		(3.32)	(1.44)
sMOM	0.39	-0.05		0.00
	(4.26)	(-2.12)		(-0.08)
dMOM	0.63	0.06	0.15	
	(5.00)	(1.29)	(3.12)	
Panel B: Non-U.S. (01/1990–12/2017)				
Ind. var.	FF_d (+MOM)	FF_d (+MOM)+cMOM	FF_d (+MOM)+sMOM	FF_d (+MOM)+dMOM
MOM	0.97	-0.04	0.07	0.66
	(6.67)	(-0.38)	(0.63)	(4.77)
cMOM	0.47		0.10	0.18
	(4.21)		(3.41)	(1.87)
sMOM	0.44	-0.06		0.13
	(3.36)	(-1.69)		(1.03)
dMOM	0.67	-0.05	0.09	
	(3.50)	(-0.40)	(0.70)	

Fig. 2. Cumulative performance of the momentum strategies: Non-U.S.
This figure displays the cumulated performance of a $1 investment in each of the momentum strategies (plus the risk-free rate since all momentum strategies state zero-cost strategies) for the non-U.S. sample. The following strategies are comprised: MOM, cMOM, sMOM, and dMOM. cMOM is momentum scaled to a constant volatility level by its six-month past volatility. sMOM is momentum scaled to a constant volatility level by its six-month past semi-volatility. dMOM is momentum scaled by its forecasted return relative to its expected variance. For details regarding variable construction, see Section 2.2. The sample period ranges from 01/1990 to 12/2017.

the models' (unbiased) maximum squared Sharpe ratios (cf. also Section 2.4).

Panel A in Table 5 shows the differences between the (bias-adjusted) sample squared Sharpe ratios (column minus row for the upper triangle; vice versa for the lower triangle) for different sets of factors and the U.S. (non-U.S.) sample in the upper (lower) triangles. Panel B reports p-values for the equality tests of the maximum squared Sharpe ratios. The p-values are computed differently depending on whether the models to be compared are nested or non-nested.

The main findings for the maximum squared Sharpe ratio test can be summarized as follows: First, the results show that the FF3FM plus momentum (Carhart, 1997) is dominated by the FF_d model plus momentum with significance at the 1% level for both samples. This result primarily stems from the more negative correlation of momentum and HML_d as identified in Table 3. When we augment the FF_d model plus MOM with enhanced strategies, the resulting five-factor models outperform the non-augmented model, irrespective of the enhanced momentum strategy (cMOM, sMOM, or dMOM), at the 1% level. As already suggested by the factor spanning tests, enhanced momentum strategies incorporate significant information, even beyond standard momentum. When comparing the models augmented with enhanced strategies among each other, the emerging picture is less clear: in the non-U.S. sample, the augmented model with cMOM outperforms the one augmented with sMOM (-0.024) at the 5% level ($p = 0.037$), and the augmented model with dMOM is outperformed by the one with cMOM (-0.034) at the 10% level ($p = 0.089$). In contrast, the difference in the sample squared Sharpe ratios between the augmented model with sMOM and dMOM is not significant. For the U.S. sample, the model with cMOM outperforms the one augmented with sMOM (-0.010) at the 5% level ($p = 0.013$), while there is no statistically significant improvement among the other combinations of enhanced strategies, as indicated by the associated p-values that are 0.144 and 0.810, respectively. Overall, the maximum squared Sharpe ratio tests confirm the spanning test results in that all enhanced strategies enlarge the investment universe consisting of the FF_d factors and MOM. A superior enhanced strategy, however, can not be identified from the perspective of a mean-variance optimizing investor.

3.2. Cross-country analysis

In the previous subsection, we demonstrated that the enhanced momentum strategies exhibit higher risk-adjusted performance than MOM and that they are distinct phenomena for the U.S. and the non-U.S. sample. Within this subsection, we investigate for which countries enhanced momentum strategies yield an improvement. Subsequently, we utilize diverse cross-country characteristics to investigate potential drivers of momentum premia.

Table 5
Tests of equality of squared Sharpe ratios.
The table presents pairwise tests of the equality of models' squared Sharpe ratios. The following models are considered: FF (RMRF (market factor), SMB, and HML) plus MOM, FF_d (RMRF (market factor), SMB, and HML_d) plus MOM, as well as each combination of FF_d plus MOM with either cMOM, sMOM, or dMOM. Panel A reports the difference between the (bias-adjusted) sample squared Sharpe ratios (column minus row for the upper triangle; vice versa for the lower triangle), and Panel B reports the associated *p*-values. The analysis is performed from 01/1930 (01/1990) to 12/2017 for the U.S. (non-U.S.) sample and depicted within the upper (lower) triangle.

	FF+MOM	FF_d+MOM	FF_d+MOM+cMOM	FF_d+MOM+sMOM	FF_d+MOM+dMOM
Panel A: Differences in Sample Squared Sharpe Ratios					
FF+MOM		0.023	0.056	0.047	0.055
FF_d+MOM	0.065		0.033	0.024	0.032
FF_d+MOM+cMOM	0.142	0.077		-0.010	-0.001
FF_d+MOM+sMOM	0.119	0.053	-0.024		0.008
FF_d+MOM+dMOM	0.108	0.042	-0.034	-0.011	
Panel B: *p*-Values					
FF+MOM		0.002	0.000	0.000	0.000
FF_d+MOM	0.000		0.000	0.000	0.000
FF_d+MOM+cMOM	0.000	0.000		0.013	0.810
FF_d+MOM+sMOM	0.000	0.000	0.037		0.144
FF_d+MOM+dMOM	0.001	0.000	0.089	0.557	

We start by presenting mean returns and t-statistics for MOM and the enhanced versions for each country in Table 6. We include only countries for which more than 120 monthly observations of the strategies are available, which reduces the number of countries from 49 to 43 for our cross-country analyses. The values printed in bold indicate statistically significant (enhanced) momentum strategy returns at the 5% level. The enhanced versions have both higher returns and risk-return ratios (t-statistics) across countries. For 19 out of 23 developed market countries, MOM has significant returns.

None of the enhanced strategies for Japan, solely cMOM for Ireland, cMOM and sMOM for Spain, and all enhanced strategies for Singapore generate significant premia, respectively. In contrast, MOM has an insignificant premium in each of these four countries. Fourteen out of twenty countries in the emerging markets have insignificant MOM returns, of which seven show significant returns for at least one enhanced momentum strategy. Special attention is paid to Asia, for which prior research finds insignificant MOM returns (e.g., Chui et al., 2010). The enhanced strategies generate statistically significant and positive returns in Asian countries where MOM does not, e.g., Indonesia, Malaysia, South Korea, or Taiwan.

To further investigate the effectiveness of the enhanced momentum strategies, we present the maximum drawdown for each country in Fig. 3. For most countries, the maximum drawdowns are reduced for the enhanced strategies as compared to MOM, providing further evidence for the lowered crash risk. This is particularly true for cMOM and sMOM, while some more exceptions exist for dMOM (e.g., Japan, Argentina, Philippines, and Indonesia). In sum, we see a robust improvement across countries.

The results above reveal that standard momentum and enhanced momentum have cross-sectional stock return predictability around the globe. However, the observed momentum premia vary across countries. Therefore, we next analyze the effect of cross-country predictors on (enhanced) momentum returns. Following Jacobs (2016), we run panel regressions of monthly momentum strategy returns as dependent variables on contemporaneous country-month averages or time-invariant country characteristics in a fixed-effects model.[15] For this purpose, we utilize proxies for overconfidence that were found to explain momentum returns by Chui et al. (2010) and Asem and Tian (2010). Additionally, we compute the comprehensive country-level predictor set from Jacobs (2016) as control variables, which can be categorized into limits-to-arbitrage, information uncertainty and differences of opinion, and market efficiency. We describe the predictor set in the following and outline their construction and definition in Appendix A.3.

First, the literature has shown that momentum returns depend on investors' overconfidence. Chui et al. (2010) argue that a country's individualism score is positively associated with overconfidence and attribution bias and therefore with momentum premia across countries. To further support this idea, the authors show that the individualism measure is positively correlated with country-level trading volume and volatility. Cakici and Zaremba (2021) utilize individualism as a cross-country predictor for salience theory portfolios but find no significant effect. Alternatively, the market state continuation dummy proposed in Asem and Tian (2010) distinguishes local market conditions into continuations and transitions. A country-month is classified as a market state continuation (transition) in case the past 12-month and the current month's market return have the same (a different) sign. Asem and Tian (2010) and Hanauer (2014) find that momentum returns *across time* are much higher in market continuations than in market transitions for the U.S. and Japan, respectively.[16] This pattern is consistent with the model of Daniel et al. (1998), which assumes that time-varying investor overconfidence (induced by confirming market movements) and self-attribution drive momentum profits.[17] If investor overconfidence is associated with the

[15] The results remain unchanged when using FF_d alphas of momentum returns instead of raw returns.

[16] Cooper et al. (2004) study momentum returns solely depending on past market state and find that momentum returns are positive following periods of positive market returns and negative after periods of negative market returns. The authors argue that this behavior is consistent with the overreaction hypothesis for the existence of the momentum premium (cf., Daniel et al., 1998; Hong and Stein, 1999). However, Asem and Tian (2010) show that momentum returns for different market states (as shown in Cooper et al., 2004) are dominated by returns for different market dynamics, where the subsequent market return is also taken into account. Asem and Tian (2010) argue that this pattern is consistent with the model of Daniel et al. (1998) but not with the competing models of Hong and Stein (1999) or Sagi and Seasholes (2007).

[17] In the model of Daniel et al. (1998), traders receive public signals after trading a stock based on a private signal. If the public signal confirms their private signal, the investors attribute the success to their skills. However, they attribute nonconfirming signals to bad luck. Because of this self-attribution bias, traders become overconfident about their stock selection skills, and this overconfidence drives momentum. Asem and Tian (2010) argue that investors, on average, traded more based on positive (negative) private signals when the past market was positive (negative).

Table 6
Momentum strategies per country.
The table presents the mean returns (in %) and corresponding t-statistics of momentum and the enhanced strategies for 43 countries in our sample. We require a country to have at least 120 monthly observations for momentum and enhanced strategies, so that the number of countries is reduced from 49 to 43. The following strategies are included: MOM, cMOM, sMOM, and dMOM. For details regarding variable construction, see Section 2.2. The analyses are performed at monthly frequency from 01/1930 (01/1990) to 12/2017 for the U.S. (non-U.S. countries). The third column shows the number of observations for the strategies. The values printed in bold indicate statistically significant (enhanced) strategy returns at the 5% level.

			MOM		cMOM		sMOM		dMOM	
Country	Market	months	R_t	$t(R_t)$	R_t	$t(R_t)$	R_t	$t(R_t)$	R_t	$t(R_t)$
Australia	DM	336	1.39	**(7.17)**	1.64	**(8.48)**	1.62	**(8.37)**	1.58	**(8.16)**
Austria	DM	318	0.98	**(3.56)**	1.35	**(4.91)**	1.36	**(4.92)**	0.94	**(3.41)**
Belgium	DM	318	1.16	**(4.33)**	1.66	**(6.21)**	1.64	**(6.14)**	1.30	**(4.87)**
Canada	DM	336	1.12	**(4.10)**	1.74	**(6.38)**	1.75	**(6.40)**	1.65	**(6.04)**
Denmark	DM	294	0.92	**(3.47)**	1.32	**(4.98)**	1.34	**(5.04)**	1.25	**(4.71)**
Finland	DM	282	1.05	**(3.03)**	1.38	**(3.98)**	1.40	**(4.04)**	0.85	**(2.46)**
France	DM	336	0.61	**(2.37)**	1.14	**(4.45)**	1.10	**(4.31)**	0.83	**(3.24)**
Germany	DM	336	0.89	**(3.46)**	1.51	**(5.85)**	1.52	**(5.89)**	1.16	**(4.52)**
Hong Kong	DM	270	0.88	**(2.59)**	1.67	**(4.88)**	1.73	**(5.06)**	2.09	**(6.12)**
Ireland	DM	212	0.79	(1.13)	1.46	**(2.01)**	1.41	(1.94)	0.89	(1.21)
Israel	DM	186	1.06	**(2.44)**	1.44	**(3.30)**	1.46	**(3.34)**	0.74	(1.69)
Italy	DM	336	0.84	**(3.20)**	1.20	**(4.57)**	1.16	**(4.42)**	0.92	**(3.52)**
Japan	DM	336	0.03	(0.13)	0.21	(0.86)	0.19	(0.78)	0.19	(0.79)
Netherlands	DM	336	0.70	**(2.16)**	1.29	**(4.01)**	1.28	**(3.97)**	1.23	**(3.83)**
New Zealand	DM	222	1.13	**(5.12)**	1.23	**(5.61)**	1.24	**(5.63)**	1.07	**(4.88)**
Norway	DM	306	0.93	**(2.94)**	1.18	**(3.74)**	1.15	**(3.64)**	0.84	**(2.66)**
Portugal	DM	272	1.57	**(3.84)**	1.84	**(4.56)**	1.79	**(4.41)**	1.55	**(3.82)**
Singapore	DM	330	0.27	(0.81)	1.06	**(3.20)**	1.06	**(3.19)**	1.12	**(3.37)**
Spain	DM	306	0.51	(1.83)	0.79	**(2.82)**	0.76	**(2.70)**	0.54	(1.94)
Sweden	DM	306	0.90	**(2.77)**	1.59	**(4.91)**	1.58	**(4.88)**	1.52	**(4.69)**
Switzerland	DM	336	0.70	**(2.68)**	1.13	**(4.32)**	1.10	**(4.22)**	0.90	**(3.44)**
U.K.	DM	336	0.97	**(4.32)**	1.61	**(7.15)**	1.60	**(7.09)**	1.58	**(7.04)**
U.S.	DM	1056	0.60	**(4.40)**	1.10	**(8.14)**	1.05	**(7.76)**	1.16	**(8.57)**
Argentina	EM	195	0.72	(1.39)	0.80	(1.48)	0.72	(1.33)	-0.69	(-1.35)
Brazil	EM	210	0.30	(0.73)	0.62	(1.52)	0.66	(1.62)	0.73	(1.80)
Chile	EM	258	0.83	**(3.62)**	0.96	**(4.21)**	1.00	**(4.38)**	0.94	**(4.11)**
China	EM	222	-0.47	(-1.58)	-0.18	(-0.62)	-0.14	(-0.46)	-0.05	(-0.18)
Colombia	EM	150	0.35	(1.09)	0.46	(1.43)	0.38	(1.18)	0.01	(0.02)
Greece	EM	270	0.67	(1.31)	1.36	**(2.66)**	1.35	**(2.63)**	1.78	**(3.46)**
Hungary	EM	129	0.12	(0.28)	0.06	(0.14)	0.00	(0.00)	0.09	(0.20)
India	EM	246	1.22	**(2.51)**	2.00	**(4.10)**	1.94	**(3.98)**	2.41	**(4.95)**
Indonesia	EM	258	0.00	(0.00)	1.39	**(2.27)**	1.37	**(2.23)**	0.77	(1.25)
Malaysia	EM	288	0.32	(0.79)	1.76	**(4.32)**	1.87	**(4.59)**	1.73	**(4.25)**
Mexico	EM	246	0.63	**(2.01)**	0.95	**(3.04)**	0.97	**(3.12)**	1.22	**(3.92)**
Pakistan	EM	246	1.01	**(2.33)**	1.48	**(3.41)**	1.61	**(3.72)**	1.37	**(3.16)**
Peru	EM	158	0.02	(0.03)	-0.03	(-0.05)	0.18	(0.33)	-0.14	(-0.26)
Philippines	EM	258	0.07	(0.12)	0.93	(1.53)	0.89	(1.47)	0.60	(0.99)
Poland	EM	207	1.07	**(3.16)**	1.61	**(4.73)**	1.66	**(4.88)**	1.74	**(5.11)**
South Africa	EM	270	1.46	**(5.21)**	1.82	**(6.48)**	1.82	**(6.47)**	1.82	**(6.46)**
South Korea	EM	286	0.31	(0.75)	1.01	**(2.47)**	1.05	**(2.56)**	-0.38	(-0.94)
Taiwan	EM	234	0.30	(0.87)	0.79	**(2.27)**	0.81	**(2.32)**	1.24	**(3.56)**
Thailand	EM	270	0.64	(1.31)	1.59	**(3.26)**	1.62	**(3.33)**	1.68	**(3.45)**
Turkey	EM	246	0.06	(0.18)	0.35	(1.04)	0.32	(0.96)	0.79	**(2.36)**

cross-country differences in (enhanced) momentum premia, we expect the coefficient to be positive and statistically significant. To the best of our knowledge, our study is the first that tests the explanatory power of market continuations *across countries*.

The second category of country characteristics comprises limits-to-arbitrage. In case that momentum constitutes market mispricing, its returns should be more pronounced in markets with stronger market frictions or trading frictions, stating a higher hurdle to trade based on arbitrage opportunities. Several studies have tested proxies for limits-to-arbitrage and their effect on equity anomaly returns in a cross-country setting (Chui et al., 2010; Watanabe et al., 2013; Jacobs, 2016; Cakici and Zaremba, 2021). We employ the following limits-to-arbitrage proxies and express their expected effect on momentum returns in parentheses: idiosyncratic volatility, defined as the standard deviation of firm-level residuals from a regression of daily excess returns on the local Fama and French (1993) three-factor models using data for the current month (higher idiosyncratic volatility states higher limits-to-arbitrage), a country's average firm size (higher firm sizes state lower limits-to-arbitrage), the average number of analysts who provide firm-level earnings estimates for the next fiscal year (more analysts state lower limits-to-arbitrage), or short-sale constraints (short-sale constraints state higher limits-to-arbitrage).

Third, we proxy for belief dispersion using countries' average analyst forecast dispersion, defined as the standard deviation of analyst forecasts, scaled by the absolute mean forecast. In line with Jacobs (2016), momentum returns could be associated with stronger mispricing in times of higher information uncertainty and differences of opinion.

The last category of characteristics comprises three proxies for market efficiency. As outlined in Jacobs (2016), for the first two proxies, there exist competing hypotheses for their relationship with market efficiency. First, we use the average coefficient of de-

Consequently, subsequent positive months should drive overconfidence more than subsequent negative months and vice versa. Therefore, momentum returns should also be higher for market continuations than for market reversals.

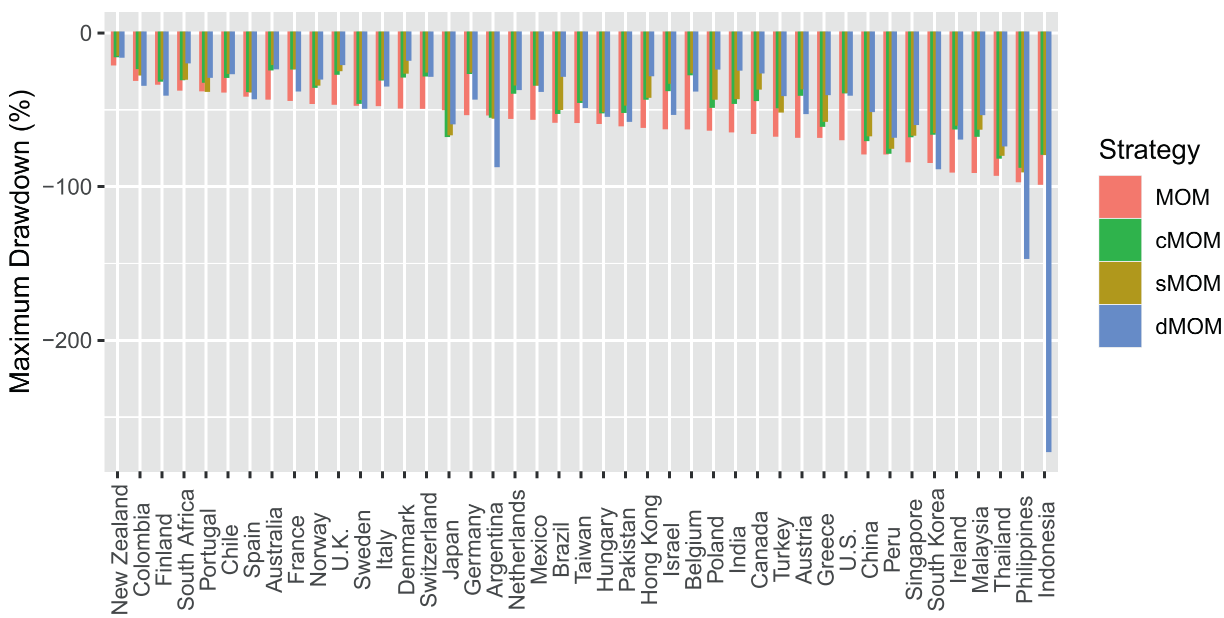

Fig. 3. Maximum drawdown per country.
The figure displays the maximum drawdown of momentum and the enhanced strategies for the 43 countries in our sample. We require a country to have at least 120 monthly observations for momentum and enhanced strategies, so that the number of countries is reduced from 49 to 43. The following strategies are included: MOM, cMOM, sMOM, and dMOM. For details regarding variable construction, see Section 2.2. The analyses are performed at monthly frequency from 01/1930 (01/1990) to 12/2017 for the U.S. (non-U.S. countries).

termination, R^2, across firms from the regression estimating idiosyncratic volatility. By construction, the R^2 is low when the firm-specific return variations that the Fama-French three-factor model does not explain are high. On the one hand, high firm-specific return variation (low R^2) could indicate that informed investors are trading on material, firm-specific information. In this case, a low R^2 would mean a relatively high market efficiency (cf., Morck et al., 2000; Wurgler, 2000; Durnev et al., 2003). On the other hand, high firm-specific return variations (low R^2) could also indicate noise trading and low R^2 would mean a relatively low market efficiency (cf., Teoh et al., 2009; Hou et al., 2013; Kelly, 2014). As a second proxy for market efficiency, we utilize the average fraction of zero return days within a country-month. On the one side, a high trading activity could capture arbitrage-trading activities (McLean and Pontiff, 2016), resulting in more efficient markets. On the other side, a high trading activity could proxy for sentiment and be caused by noise traders, reflecting more inefficient markets (Daniel et al., 1998). Jacobs (2016) finds that both the R^2 and the average fraction of zero return days are negatively related to mispricing, highlighting the importance of noise trading. Hence, we expect both proxies to be negatively associated with momentum returns in case noise traders affect momentum premia. As a third proxy, we apply the developed market status of a country. Watanabe et al. (2013) argue that developed markets are more efficient than emerging markets.

Table A.7 in the Appendix shows the time-series means of country-characteristic averages for the countries in our sample as well as the means for developed and emerging markets. On average, developed market stocks are larger, have lower $R2$, a lower fraction of zero return days, and have higher analyst coverage. Furthermore, developed markets exhibit higher individualism and short selling is more common. In contrast, the differences in the market continuation dummy and idiosyncratic volatility are small.

We start by analyzing momentum returns in a fixed-effects model and estimate the following equation:

$$Ret_{i,t} = \beta_i X_{i,t} + controls + e_{i,t}, \tag{10}$$

where $X_{i,t}$ is a matrix of country characteristics and β_i is the corresponding vector of coefficients. We include time-fixed effects to account for country-invariant time effects, e.g., global macroeconomic shocks that affect countries across the globe, and subsequently add country-fixed effects to control for time-invariant country characteristics that affect momentum, such as the accessibility of the local stock market. Standard errors are double-clustered by country and month. All explanatory variables (except dummy variables) are standardized to have a mean of zero and a variance of one.[18] Furthermore, we also estimate a fixed-effects model to investigate the differences in exposure to the cross-country predictors between MOM and enhanced momentum strategies.

Table 7 shows the results of the cross-country analysis. We find by far the highest significance (t-statistic of 6.96!) for the market continuation dummy. For countries in a market continuation month (e.g., positive market return following a positive year for the market), MOM returns are, on average, 1.86% higher than for countries in a market reversal month (e.g., positive market return following a negative year for the market). This result expands the findings of Asem and Tian (2010) and Hanauer (2014), who provide evidence for the time-series MOM predictability of the market continuation dummy in single markets. The individualism score is statistically significant but economically and statistically weaker (t-statistic of 2.07), suggesting that time-invariant overconfidence

[18] As outlined in Petersen (2008), a cross-sectional regression in the spirit of Fama and MacBeth (1973) is econometrically comparable to a pooled panel regression, including time-fixed effects and standard errors clustered by time. In this context, Jacobs and Müller (2018) argue that "both methods are econometric valid approaches to account for dependence in the time dimension, which is typically observed for regressions of stock returns." An argument for pooled panel regressions is that they offer the flexibility of controlling for heterogeneity in the data, such as time-invariant or country-invariant effects driven by unobserved country- or month-heterogeneity. Another argument for using a panel regression instead of a cross-sectional Fama and MacBeth (1973) regression is that the regression coefficients can be estimated even when an estimator is non-varying across countries within a given month. In unreported tests, we find comparable results when applying a cross-sectional Fama and MacBeth (1973) regression.

Table 7
Panel regressions of momentum returns and cross-country characteristics.
The table presents results from panel regressions of momentum strategy returns and country-month averages of firm-level as well as other country characteristics. The dependent variable is the monthly return for each country of the following momentum strategies: MOM, cMOM, sMOM, and dMOM. We estimate the following regression for each strategy: $Ret_{i,t} = \beta_i X_{i,t} + controls + e_{i,t}$, where $X_{i,t}$ is a vector of country characteristics. The country-level control variables are described in Appendix A.3 and summarized in Table A.7. All regressions include month-fixed effects, whereas the last four columns additionally include country-fixed effects. Standard errors are double-clustered by country and month. All covariates (except dummy variables) are standardized to have a mean of zero and a variance of one. Corresponding t-statistics are reported in parentheses. The analysis is performed at monthly frequency from 01/1990 to 12/2017.

	(1) MOM	(2) cMOM	(3) sMOM	(4) dMOM	(5) MOM	(6) cMOM	(7) sMOM	(8) dMOM
Market continuation dummy	1.86	1.74	1.71	0.70	1.87	1.75	1.72	0.70
	(6.96)	(7.09)	(7.06)	(3.63)	(7.06)	(7.16)	(7.13)	(3.61)
Firm size	-0.32	-0.38	-0.39	-0.29	-0.37	-0.48	-0.49	-0.31
	(-3.62)	(-3.98)	(-4.15)	(-3.26)	(-2.59)	(-3.40)	(-3.61)	(-2.87)
Return R^2	-0.32	-0.48	-0.51	-0.29	-0.31	-0.39	-0.42	-0.24
	(-2.72)	(-4.74)	(-4.92)	(-2.46)	(-1.94)	(-3.04)	(-3.16)	(-2.31)
Idiosyncratic volatility	-0.44	-0.38	-0.39	-0.07	-0.74	-0.76	-0.78	-0.32
	(-2.83)	(-3.62)	(-3.73)	(-0.59)	(-3.58)	(-5.22)	(-5.01)	(-1.68)
Fraction zero return days	-0.03	-0.09	-0.09	-0.09	0.02	-0.05	-0.05	-0.07
	(-0.39)	(-1.02)	(-1.02)	(-0.68)	(0.11)	(-0.26)	(-0.23)	(-0.29)
Number of analysts	0.09	0.14	0.14	0.12	0.03	-0.09	-0.11	-0.07
	(1.43)	(1.40)	(1.25)	(1.01)	(0.25)	(-0.71)	(-0.74)	(-0.31)
Analysts forecast dispersion	-0.08	-0.06	-0.06	-0.09	-0.06	-0.05	-0.04	-0.05
	(-1.02)	(-1.13)	(-1.05)	(-1.26)	(-0.77)	(-0.86)	(-0.77)	(-0.67)
Short selling dummy	-0.02	-0.19	-0.21	0.25				
	(-0.09)	(-0.78)	(-0.88)	(0.82)				
Developed market dummy	-0.15	-0.26	-0.27	-0.19				
	(-0.63)	(-1.13)	(-1.15)	(-0.66)				
Individualism	0.01	0.01	0.01	0.005				
	(2.07)	(1.75)	(1.68)	(0.82)				
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	11,217	11,217	11,217	11,217	11,217	11,217	11,217	11,217
No. of Countries	43	43	43	43	43	43	43	43
Adjusted R^2	0.25	0.19	0.18	0.06	0.25	0.20	0.19	0.07

proxied by the individualism score affects MOM returns for the full sample period.[19]

Among the cross-country predictor variables, only the estimated coefficients on firm size, return R^2, and idiosyncratic volatility are significant. The estimated coefficient on firm size is negative, indicating that MOM returns are associated with limits-to-arbitrage. R^2 is negatively associated with MOM returns, a finding consistent with Jacobs (2016) for the mispricing factor. Therefore, our findings support the noise trading interpretation of this variable, i.e., countries with low R^2 experience more noise trading and have higher momentum returns. The negative coefficient for idiosyncratic volatility differs from the predicted sign but aligns with Chui et al. (2010) findings when using stock market volatility as a predictor. This finding is potentially related to the fact that MOM returns are lower or even experience crashes when market volatility is high (cf. Daniel and Moskowitz, 2016, p. 232). Potentially, this negative relation thereby overturns the expected positive relation when interpreting idiosyncratic volatility as a proxy for limits-to-arbitrage.[20]

The remaining predictors are not significant at conventional levels. The fraction of zero return days is negatively related to MOM returns, as expected in the case of higher noise trader activity. Momentum returns are positively associated with the average number of analysts and negatively associated with short-sale constraints and the developed market dummy, economically confirming the limits-to-arbitrage explanation. Finally, average analyst forecast dispersion unexpectedly reveals a negative coefficient, so that higher information uncertainty and differences of opinion are likely not explanations for cross-country MOM returns.

The results for the market continuation dummy remain unchanged when including country-fixed effects to address unobserved time-invariant country characteristics. However, the estimated coefficient on return R^2 is no longer significant. Therefore, we conclude that the market continuation dummy (proxying time-varying investor overconfidence) has the strongest impact on differences in MOM returns. For the enhanced momentum strategies, we focus on the effect of the market continuation dummy for their explanation.

The returns of cMOM and sMOM have a similar cross-country behavior as momentum, but more variation can be attributed to R^2 (more noise trading). Importantly, both enhanced strategies are comparably affected by the market continuation dummy as momentum. The point estimates of 1.74% and 1.71% are both highly statistically significant, suggesting an almost unaltered market-state dependence of cMOM and sMOM. This is confirmed by the insignificant difference in exposure towards the market continuation dummy as compared to momentum in Table A.8.[21] The other cross-country predictors all show effects on cMOM and sMOM which are comparable to those on momentum. dMOM is significantly less affected by the market continuation dummy than momentum, with a point estimate amounting to 0.70%. Table A.8 shows that the difference in exposure toward the mar-

[19] Our results remain unchanged when including the long-term orientation proxy from Docherty and Hurst (2018) as an additional predictor.

[20] We thank an anonymous reviewer for suggesting this potential explanation.

[21] To evaluate if the difference in an exposure for momentum and an enhanced momentum strategy is statistically significant, we follow Ozdagli (2017), who compares the point estimates between rated and unrated firms within a panel regression framework, including variation across firms and time. Specifically, we estimate the following equation: $Ret_{i,t} = \beta_i X_{i,t} + \gamma_i X_{i,t} \times EnhMom + controls + e_{i,t}$, where $X_{i,t}$ is a matrix of country characteristics and $EnhMom$ is a dummy equal to one if the return is from an enhanced momentum strategy. The differences in exposure to the cross-country predictors is then measured by the coefficient vector γ_i and the corresponding statistical significance. The results of this specification are presented in Table A.8 of the appendix.

Table 8
Panel regressions of momentum returns and cross-country characteristics (sub-periods).
The table presents results from panel regressions of momentum strategy returns and country-month averages of firm-level as well as other country characteristics. The dependent variable is the monthly return for each country of the following momentum strategies: MOM, cMOM, sMOM, and dMOM. We estimate the following regression for each strategy: $Ret_{i,t} = \beta_i X_{i,t} + controls + e_{i,t}$, where $X_{i,t}$ is a vector of country characteristics. The country-level control variables are described in Appendix A.3 and summarized in Table A.7. All regressions include month-fixed effects. Standard errors are double-clustered by country and month. All covariates (except dummy variables) are standardized to have a mean of zero and a variance of one. Corresponding t-statistics are reported in parentheses. The analysis is performed at monthly frequency from 01/1990 to 12/2003 and from 01/2004 to 12/2017.

	01/1990 to 12/2003				01/2004 to 12/2017			
	(1) MOM	(2) cMOM	(3) sMOM	(4) dMOM	(5) MOM	(6) cMOM	(7) sMOM	(8) dMOM
Market continuation dummy	2.82	2.41	2.37	0.99	1.08	1.18	1.16	0.46
	(5.96)	(6.09)	(6.01)	(2.72)	(5.61)	(5.93)	(5.97)	(2.62)
Firm size	-0.54	-0.41	-0.35	-0.19	-0.30	-0.36	-0.38	-0.23
	(-2.06)	(-1.75)	(-1.34)	(-0.92)	(-3.07)	(-3.70)	(-3.86)	(-2.08)
Return R^2	-0.62	-0.46	-0.47	-0.16	-0.10	-0.45	-0.47	-0.33
	(-3.04)	(-3.35)	(-3.29)	(-1.20)	(-0.87)	(-3.22)	(-3.33)	(-1.89)
Idiosyncratic volatility	-0.78	-0.55	-0.55	-0.24	-0.20	-0.19	-0.20	0.11
	(-2.60)	(-3.28)	(-3.15)	(-1.16)	(-2.36)	(-1.85)	(-2.09)	(0.94)
Fraction zero return days	-0.35	-0.14	-0.12	-0.02	0.12	-0.08	-0.08	-0.15
	(-2.94)	(-1.38)	(-1.14)	(-0.12)	(1.49)	(-0.67)	(-0.71)	(-0.97)
Number of analysts	0.11	0.14	0.13	0.16	0.25	0.35	0.34	0.16
	(1.57)	(1.95)	(1.77)	(1.48)	(1.31)	(1.84)	(1.77)	(0.72)
Analysts forecast dispersion	-0.02	-0.01	-0.001	0.003	-0.07	-0.11	-0.12	-0.28
	(-0.23)	(-0.20)	(-0.01)	(0.04)	(-0.71)	(-1.23)	(-1.30)	(-2.44)
Short selling dummy	-0.15	-0.38	-0.40	0.01	0.20	-0.02	-0.06	0.44
	(-0.38)	(-1.08)	(-1.18)	(0.02)	(1.08)	(-0.08)	(-0.20)	(1.09)
Developed market dummy	- 1.09	-0.94	-0.94	-0.93	0.25	-0.01	-0.03	0.13
	(-3.41)	(-3.70)	(-3.50)	(-3.28)	(1.25)	(-0.05)	(-0.10)	(0.32)
Individualism	0.03	0.03	0.03	0.03	-0.001	-0.01	-0.01	-0.01
	(4.13)	(4.56)	(4.61)	(4.00)	(-0.11)	(-1.24)	(-1.35)	(-1.84)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No	No	No
Observations	4527	4527	4527	4527	6690	6690	6690	6690
No. of Countries	41	41	41	41	43	43	43	43
Adjusted R^2	0.21	0.19	0.19	0.05	0.30	0.20	0.19	0.08

ket continuation dummy between momentum and dMOM is statistically significant. This finding highlights that dMOM hedges out a substantial part of the market state dependence of momentum. Moreover, we find that the returns of dMOM are more positively related to idiosyncratic volatility than the returns of standard momentum, leading to an insignificant point estimate of -0.07. The coefficients on the other predictors do not differ significantly as compared to momentum, except for the positive short-selling dummy coefficient, which is contrary to our expectations. Finally, the individualism dummy has no effect on dMOM. Controlling for country-fixed effects leads to similar results.

When we compare the explanatory power of the cross-country analysis in terms of the adjusted regression R2, we see that the investigated country characteristics explain most variation for standard momentum, but less for the enhanced momentum strategies, especially for dMOM. This result is consistent with dMOM being significantly less correlated with the market continuation dummy and idiosyncratic volatility.

We further conduct a robustness test in Table 8 and split up our sample into two sub-periods. We confirm the positive, significant effect of individualism on MOM returns for the first sub-period from January 1990 to December 2003, which aligns with the sample period in Chui et al. (2010). Moreover, we show that enhanced momentum returns are significantly affected by individualism across countries as well. However, for the second sub-period from January 2004 to December 2017, a country's individualism score is not related to either MOM or enhanced momentum returns, suggesting that the results in Chui et al. (2010) do not hold out-of-sample. In contrast, we identify a robust effect of the market continuation dummy on all momentum strategies in both sub-samples. Our study thereby provides out-of-sample evidence for the explanatory power of individualism scores for MOM returns and suggests that time-varying investor overconfidence, proxied by the market continuation dummy, is superior to time-invariant investor overconfidence, as proxied by individualism.

In sum, our results suggest that MOM, cMOM, and sMOM show the strongest relationship with the proxy for time-varying investor overconfidence, while dMOM is significantly less affected by this proxy. Furthermore, we also find some evidence that all momentum strategies are related to proxies for the presence of noise trading.

To further investigate the lower sensitivity of dMOM toward the market continuation dummy, we analyze the market continuation dummy separately for bull or bear markets. Specifically, we apply the same cross-country panel analysis design as in Table 7 and regress momentum returns on a dummy that is one for market continuations after a bear (bull) market while controlling for bull (bear) market states with another dummy. The results are shown in Table 9.

Table 9 shows that MOM, cMOM, and sMOM are more related to market continuations in bear than to market continuations in bull markets. Specifically, we find that during bear markets, a market continuation, defined as a contemporaneous down-movement of the market, generates significantly higher returns (between 2.96% and 3.73%) as compared to a market reversal, defined as a contemporaneous market up-movement. However, the difference is statistically insignificant (t=1.34) and with 0.62% also economically smaller for dMOM. During bull markets, a market continuation generates significantly higher returns than a reversal across all four strategies, although the difference is economically weaker for dMOM. The cross-country results for MOM, cMOM, and sMOM provide strong evidence for the investor overconfidence model in Daniel et al. (1998) and Asem and Tian (2010). However, for dMOM, the sensitivity toward the market continuation dummy

Table 9
Panel regressions of momentum returns and market continuation dummies for different market states.
The table presents results from panel regressions of momentum strategy returns and two market continuation dummies after bull or bear markets. The dependent variable is the monthly return for each country of the following momentum strategies: MOM, cMOM, sMOM, and dMOM. We estimate the following regression: $Ret_{i,t} = \beta_i X_{i,t} + controls + e_{i,t}$, where $X_{i,t}$ is a market continuation dummy during bear or bull markets, respectively. The country-level control variables are described in Appendix A.3 and summarized in Table A.7. All regressions include month-fixed effects, country-fixed effects, and a dummy controlling for being in the opposite market state as the market continuation dummy, i.e., in a bull or bear market, respectively. Standard errors are double-clustered by country and month. All covariates (except dummy variables) are standardized to have a mean of zero and a variance of one. Corresponding t-statistics are reported in parentheses. The analysis is performed at monthly frequency from 01/1990 to 12/2017.

	(1) MOM	(2) cMOM	(3) sMOM	(4) dMOM	(5) MOM	(6) cMOM	(7) sMOM	(8) dMOM
Market Cont. Dummy (Bear Market)	3.73	3.03	2.96	0.62				
	(7.50)	(7.54)	(7.55)	(1.34)				
Market Cont. Dummy (Bull Market)					1.18	1.33	1.31	0.82
					(5.22)	(5.42)	(5.28)	(4.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Countries	43	43	43	43	43	43	43	43

is economically smaller for both market states and statistically only significant for bull but not for bear markets. While the behavior (the sign of the slope) of dMOM is still consistent with the investor overconfidence model in Daniel et al. (1998), the empirical evidence is less strong compared to the other momentum strategies.

The higher sensitivity of momentum to market continuations in bear markets is also consistent with the option-like behavior of momentum during bear markets described in Daniel and Moskowitz (2016), i.e., momentum in bear markets behaves like a written (short) call option on the market. This behavior can be seen as consistent with the theory of Merton (1974) that a common stock is a call option on the value of the firm. As a consequence, expected momentum returns are low in bear markets with high volatility and the market rebounds. As the weight of dMOM in MOM linearly increases with the expected momentum return for the next month (see Eq. (6)), it is the smallest in these moments.[22] These mechanics explain why the sensitivity of dMOM to market continuations is reduced more in bear markets than in bull markets.

3.3. Turnover and transaction costs

All momentum strategies are constructed as zero-cost long-short strategies. The returns reported in Table 2, however, ignore transaction costs for implementing the strategies. As mentioned in Barroso and Santa-Clara (2015), "[o]ne relevant issue is whether time-varying weights induce such an increase in turnover that eventually offsets the benefits of the strategy after transaction costs." Table 10 shows the average (over time) one-way portfolio turnover of the long leg plus the short leg. We find, on average, a turnover of more than 50% per month when using value-weighted returns for all strategies.[23] For the U.S. sample in Panel A, turnover increases for all enhanced strategies, especially for dMOM, reaching a maximum of 85.43% monthly and an increase in turnover of 30.09 (85.43–55.34) percentage points as compared to MOM. Similar results hold for the shorter global sample (from January 1990 to December 2017) in Panel B, where dMOM generates a maximum average monthly turnover of 74.24%. Next, we aim to investigate whether the increase in turnover offsets the benefits of volatility scaling.

Round-trip costs describe transaction cost levels (in percent) that would render the strategies' returns statistically insignificant at confidence levels of 5% and 1%. Panel A of Table 10 shows that momentum investors within the U.S. are only 5% sure that their strategy will have positive net profits when transaction costs do not exceed 0.60%. Comparing the enhanced strategies, the transaction costs that would remove the statistical significance of profits (at the 5% level) are higher than for conventional momentum and highest for dynamic-scaled momentum (1.03%). When increasing the confidence level, a similar picture emerges. Panel B shows that constant volatility-scaled momentum clearly gives the highest bounds for round-trip costs for the global sample.

Our approach does not explicitly test the after-trading cost performance of the different momentum strategies, nor does it analyze the effectiveness of transaction cost mitigation techniques.[24] Instead, this break-even cost study reveals how profitable each strategy remains when assuming a certain level of transaction costs. Stated differently, it merely defines an upper transaction cost bound for momentum investors. In this regard, Frazzini et al. (2014) and Novy-Marx and Velikov (2016) show for the U.S. that even standard momentum, which reveals the lowest break-even round-trip costs within our analysis, is a profitable and thus implementable trading strategy. Notably, we are aware of the following caveats with respect to our argumentation: the potential interaction effects between stock market volatility (and thus also realized volatility of momentum) and transaction costs (especially bid-ask spreads) due to liquidity reasons. For the non-U.S. sample, we argue that all enhanced strategies are at least as implementable as standard momentum, as indicated by higher break-even round-trip costs.

3.4. Momentum strategies and the January effect

Jegadeesh and Titman (1993) document that momentum returns are positive in all months except January, but losers significantly outperform winners in January. This result has been confirmed by Jegadeesh and Titman (2001), Grundy and Martin (2001), and Blitz et al. (2011), among others. Importantly, Grundy and Martin (2001) point out that in January, the momentum strategy "[...] goes short in prior losers, and prior losers tend to have become extremely small firms," which is traced back to fund managers selling small-cap loser stocks in December that re-

[22] The estimated value for γ_{int} in Eq. (6) is negative for nearly all months

[23] Our monthly turnover for MOM, however, is lower than the 74% in Barroso and Santa-Clara (2015). We trace the difference back to not using decile momentum portfolios but forming HML-style portfolios based on 70/30% percentile breakpoints and double-sorts including size. We are able to validate the turnover for the equivalent sub-sample period using the more extreme decile breakpoints and single sorts.

[24] See Novy-Marx and Velikov (2016) for details on these two subjects.

Table 10
Turnover and break-even round-trip costs.
The table presents the following turnover and trading cost measures for MOM, cMOM, sMOM, and dMOM: (1) average long-short portfolio turnover (monthly, in %), (2) break-even round-trip costs significant at the 5% level, stating the upper border for trading costs so that the strategy is profitable with 5% significance, and (3) break-even round-trip costs significant at the 1% level. For details regarding the measure construction, see Section 2.4. The analysis is performed from 01/1930 (01/1990) to 12/2017 for the U.S. (non-U.S.) sample.

	MOM	cMOM	sMOM	dMOM
Panel A: U.S. (01/1930 - 12/2017)				
Turnover (in %)	55.34	82.88	81.46	85.43
Round-trip costs at 5% sign. level (in %)	0.6	1.01	0.97	1.05
Round-trip costs at 1% sign. level (in %)	0.44	0.91	0.86	0.95
Panel B: Non-U.S. (01/1990 - 12/2017)				
Turnover (in %)	49.26	70.77	70.26	74.24
Round-trip costs at 5% sign. level (in %)	0.33	0.88	0.82	0.79
Round-trip costs at 1% sign. level (in %)	0.09	0.71	0.65	0.63

Table 11
Momentum strategies in January versus non-January months.
The table presents the mean returns (in %) and corresponding t-statistics of momentum and the enhanced momentum strategies in January and Non-January months. The following strategies are included: MOM, cMOM, sMOM, and dMOM. For details regarding variable construction, see Section 2.2. The results relate to January (Jan.) months, Non-January (Non-Jan.) months and the difference between Non-January and January months. The analyses are performed from 01/1930 (01/1990) to 12/2017 for the U.S. (non-U.S.) sample.

	MOM	cMOM	sMOM	dMOM
Panel A: U.S. (01/1930 - 12/2017)				
Jan.	-1.42	-1.16	-1.13	-0.68
	(-3.00)	(-2.11)	(-1.98)	(-1.21)
Non-Jan.	0.78	1.31	1.25	1.33
	(5.56)	(9.53)	(9.14)	(9.66)
Diff.	2.20	2.47	2.38	2.01
	(4.45)	(4.36)	(4.06)	(3.47)
Panel B: Non-U.S. (01/1990 - 12/2017)				
	MOM	cMOM	sMOM	dMOM
Jan.	-0.16	0.31	0.27	1.06
	(-0.22)	(0.35)	(0.33)	(1.08)
Non-Jan.	0.61	1.07	1.02	0.96
	(3.04)	(5.47)	(5.17)	(5.00)
Diff.	0.77	0.76	0.75	-0.10
	(1.02)	(0.84)	(0.90)	(-0.10)

verse in January. In Table 11, we split up our sample into January and non-January months.

Panel A shows the mean percentage returns and t-statistics for the U.S. sample. Even though all enhanced momentum strategies exhibit higher returns than conventional momentum in January, none of the returns are positive on average. Furthermore, the difference between non-January and January month returns is statistically significant for momentum and all enhanced strategies. Panel B shows results for the non-U.S. sample: all strategies have higher returns in non-January than in January months, but the difference between January and non-January returns is not statistically significant. In sum, all enhanced strategies exhibit their performance mainly during non-January months.

4. Conclusion

This paper studies the performance of three enhanced momentum strategies proposed in the literature—constant volatility-scaled momentum (cMOM), constant semi-volatility-scaled momentum (sMOM), and dynamic-scaled momentum (dMOM)—for a total of 49 developed and emerging market countries and a sample period of about 28 years (88 years for the U.S.). We document that all three enhanced momentum strategies substantially increase in Sharpe rations. Also, both skewness and kurtosis decrease in magnitude and suffer from less pronounced drawdowns. Furthermore, enhanced momentum strategies generate significantly positive alphas in mean-variance spanning tests on asset pricing factors that include standard momentum (MOM). Ex-post maximum Sharpe ratio tests, as in Barillas et al. (2019), confirm that all enhanced momentum strategies significantly increase the maximum Sharpe ratio as compared to the factor opportunity set that already includes momentum for both the U.S. and the non-U.S. sample. However, no clear picture emerges when we compare the three enhanced approaches with this methodology.

We then exploit the dispersion in both country characteristics and momentum returns of our international dataset and conduct panel regressions to explain the variation of momentum returns across countries. Our results show that MOM, constant volatility-scaled momentum, and constant semi-volatility-scaled momentum are most affected by proxies for time-varying investor overconfidence, while dynamic-scaled momentum is significantly less affected by these proxies. This result is robust when we split up our sample into two sub-periods from 01/1990 to 12/2003 and from 01/2004 to 12/2017. In contrast, a country's individualism score is only significantly related to momentum returns for the first subperiod, suggesting that the results in Chui et al. (2010) do not hold out-of-sample. Furthermore, we find some evidence that all momentum strategy returns are positively related to proxies for the presence of noise trading.

Finally, enhanced momentum strategies should be at least as implementable as standard momentum, as their break-even costs (i.e., transaction costs that theoretically would render the strategies insignificant) are higher than the ones for standard momentum. Moreover, both MOM and enhanced momentum strategies generate their performance mainly during non-January months.

CRediT authorship contribution statement

Matthias X. Hanauer: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – review & editing. **Steffen Windmüller:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share raw stock and company data. However, aggregated time-series data may be made available on request.

Appendix A. Appendix

A1. Datastream sample definition

Constituent lists

Datastream comprises three types of constituent lists: (1) research lists, (2) Worldscope lists, and (3) dead lists. By using dead lists, we ensure to obviate any survivorship bias. For every country, we use the union of all available lists and eliminate any duplicates. As a result, we have one remaining list for every country, which can subsequently be used in the static filter process. Tables A.1 and A.2 provide an overview of the constituent lists for developed markets and emerging markets, respectively, used in our study.

Static screens

We restrict our sample to common equity stocks by applying several static screens, as shown in Table A.3. Screens (1) to (7) are standard filters as common in the literature.

Screen (8) is related to, among others, the following work: Ince and Porter (2006), Campbell et al. (2010), Griffin et al. (2010), Karolyi et al. (2012). The authors provide generic filter rules in order to exclude non-common equity securities from Refinitiv Datastream. We apply the identified keywords and match them with the security names provided by Datastream. A security is excluded from the sample in case a keyword coincides with part of the security name. The following three Datastream items store security names and are applied for the keyword filters: “NAME”, “ENAME”, and “ECNAME”. Table A.4 gives an overview of the keywords used.

In addition, Griffin et al. (2010) introduce specific keywords for individual countries. Thus, the keywords are only applied to the security names of the respective country. Exemplary, German security names are parsed to contain the word “GENUSSSCHEINE”, which declares the security to be non-common equity. In Table A.5, we give an overview of country-specific keyword deletions conducted in our study.

Table A.1
Constituent lists: Developed markets.
The table contains the Research lists, Worldscope lists, and Dead lists of developed markets countries in our sample.

Country	Lists	Country	Lists
Australia	DEADAU	**Israel**	DEADIS
	FAUS		FISRAEL
	WSCOPEAU		WSCOPEIS
Austria	DEADOE	**Italy**	DEADIT
	FOST		FITA
	WSCOPEOE		WSCOPEIT
Belgium	DEADBG	**Japan**	DEADJP
	FBEL		FFUKUOKA
	FBELAM		FJASDAQ
	FBELCM		FOSAKA
	WSCOPEBG		FTOKYO
Canada	DEADCN1		JAPOTC
	DEADCN2		WSCOPEJP
	DEADCN3	**Netherlands**	DEADNL
	DEADCN4		FHOL
	DEADCN5		WSCOPENL
	DEADCN6	**New Zealand**	DEADNZ
	FTORO		FNWZ
	FVANC		WSCOPENZ
	LTTOCOMP	**Norway**	DEADNW
	WSCOPECN		FNOR
Denmark	DEADDK		WSCOPENW
	FDEN	**Portugal**	DEADPT
	WSCOPEDK		FPOR
Finland	DEADFN		WSCOPEPT
	FFIN	**Singapore**	DEADSG
	WSCOPEFN		FSIN
France	DEADFR		FSINQ
	FFRA		WSCOPESG
	WSCOPEFR	**Spain**	DEADES
Germany	DEADBD1		FSPN
	DEADBD2		WSCOPEES
	DEADBD3	**Sweden**	DEADSD
	DEADBD4		FAKTSWD
	DEADBD5		FSWD
	DEADBD6		WSCOPESD
	FGER1	**Switzerland**	DEADSW
	FGER2		FSWA
	FGERIBIS		FSWS
	FGKURS		FSWUP
	WSCOPEBD		WSCOPESW
Hong Kong	DEADHK	**U.K.**	DEADUK
	FHKQ		FBRIT
	WSCOPEHK		LSETSCOS
Ireland	DEADIR		LSETSMM
	FIRL		LUKPLUSM
	WSCOPEIR		WSCOPEJE
			WSCOPEUK

Table A.2
Constituent lists: Emerging markets.
The table contains the Research lists, Worldscope lists, and Dead lists of emerging markets countries in our sample.

Argentina	DEADAR	**Morocco**	DEADMOR
	FPARGA		FMOR
	WSCOPEAR		WSCOPEMC
Brazil	DEADBRA	**Pakistan**	DEADPA
	FBRA		FPAK
	WSCOPEBR		FPAKUP
Chile	DEADCHI		WSCOPEPK
	FCHILE	**Peru**	DEADPE
	FCHILE10		FPERU
	WSCOPECL		WSCOPEPE
China	DEADCH	**Philippines**	DEADPH
	FCHINA		FPHI
	WSCOPECH		FPHILA
Colombia	DEADCO		FPHIMN
	FCOL		FPHIQ
	WSCOPECB		WSCOPEPH
Czech Republic	DEADCZ	**Poland**	DEADPO
	FCZECH		FPOL
	FCZECHUP		WSCOPEPO
	WSCOPECZ	**Qatar**	DEADQT
Egypt	DEADEGY		FQATAR
	EGYPTALL		WSCOPEQA
	FEGYPT	**Russia**	DEADRU
	WSCOPEEY		FRTSCL
Greece	DEADGR		FRUS
	FGREE		FRUSUP
	FGRMM		WSCOPERS
	FGRPM	**South Africa**	DEADSAF
	FNEXA		DEADSAF
	WSCOPEGR		FSAF
Hungary	DEADHU		WSCOPESA
	FHUN		WSCOPESA
	WSCOPEHN	**South Korea**	DEADKO
India	DEADIND		FKONEX
	FBSE		FKOR
	FINDIA		WSCOPEKO
	FINDNW	**Taiwan**	DEADTW
	FINDUP		FTAIQ
	FNSE		WSCOPETA
	WSCOPEIN	**Thailand**	DEADTH
Indonesia	DEADIDN		FTHAQ
	FINO		WSCOPETH
	WSCOPEID	**Turkey**	DEADTK
Malaysia	DEADMY		FTURK
	FMAL		FTURKUP
	FMALQ		WSCOPETK
	WSCOPEMY	**United Arab Emirates**	DEADAB
Mexico	DEADME		DEADDB
	FMEX		FABUD
	MEX101		FDUBAI
	WSCOPEMX		WSCOPEAE

Table A.3
Static screens.
The table displays the static screens applied in our study, mainly following Ince and Porter (2006), Schmidt et al. (2017), and Griffin et al. (2010). Column 3 lists the Datastream items involved (on the left of the equality sign) and the required values in the filter process (on the right of the equality sign). Finally, Column 4 indicates the source of the screens.

Nr.	Description	Datastream item(s) involved	Source
(1)	For firms with more than one security, only the one with the biggest market capitalization and liquidity is used.	MAJOR = Y	Schmidt et al. (2017)
(2)	The type of security must be equity.	TYPE = EQ	Ince and Porter (2006)
(3)	Only the primary quotations of a security are analyzed.	ISINID = P	Fong et al. (2017)
(4)	Firms are located in the respective domestic country.	GEOGN = country shortcut	Ince and Porter (2006)
(5)	Securities are listed in the respective domestic country.	GEOLN = country shortcut	Griffin et al. (2010)
(6)	Securities with quoted currency different from the one of the associated country are disregarded.[a]	PCUR = currency shortcut of the country	Griffin et al. (2010)
(7)	Securities with ISIN country code different from the one of the associated country are disregarded.[b]	GGISN = country shortcut	Annaert et al. (2013)
(8)	Securities whose name fields indicate non-common stock affiliation are disregarded.	NAME, ENAME, ECNAME	Ince and Porter (2006), Campbell et al. (2010), Griffin et al. (2010) and Karolyi et al. (2012)

[a] In this filter rule, also the respective pre-euro currencies are accepted for countries within the eurozone. Moreover, in Russia, "USD" is also accepted as currency, besides "RUB".
[b] In Hong Kong, ISIN country codes equal to "BM" or "KY" and in the Czech Republic ISIN country codes equal to "CS" are also accepted.

Table A.4
Generic keyword deletions.
The table reports the generic keywords, which are searched for in the names of all stocks of all countries. If the stock name contains a harmful keyword, the respective stock is removed from the sample.

Non-common equity	Keywords
Duplicates	1000DUPL, DULP, DUP, DUPE, DUPL, DUPLI, DUPLICATE, XSQ, XETa
Depository Receipts	ADR, GDR
Preferred Stock	PF, 'PF', PFD, PREF, PREFERRED, PRF
Warrants	WARR, WARRANT, WARRANTS, WARRT, WTS, WTS2
Debt	%, DB, DCB, DEB, DEBENTURE, DEBENTURES, DEBT
Unit Trusts	.IT,.ITb, TST, INVESTMENT TRUST, RLST IT, TRUST, TRUST UNIT, TRUST UNITS, TST, TST UNIT, TST UNITS, UNIT, UNIT TRUST, UNITS, UNT, UNT TST, UT
ETFs	AMUNDI, ETF, INAV, ISHARES, JUNGE, LYXOR, X-TR
Expired securities	EXPD, EXPIRED, EXPIRY, EXPY
Miscellaneous (mainly taken from Ince and Porter (2006))	ADS, BOND, CAP.SHS, CONV, DEFER, DEP, DEPY, ELKS, FD, FUND, GW.FD, HI.YIELD, HIGH INCOME, IDX, INC.&GROWTH, INC.&GW, INDEX, LP, MIPS, MITS, MITT, MPS, NIKKEI, NOTE, OPCVM, ORTF, PARTNER, PERQS, PFC, PFCL, PINES, PRTF, PTNS, PTSHP, QUIBS, QUIDS, RATE, RCPTS, REAL EST, RECEIPTS, REIT, RESPT, RETUR, RIGHTS, RST, RTN.INC, RTS, SBVTG, SCORE, SPDR, STRYPES, TOPRS, UTS, VCT, VTG.SAS, XXXXX, YIELD, YLD

Table A.5
Country-specific keywords deletions.
The table reports the country-specific keywords, which are searched for in the names of all stocks of the respective countries. If the stock name contains a harmful keyword, the respective stock is removed from the sample.

Country	Keywords
Australia	PART PAID, RTS DEF, DEF SETT, CDI
Austria	PC, PARTICIPATION CERTIFICATE, GENUSSSCHEINE, GENUSSCHEINE
Belgium	VVPR, CONVERSION, STRIP
Brazil	PN, PNA, PNB, PNC, PND, PNE, PNF, PNG, RCSA, RCTB
Canada	EXCHANGEABLE, SPLIT, SPLITSHARE, VTG\\., SBVTG\\., VOTING, SUB VTG, SERIES
Denmark	\\)CSE\\)
Finland	USE
France	ADP, CI, SICAV, \\)SICAV\\), SICAV-
Germany	GENUSSCHEINE
Greece	PR
India	FB DEAD, FOREIGN BOARD
Israel	P1, 1, 5
Italy	RNC, RP, PRIVILEGIES
Korea	1P
Mexico	'L', 'C'
Malaysia	'A'
Netherlands	CERTIFICATE, CERTIFICATES, CERTIFICATES\\), CERT, CERTS, STK\\.
New Zealand	RTS, RIGHTS
Peru	INVERSION, INVN, INV
Philippines	PDR
South Africa	N', OPTS\\., CPF\\., CUMULATIVE PREFERENCE
Sweden	CONVERTED INTO, USE, CONVERTED-, CONVERTED - SEE
Switzerland	CONVERTED INTO, CONVERSION, CONVERSION SEE
United Kingdom	PAID, CONVERSION TO, NON VOTING, CONVERSION 'A'

Table A.6
Dynamic screens.
The table displays the dynamic screens applied to the data in our study, following Ince and Porter (2006), Griffin et al. (2010), Jacobs (2016), and Schmidt et al. (2017). If screens are adapted solely to monthly (daily) returns, this is indicated by *m* (*d*).

No.	Description	Reference
(1)	We delete the zero returns at the end of the return time-series, which exist, because in case of a delisting Datastream displays stale prices from the date of delisting until the end of the respective time-series. We also delete the associated market capitalizations.	Ince and Porter (2006)
(2)	We delete the associated returns and market capitalizations in case of abnormal prices (unadjusted prices > 1000000).	The screen originally stems from Schmidt et al. (2017), whereby we employ it on the unadjusted price.
(3*m*)	We delete monthly returns and the associated market capitalizations in case of return spikes (returns > 990%).	Schmidt et al. (2017)
(3*d*)	We delete daily returns and the associated market capitalizations in case of return spikes (returns > 200%).	Griffin et al. (2010)
(4*m*)	We delete monthly returns and the associated market capitalizations in case of strong return reversals, defined as follows: R_{t-1} or $R_t >= 3.0$ and $(1+R_{t-1})(1+R_t)-1<0.5$.	Ince and Porter (2006)
(4*d*)	We delete daily returns and the associated market capitalizations in case of strong return reversals, defined as follows: R_{t-1} or $R_t >= 1.0$ and $(1+R_{t-1})(1+R_t)-1<0.2$.	Ince and Porter (2006), Griffin et al. (2010), Jacobs (2016)

Dynamic screens

For the securities remaining from the static screens above, we obtain return and market capitalization data from Datastream and accounting data from Worldscope. Several dynamic screens that are common in the literature were installed to account for data errors, mainly within return characteristics. The dynamic screens are shown in Table A.6.

A2. Turnover calculation

Specifically, (one-way portfolio) turnover in month t for both the long or short portfolio leg is calculated as:

$$Turnover_{t,Long(Short)} = 0.5 \times \sum_{i}^{N_t} |x_{i,t} - \tilde{x}_{i,t-1}| \tag{11}$$

where $x_{i,t}$ is the weight of stock i in the respective portfolio leg in month t (i.e., the value proportion since we use value-weighted portfolio returns), N_t amounts to the total number of stocks in the portfolio leg at month t, and $r_{i,t}$ is the return of stock i during month t, and $x_{i,\tilde{t}-1}$ is the weight at the end of month $t-1$ resp. at the beginning of month t, right before trading. We define $\tilde{x}_{i,t-1}$ as:

$$\tilde{x}_{i,t-1} = \frac{x_{i,t-1}(1+r_{i,t-1})}{\sum_{j}^{N_t} x_{j,t-1}\left(1+r_{j,t-1}\right)} \tag{12}$$

The turnover of the long-short momentum strategies is then the sum of the average turnover in the long and short legs, i.e., the sum of $Turnover_{Long}$ and $Turnover_{Short}$. For the volatility-scaled strategies, the turnover is derived from Eq. (11) by weighting the turnover in month t with the corresponding strategy weight:

$$Turnover_{s,t,Long/Short} = 0.5 \times \sum_{i}^{N_t} |w_{scaled,t} x_{i,t} - w_{scaled,t-1}\tilde{x}_{i,t-1}| \tag{13}$$

A3. Cross-country variable construction and definition

This section outlines the construction and definition of contemporaneous country variables used in the paper. For each variable, we provide the category (investor overconfidence, limits-to-arbitrage, belief dispersion, market efficiency), the frequency (yearly, monthly, or static), the paper reference, and the respective data source, if appropriate.

Individualism, Investor Overconfidence, Static As Chui et al. (2010), we use the country-specific, time-invariant individualism index introduced by Hofstede (2001) and made available on Hofstede Insights[25] as a proxy for investor overconfidence.

Market Continuation Dummy, Investor Overconfidence, Monthly Following Asem and Tian (2010), we construct a dummy variable for each country-month which equals one in case of a market state continuation and zero in case of a market state transition. A market state continuation (transition) is present if the cumulative past 12-month and the current month total market return have the same (opposite) sign.

Idiosyncratic Volatility, Limits-to-Arbitrage, Monthly Similar to Watanabe et al. (2013), Jacobs (2016), and Cakici and Zaremba (2021), we estimate idiosyncratic volatility as the country-month average of firm-level idiosyncratic volatility, estimated as the standard deviation of firm-level residuals from rolling regressions of daily excess returns on local Fama and French (1993) three-factor models using data in the current month.

Average Firm Size, Limits-to-Arbitrage, Monthly Following Chui et al. (2010), Jacobs (2016), and Cakici and Zaremba (2021), a country's average firm size is measured as the median USD market value of equity (item: MV) across firms at the end of a given month.

Average Number of Analysts, Limits-to-Arbitrage, Monthly The average number of analysts equals the average number of analysts per firm (item: EPS1NE), providing firm-level fiscal-year-one earnings estimates. The analyst data for all markets stems from I/B/E/S as in Jacobs (2016).

Short-sale Constraints, Limits-to-Arbitrage, Static The short-sale dummy variable equals one if short-selling is allowed in a country and zero otherwise. We collect the data from Brit et al. (2007) as described in Watanabe et al. (2013) and Jacobs (2016).

Average Analyst Forecast Dispersion, Belief Dispersion, Monthly The average analyst forecast dispersion is the country-month average of firm-level analyst forecast dispersion, which in turn equals the standard deviation of firm-level earnings per share for FY1 esti-

[25] https://www.hofstede-insights.com/fi/product/compare-countries/.

Table A.7
Descriptive statistics: cross-country Variables.
The table presents summary statistics for cross-country variables of 43 countries from our CRSP and Datastream/Worldscope sample. For a country to be considered for the cross-country analyses, we require that it has non-missing returns for momentum and all enhanced momentum strategies in at least 120 months. The column *Market* states the market affiliation, according to MSCI, with DM as Developed Markets and EM as Emerging Markets. The last column states each country's individualism index reported by Hofstede (2001). The other columns report time-series averages for the monthly cross-country variables depicted in Appendix A.3. We also report the pooled variable averages for developed and emerging markets and their differences.

Country	Market	Mkt. cont. dummy	Firm size	R^2 (%)	IVOL	Frac. zero return days (%)	No. analysts	Anal. forecast disp.	Short dummy	Individualism
Australia	DM	0.58	761.56	14.36	3.93	44.47	3.31	28.99	1.00	90
Austria	DM	0.55	1023.78	23.86	2.06	38.31	3.78	33.08	1.00	55
Belgium	DM	0.58	1829.31	20.28	2.00	30.44	4.23	31.11	1.00	75
Canada	DM	0.53	757.41	8.12	4.83	36.53	3.38	47.13	1.00	80
Denmark	DM	0.59	944.76	15.41	2.34	44.61	2.87	44.16	1.00	74
Finland	DM	0.57	1614.11	18.78	2.32	30.05	6.10	30.20	0.85	63
France	DM	0.57	1896.18	14.08	2.62	32.68	4.04	37.07	1.00	71
Germany	DM	0.56	1640.07	15.69	2.60	35.62	4.33	44.21	1.00	67
Hong Kong	DM	0.61	540.70	10.74	3.60	35.23	2.71	29.88	0.98	25
Ireland	DM	0.59	1155.51	16.48	3.21	49.87	3.98	17.89	1.00	70
Israel	DM	0.52	481.37	20.98	2.31	30.59	0.35	34.60	1.00	54
Italy	DM	0.51	1957.96	25.07	2.03	18.39	5.29	37.15	1.00	76
Japan	DM	0.55	1184.32	22.30	2.35	26.37	1.95	30.79	1.00	46
Netherlands	DM	0.55	2727.53	22.70	2.14	22.94	9.39	35.74	1.00	80
New Zealand	DM	0.57	381.43	21.54	2.66	49.63	2.43	15.49	1.00	79
Norway	DM	0.56	942.30	16.63	2.93	40.02	4.03	52.16	1.00	69
Portugal	DM	0.56	1118.58	21.42	2.61	42.09	3.78	32.28	1.00	27
Singapore	DM	0.56	598.20	16.78	3.23	45.58	5.26	26.31	0.00	20
Spain	DM	0.53	3550.06	25.75	1.87	29.07	8.99	32.67	1.00	51
Sweden	DM	0.56	1001.23	18.58	3.30	26.69	3.78	46.46	1.00	71
Switzerland	DM	0.57	3654.92	21.09	1.92	34.53	5.80	28.77	1.00	68
U.K.	DM	0.57	1626.10	15.36	2.46	51.41	3.97	25.20	1.00	89
U.S.	DM	0.63	2907.11	13.69	3.48	12.44	5.23	3.24	1.00	91
Argentina	EM	0.57	452.90	22.55	2.34	50.68	0.74	60.71	1.00	46
Brazil	EM	0.54	2574.40	29.66	2.79	44.48	2.95	52.23	1.00	38
Chile	EM	0.52	917.97	26.92	1.54	66.10	1.05	24.45	0.88	23
China	EM	0.58	1363.22	41.26	2.05	13.97	1.52	22.00	0.00	20
Colombia	EM	0.58	2869.86	39.37	1.46	61.32	0.61	22.71	0.00	13
Greece	EM	0.57	343.61	26.54	2.92	28.99	2.01	42.36	0.00	35
Hungary	EM	0.55	642.91	27.31	3.10	37.62	1.79	36.79	1.00	80
India	EM	0.54	540.14	19.89	3.10	15.93	1.96	24.33	0.54	48
Indonesia	EM	0.56	521.03	17.65	3.67	55.62	2.27	53.71	0.00	14
Malaysia	EM	0.57	379.70	22.05	2.96	36.36	3.07	35.08	0.08	26
Mexico	EM	0.56	1869.09	30.00	1.90	49.61	3.71	48.98	1.00	30
Pakistan	EM	0.52	150.35	18.63	2.78	46.13	0.57	24.58	0.00	14
Peru	EM	0.58	616.01	19.31	1.49	80.66	0.21	24.98	0.00	16
Philippines	EM	0.55	492.54	12.17	3.47	56.49	2.31	32.40	0.93	32
Poland	EM	0.56	405.77	20.79	3.04	23.99	1.28	45.67	1.00	60
South Africa	EM	0.51	1090.83	21.65	3.61	42.63	2.50	28.43	1.00	65
South Korea	EM	0.55	485.96	26.49	3.04	13.55	2.40	47.49	0.00	18
Taiwan	EM	0.56	551.91	29.03	2.18	18.21	1.56	37.37	1.00	17
Thailand	EM	0.55	388.87	17.59	2.80	41.07	2.48	46.95	0.93	20
Turkey	EM	0.48	586.83	43.46	2.60	20.42	3.25	38.83	1.00	37
Avg. DM	DM	0.56	1544.65	0.18	2.75	0.34	4.42	32.72	0.92	65
Avg. EM	EM	0.55	833.12	0.25	2.70	0.38	2.12	37.91	0.61	32
Diff. DM-EM		0.01	711.53	-0.07	0.05	-0.04	2.30	-5.19	0.32	34

mates across analysts, scaled by the absolute mean forecast (item: EPS1CV). See Jacobs (2016).

Average Coefficient of Determination (R^2), Market Efficiency, Monthly As in Jacobs (2016), the average coefficient of determination is the average R^2 across firms in a given country-month from the regression that estimates idiosyncratic volatility. The R^2, expressing the variation explained by the local Fama and French (1993) three-factor model, is inversely related to the corresponding idiosyncratic volatility.

Average Fraction of Zero Return Days, Market Efficiency, Monthly Following Jacobs (2016), we calculate the average fraction of zero return days as the country-level average of the firm-level fraction of zero local currency return days as compared to all return days in the current month. As described in Lesmond et al. (2015), the fraction of zero return days proxies for the efficiency of markets.

Developed Market Dummy, Market Efficiency, Yearly Following Watanabe et al. (2013) and Jacobs (2016), we include a developed market dummy. The classification is based on the Morgan Stanley Capital International (MSCI) Annual Market Classification and is updated at the end of June of each year.[26] Developed stock markets are considered more informationally efficient than emerging ones.

[26] https://www.msci.com/market-classification.

Table A.8
Panel regressions of momentum returns and cross-country characteristics.
The table presents results from panel regressions of momentum strategy returns and country-month averages of firm-level as well as other country characteristics. The dependent variable is the monthly return for each country of the following momentum strategies: MOM, cMOM, sMOM, and dMOM. For columns 2–4 and 6–8, we estimate the following regression pairwise for MOM and one enhanced momentum strategy: $Ret_{i,t} = \beta_i X_{i,t} + \gamma_i X_{i,t} \times EnhMom + controls + e_{i,t}$, where $X_{i,t}$ is a vector of country characteristics, *EnhMom* is a dummy equal to one if the return is from an enhanced momentum strategy. The country-level control variables are described in Appendix A.3 and summarized in Table A.7. Columns 1 and 5 show the regression coefficients $beta_i$ and columns 2–4 and 6–8 show the regression coefficients γ_i. All regressions include month-fixed effects, columns 2–4 and 6–8 contain month-EnhMom fixed effects, and the last four columns additionally include country fixed-effects. Standard errors are double-clustered by country and month. All covariates (except dummy variables) are standardized to have a mean of zero and a variance of one. Corresponding t-statistics are reported in parentheses. The analysis is performed at monthly frequency from 01/1990 to 12/2017.

	(1) MOM	(2) cMOM	(3) sMOM	(4) dMOM	(5) MOM	(6) cMOM	(7) sMOM	(8) dMOM
Market continuation dummy	1.86	-0.12	-0.15	- 1.15	1.87	-0.12	-0.15	- 1.16
	(6.96)	(-1.50)	(-1.78)	(-5.11)	(7.06)	(-1.50)	(-1.77)	(-5.14)
Firm size	-0.32	-0.06	-0.07	0.02	-0.37	-0.11	-0.13	-0.03
	(-3.62)	(-1.15)	(-1.30)	(0.25)	(-2.59)	(-2.02)	(-2.21)	(-0.25)
Return R^2	-0.32	-0.16	-0.19	0.03	-0.31	-0.10	-0.12	0.08
	(-2.72)	(-2.58)	(-2.81)	(0.24)	(-1.94)	(-1.56)	(-1.77)	(0.78)
Idiosyncratic volatility	-0.44	0.06	0.04	0.36	-0.74	0.05	0.03	0.32
	(-2.83)	(0.73)	(0.52)	(2.65)	(-3.58)	(0.57)	(0.36)	(2.44)
Fraction zero return days	-0.03	-0.06	-0.06	-0.06	0.02	-0.05	-0.05	-0.03
	(-0.39)	(-1.36)	(-1.34)	(-0.50)	(0.11)	(-1.01)	(-0.94)	(-0.28)
Number of analysts	0.09	0.05	0.04	0.03	0.03	0.01	0.0005	0.005
	(1.43)	(0.68)	(0.51)	(0.23)	(0.25)	(0.19)	(0.01)	(0.04)
Analysts forecast dispersion	-0.08	0.01	0.02	-0.02	-0.06	0.01	0.02	-0.01
	(-1.02)	(0.32)	(0.36)	(-0.17)	(-0.77)	(0.29)	(0.33)	(-0.06)
Short selling dummy	-0.02	-0.17	-0.19	0.27				
	(-0.09)	(-1.17)	(-1.25)	(0.92)				
Developed market dummy	-0.15	-0.11	-0.12	-0.05				
	(-0.63)	(-1.01)	(-1.06)	(-0.16)				
Individualism	0.01	-0.003	-0.003	-0.01				
	(2.07)	(-0.85)	(-0.86)	(-1.46)				
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-EnhMom FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Country FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	11,217	22,434	22,434	22,434	11,217	22,434	22,434	22,434
No. of Countries	43	43	43	43	43	43	43	43
Adjusted R^2	0.25	0.22	0.22	0.16	0.25	0.23	0.22	0.16

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