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Empirical determinants of momentum: a perspective using international data

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Abstract

Although momentum exists in many markets throughout the world, explanations for momentum have largely been tested using US data. We investigate the extent to which US-based momentum explanations extend to the international context, using regression-based and portfolio approaches. Among the several hypotheses we consider, we find reliable support for the hypothesis that due to limited attention, investors underreact to information arriving in small bits rather than in large chunks, which results in momentum. We also find secondary support for the overconfidence hypothesis for momentum. Finally, we find that momentum is stronger in up-markets and less-volatile markets in the international context just as in the USA. This finding also accords with the investor overconfidence hypothesis, under the proviso that investors are more confident in rising, low-volatility markets.

Keywords: Momentum, International, News diffusion.
JEL classifications: G10, G12, G14, G15.

1. Introduction

The market efficiency debate is central to the field of finance, and it continues unabated. A key contribution to this debate is the extensive evidence of momentum, which is the tendency of stocks' relative performance to be predictable from their relative performance in the past 3 to 12 months. This pattern, uncovered by Jegadeesh and Titman (1993), appears to contradict the notion of weak-form market efficiency, which makes it intriguing. Widely used asset pricing models such as the CAPM or the Fama–French three-factor model do not explain momentum. Therefore, the literature proposes and tests several other explanations for momentum.[1]

Although the empirical work on testing momentum explanations mostly uses US data, momentum strategies are profitable in many markets outside the USA as well (see, e.g., Rouwenhorst 1998; Griffin, Ji, and Martin 2003; Asness, Moskowitz, and Pedersen 2013). Because the pattern of momentum is similar in both the USA and internationally, a natural question that arises is which, if any, of the explanations proposed using US data apply internationally. This is the issue we address in our article.

One strand of momentum explanations proposes behavioral theories. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) present a model where investor overconfidence leads to momentum. The idea here is that overconfidence builds as investors receive

[1] Jegadeesh and Titman (2011) and Subrahmanyam (2018) review the momentum literature.

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public signals that confirm their initial trading decisions but does not subside equally when they receive contradictory ones. This leads to momentum due to continuing overreaction, on average. Daniel and Titman (1999) argue that overconfidence plays a bigger role in the valuation of stocks with bigger growth options relative to their assets-in-place, and hence propose book-to-market (B/M) as a proxy for the impact of overconfidence. Lee and Swaminathan (2000) argue that the degree of investor overconfidence is reflected in the volume of trading,[2] and hence use this quantity as a proxy for overconfidence.

Hong and Stein (1999) propose the gradual diffusion of information as another hypothesis to explain momentum. In their model, one category of investors conditions their demands on the private information they receive but not on market prices, and another category of investors does not receive private information and they condition their demand only on market prices. Hong and Stein (1999) show that information propagates in a delayed fashion in this setting, which results in momentum. Hong, Lim, and Stein (2000) test this hypothesis using analyst following conditional on firm size as a proxy for the speed of information diffusion.

Da, Gurun, and Warachka (2014) propose a frog-in-the-pan (FIP) hypothesis to explain momentum. Under this hypothesis, because of limited attention as proposed by (Hirshleifer and Teoh 2003), investors underreact to information that arrives in small bits but correctly react when information arrives in large chunks. Da, Gurun, and Warachka (2014) propose a proxy for the discreteness of information arrival and show that momentum is inversely related to this proxy. George and Hwang (2004) propose and find evidence for the notion that the ratio of current prices to their 52-week high is related to the degree of underreaction to news because investors are anchored to that high.

Another line of the literature proposes explanations for momentum (see, e.g., Johnson 2002; Sagi and Seasholes 2007) using a neoclassical reward–risk argument. In Johnson (2002), stock price is a convex function of growth rates and growth rate risk increases with the level of growth rates. Because winners are more likely to be stocks that received positive growth rate shocks, they are riskier than losers. According to Sagi and Seasholes (2007), a firm's real options are the source of its growth rate risk. They use comparative statistics results to derive testable predictions about how momentum varies across stocks with different characteristics and test those predictions. Sagi and Seasholes (2007) use the cost of goods sold (COGS) as an inverse proxy for real options.[3] They also use volatility of sales growth as a real options proxy but many of the firms in our sample do not have sufficient data to compute sales volatility. In Sagi and Seasholes (2007), bigger sales volatility also implies bigger return volatility and Sagi and Seasholes (2007) note that momentum increases with return volatility as well.[4]

We use Fama and MacBeth (1973) type analyses, a regression regularization approach (i.e., penalized regression), and a portfolio sorting approach, to consider the extent to which the preceding proxies for momentum explanations extend to the international context. Across all of our tests, we find supportive evidence for the FIP proxy in both emerging and non-US developed markets. This finding indicates that underreaction to continuous news plays a key role in generating momentum internationally. We find more modest evidence for the overconfidence hypothesis using the B/M ratio as the proxy in some tests.

2 For instance, Odean (1998) argues that overconfidence leads to greater trading activity. Intuitively, overconfident investors tend to overestimate the precision of their signals and hence make bigger trades based on any given signal.

3 In Sagi and Seasholes (2007)'s model, firms with low costs benefit more from real options, leading to greater momentum.

4 In a different rationale for the momentum-volatility link, Zhang (2006) proposes that biases which cause underreaction have a bigger impact when there is more uncertainty. However, this argument does not form an explanation for momentum.

We also examine the time-series relations between momentum profits and market states. Cooper, Gutierrez, and Hameed (2004) find that momentum profits are higher in up-market states than in down-market ones,[5] and attribute this finding to the notion that investors are more overconfident in up-markets. The logic is that investors who face shorting constraints receive more validating signals for their buy trades in up-markets, thus causing momentum due to continuing overreaction. Furthermore, Wang and Xu (2015) document that momentum profits are lower in high-volatility states. Wang and Xu (2015) hypothesize that investors become overly fearful (i.e., less confident) in highly volatile markets and "over-sell" losers. The subsequent recovery of losers results in the poor performance of momentum in high-volatility states. We find that momentum profits are bigger and more significant in up-markets and during less volatile periods internationally, consistent with the US-based evidence of Cooper, Gutierrez, and Hameed (2004) and Wang and Xu (2015).[6]

To reiterate, our article, rather than testing one particular theory, takes the US evidence as given and analyzes the extent to which the explanations proposed hold internationally. We find that slow diffusion of news best explains momentum in the international context. However, it should be noted that to minimize subjective judgment calls, we use only the empirical proxies for various explanations that have already been identified in the literature, and we do not experiment with new proxies.[7] This design choice results from the recognition that creating our own proxies for tested or untested theories, we would run into the issue of (possibly subconsciously) selecting some theoretical explanations and empirical results over the exclusion of others. Note that we assign the same interpretation to the proxies as the original papers that seek to explain momentum. To the extent that such proxies are imperfect, our exercise implies a joint test of the proposed explanation and the proxy for the explanation.[8]

The remainder of this article is organized as follows. Section 2 describes our dataset and lays out the cross-sectional empirical tests. Section 3 implements the cross-sectional tests. Section 4 performs some additional analyses that control for risk and consider subsamples. Section 5 uses a method based on penalized regressions. Section 6 considers the cross-sectional evidence using portfolio-based analyses. Section 7 presents the time-series tests on market states as proxies for investor confidence. Section 8 concludes. Tables in the Supplementary Appendix are prefixed with "IA."

2. Data and cross-sectional regression method

This section first describes our data and presents an overview of our tests. We then discuss the empirical proxies that the literature uses to empirically test the cross-sectional

5 A closely related finding is that of Antoniou, Doukas, and Subrahmanyam (2013), who show that momentum profits are higher in periods of optimistic sentiment (Baker and Wurgler 2006). However, we are unable to examine this hypothesis internationally because sentiment measures are not available.

6 Other independent work has looked at issues similar to the one we examine. Muller and Muller (2020) analyze variation in momentum profits at the country level. We instead investigate variation in momentum across individual stocks within an international setting. Guo, Li, and Li (2022) assess the extent to which different variables explain momentum with US data, whereas our tests use international data. Further, they do not consider Da, Gurun, and Warachka (2014)'s FIP proxy for which we find good support. Finally, they use the component of past returns that is correlated with a cross-sectional variable X to test whether X accounts for the momentum effect. Note that since correlations are not transitive, the ability of X to explain the correlation between past and future returns (momentum) is not related to the correlation of X with past returns. Our regression method, which examines how future returns are related to the interaction between past returns and X, directly tests theories which predict that momentum depends on X.

7 For example, Barberis, Shleifer, and Vishny (1998) propose the representativeness bias as an explanation for momentum, and Hong, Stein, and Yu (2007) suggest that investors use overly simplified models to evaluate stocks, and make persistent forecast errors, which also leads to momentum. Since the empirical literature does not directly consider proxies for their theories, we do not address these papers.

8 Lou, Polk, and Skouras (2019) indicate that momentum profits primarily emanate from overnight, as opposite to intraday, return realizations (see also Barardehi, Bogousslavsky, and Muravyev 2022). Huang (2022) shows that momentum profits inversely depend on the spread in returns between the winner and loser portfolios during the formation period. Our focus is more on explanations for momentum, while the above papers tend to document stylized facts about momentum.

implications of these hypotheses. Broadly, these proxies imply that the underlying phenomenon that leads to momentum falls in one of the following categories: (1) underreaction to information due to cognitive limitations; (2) overconfidence, which implies a continuing overreaction to information; and (3) time-varying expected returns due to variations in risk. The second subsection presents our methodology.

2.1 Data

We obtain data for all countries from the MSCI Developed (ex-USA) and the MSCI Emerging Markets indexes. There are a total of twenty-two developed markets and twenty-seven emerging markets in the MSCI indexes for which we are able to get the necessary data.[9] The stock market data are from Datastream and the annual accounting data are from Worldscope. Appendix Table A1 provides details on the accounting variables.

For each country, we download data for both listed and delisted companies which have an exchange code (EXDSCD) corresponding to that of the primary exchange of that country, for which the type of instrument (TYPE) is equity, the indicator ISINID identifies the equity as the primary security, the geography code (GEOGN) identifies the home or listing country of the equity as the same country, and the currency of the equity is the same as that of the country.[10] We exclude depositary receipts (DRs), REITS, and preferred stocks, and apply filters described in Tables B.1 and B.2 of Griffin, Kelly, and Nardari (2010).

Because of potential data errors in Datastream and Worldscope, we use data cleaning procedures used, for example, by Griffin, Kelly, and Nardari (2010) and Jacobs and Müller (2020). Specifically, we proceed as follows. We download all data in US dollars with five decimal places to minimize return errors stemming from currency conversions. We then apply return filters in the following order. If the return in any month is greater than 300 percent and the cumulative return across the two consecutive months surrounding this month is less than 50 percent, then we set returns in both months as missing. Next, we apply an equivalent filter for daily returns, for which the corresponding numbers are 100 percent and 20 percent. Finally, we discard all daily returns exceeding 100 percent and all monthly returns exceeding 200 percent. We also exclude micro-cap stocks by including only those stocks that are in the top 97 percent of the market capitalization of each region. For each period (day or month), we winsorize returns in each country at the 0.1 percent and 99.9 percent levels. If 90 percent or more of stocks have zero returns in a period (day or month) for a country, we set all of them to missing.

2.2 Momentum in international markets

This subsection tests for momentum in international markets during our sample period. The momentum variable that we use is a stock's return over the previous 11 months, excluding the previous month. Specifically, for stock i, the momentum variable for month t is the return from month $t-12$ to $t-2$. We country-neutralize this return by subtracting its cross-sectional mean across all stocks from that country in our sample. We then rank stocks based on country-neutralized returns and assign each stock to one of ten momentum deciles. Because we country-neutralize the momentum variable, country-specific returns do not affect a stock's decile rank. We define the value-weighted portfolio of stocks in the winner decile minus stocks in the loser decile as the winner minus loser (WML) portfolio, and we rebalance it monthly.

[9] The developed countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the UK. The emerging countries are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Kuwait, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey, and the United Arab Emirates.

[10] We use both Toronto and TSX Ventures for Canada, Shanghai and Shenzhen for China, Deutsche Boerse and Xetra for Germany, BSE and National Stock Exchange for India, Tokyo and Osaka for Japan, and the Korea main exchange as well as KOSDAQ for South Korea as primary exchanges.

Table 1. Momentum outside the USA.
This table presents momentum profits outside the USA. We form momentum portfolios based on stock returns over the previous 12 months, excluding the previous month. Specifically, the momentum variable for month t is the return from month $t-12$ to $t-2$. We country neutralize the momentum variable by subtracting its cross-sectional mean across all stocks from that country in our sample. We then rank stocks based on country-neutralized returns and assign each stock to one of ten momentum deciles. The WML portfolio is long the value-weighted portfolio of stocks in the winner decile and short the corresponding loser decile. The table reports summary statistics for returns on the WML portfolio in percent. The sample excludes microcap stocks (stocks not in the top 97 percent of the market capitalization of each region). The sample period is 1993–2020.

	All ex-USA	Developed ex-USA	Emerging
Mean	0.887	0.853	0.744
Median	1.16	1.05	0.764
StdDev	5.44	6.11	5.12
Skewness	− 0.644	− 0.743	− 0.443
Minimum	− 33.8	− 39.1	− 22.6
Maximum	21.6	24.7	18.1

Table 1 presents the returns on the WML portfolio, which long the winner decile and short the loser decile. The monthly WML portfolio returns across All ex-USA, Developed ex-USA, and Emerging markets are, on average, 0.89 percent, 0.85 percent, and 0.74 percent, respectively, and are of a magnitude comparable to those in Jegadeesh and Titman (1993). The medians are slightly greater than the means, and momentum profits are more volatile and more negatively skewed for Developed ex-USA. Thus, our updated sample results confirm earlier international momentum evidence in Griffin, Ji, and Martin (2003) and Rouwenhorst (1998).

2.3 An overview of the regression-based tests

The literature proposes a number of behavioral and rational hypotheses to explain momentum, which have been tested using US data. Our tests examine these hypotheses internationally using the same empirical proxies. In order to be parsimonious, we consider the central measure, that is, the measure that is the main focus, of each article.

We use the following cross-sectional Fama and MacBeth (1973) regression:

$$R_{i,t} = \gamma_{0,t} + \gamma_{1,t} MOM_{i,t-1} + \gamma_{2,t} X_{i,t-1} + \gamma_{3,t} X_{i,t-1} \times MOM_{i,t-1} + e_{i,t}, \qquad (1)$$

where $R_{i,t}$ is the return of stock i in month t, MOM is the momentum variable used in Table 1, and X is one of the explanatory variables for momentum that are described below. The $t-1$ subscript implies that all right-hand variables are computed at a one-month lag. Note that for MOM, the computation stops at $t-2$ to skip the monthly reversal which might arise due to illiquidity or bid–ask spreads; this is as per convention (Brennan, Chordia, and Subrahmanyam 1998).[11] For convenience, we often drop the time subscripts from these right-hand variables henceforth. We process the variables MOM and X on the right hand through the following steps every month (1) we winsorize at the 0.5 percent and 99.5 percent levels, (2) we country-neutralize by subtracting the cross-sectional mean across all stocks in our sample from that country, and (3) we standardize across the entire sample to have zero mean and unit standard deviation.[12] The processed variables are used

[11] While we use the most current values of the X variables (measured at month t−1) in Regression (1), measuring these instead at month t−2 makes no substantive difference to our conclusions.

[12] We have verified that the alternative method of standardizing the variables country-by-country preserves the robustness of the results.

in the interaction terms. To minimize concerns about transaction costs and illiquidity of some international markets, we include only nonmicrocap stocks. These are defined as stocks in the top 97 percent of the market capitalization of each region, as in Fama and French (2017).

As stated in earlier literature (see, e.g., Fama 1976; Back, Kapadia, and Ostdiek 2015), the coefficients in a Fama and MacBeth (1973) regression may be interpreted as the performance of a pure factor play portfolio that bets on the relevant right-hand variable. Hence the interaction of *MOM* momentum with *X* represents a portfolio that simply tests whether, *ceteris paribus*, high values of *X* imply higher or lower profitability of the *MOM* characteristic. We now provide details of these *X* variables. We discuss hypotheses underlying these variables in later sections.

- Book-to-market ratio (B/M): B/M is the ratio of the book value of equity to the market value. Appendix Table A1 describes the precise formula we use to compute B/M.
- Turnover (Turn): We compute turnover as the number of shares traded in a month divided by shares outstanding as of the end of the previous month.
- Residual Analysts (ResAnly): We compute residual analysts as in Hong, Lim, and Stein (2000). Specifically, we cross-sectionally regress the log of one plus the number of analysts covering a stock on the log market capitalization of that stock each month, using the full sample. ResAnly is the residual from this regression.
- 52-week high (52wHi): We compute 52wHi for each stock each month as the ratio of the stock price at the end of the previous month to its highest price over the previous 12 months.
- Information discreteness (ID): Following Da, Gurun, and Warachka (2014), we define ID as follows:

$$\mathrm{ID}_{i,t-1} = \mathrm{sign}(\mathrm{PRET}) \times (\%\mathrm{neg} - \%\mathrm{pos}), \tag{2}$$

  where %pos and %neg are the percentage of daily returns that are positive and negative, respectively, and PRET is the past 11-month return.
- COGS: COGS is the ratio of the COGS divided by the total assets as of the previous year.
- Return Volatility (RetVol): This is the standard deviation of daily returns over the previous 12 months for stocks with at least 100 days of return data. If volatility is greater than 300 percent, we suspect an error in the data and set it to a missing value.

In Table 2, we present summary statistics for the explanatory variables by each region. We present statistics for the number of analysts, rather than ResAnly, as the former is more informative. We observe that mean turnover tends to be higher, while COGS tends to be lower in emerging markets. These markets also tend to be more volatile. The values for the other variables are not materially different across the three groups we consider.

3. Cross-sectional tests

This section examines the robustness of the hypotheses proposed to explain momentum. As a starting point, we fit equation (1) with only *MOM* as the independent variable, without any interaction variables. We estimate monthly cross-sectional regressions and we use the Fama and MacBeth (1973) approach to obtain the coefficients and standard errors. Column (1) in Panel A of Table 3 presents the results. The coefficients on *MOM* are 0.217, 0.277, and 0.135 for All ex-USA, Developed ex-USA, and Emerging markets, respectively. These coefficients are all statistically significant and confirm the evidence of momentum in Table 1. For ease of interpretation, we flip the signs on some of the *X* variables, so that the

Table 2. Summary statistics.

This table presents summary statistics for variables that have been proposed to explain momentum profits. The variables are defined in Section 2.

	B/M	Turn	Anly	52wHi	ID	COGS	RetVol
				All ex-USA			
5th percentile	0.105	0.001	0.000	0.500	−0.147	0.052	0.070
Median	0.523	0.04	0.231	0.895	−0.044	0.532	0.302
Mean	0.708	0.095	3.415	0.844	−0.044	0.648	0.305
95th percentile	1.900	0.376	16.595	1.000	0.056	1.695	0.645
StdDev	0.665	0.156	5.875	0.174	0.062	0.521	0.198
No. of stocks	7,022	7,142	10,951	10,818	10,951	6,324	10,950
				Developed ex-USA			
5th percentile	0.111	0.001	0.000	0.546	−0.138	0.049	0.070
Median	0.586	0.033	0.190	0.950	−0.043	0.567	0.228
Mean	0.753	0.053	3.615	0.876	−0.044	0.678	0.260
95th percentile	1.922	0.168	17.625	1.000	0.05	1.765	0.595
StdDev	0.660	0.069	6.195	0.160	0.058	0.539	0.186
No. of stocks	3,874	3,856	6,982	6,887	6,982	3,462	6,982
				Emerging			
5th percentile	0.103	0.001	0.000	0.449	−0.160	0.059	0.084
Median	0.480	0.065	0.653	0.795	−0.044	0.458	0.400
Mean	0.728	0.153	2.893	0.773	−0.046	0.580	0.406
95th percentile	2.134	0.580	13.56	1.000	0.066	1.534	0.721
StdDev	0.806	0.241	4.943	0.180	0.069	0.480	0.191
No. of stocks	3,293	3,484	4,148	4,110	4,148	3,080	4,148

interaction of $MOM \times X$ is predicted to be positive. Thus, a positive sign on the interaction supports the proposed explanation for momentum, and vice versa. As we discuss in later sections, the variables whose signs we flip are B/M, ResAnly, 52wHi, ID, and COGS.

3.1 B/M ratio and turnover

Daniel, Hirshleifer, and Subrahmanyam (1998) present a behavioral model to explain momentum. Investors in Daniel, Hirshleifer, and Subrahmanyam (1998) are subject to a self-attribution bias whereby they attribute profitable investments to their own skills and unprofitable ones to chance. As a result, investors become overconfident about the precision of their private signals over time and they overweight their private information when they value stocks. Daniel, Hirshleifer, and Subrahmanyam (1998) show that this behavioral bias results in momentum due to a continuing overreaction.

Daniel and Titman (1999) hypothesize that the impact of overconfidence is likely to be stronger when it is harder to determine the intrinsic value of a firm. They argue that firms with bigger growth options relative to their assets in place are likely harder to value than firms with smaller growth options. Because the book value of a stock is the accounting value of assets-in-place, Daniel and Titman (1999) use B/M as an observable proxy for overconfidence. They report that momentum profits are bigger for growth firms than for value firms.

We fit equation (1) with B/M ratio as the interaction variable to test the robustness of the Daniel and Titman's (1999) evidence outside the USA. Column (2) of Panel A of Table 3 presents the results by regions. The interaction coefficients in All ex-USA, Developed ex-USA, and Emerging markets are 0.034, 0.038, and 0.043, respectively, and are of the sign predicted by Daniel and Titman (1999). However, the statistical significance of these interaction coefficients is small, amounting to a t-statistic of 1.3. We revisit this

Table 3. Fama–MacBeth regressions of future returns on past momentum return and explanatory variables.
This table presents the results of Fama–MacBeth cross-sectional regressions. Panel A runs the regression:

$$R_{i,t} = \gamma_{0,t} + \gamma_{1,t}\, MOM_{i,t-1} + \gamma_{2,t}\, X_{i,t-1} + \gamma_{3,t}\, MOM_{i,t-1} \times X_{i,t-1} + e_{i,t},$$

where $MOM_{i,t-1}$ is the return from month $t-12$ to $t-2$ and X represents each of the variables listed in the top row of Table 2. We process the variables MOM and X on the right-hand through the following steps every month (1) we winsorize at the 0.5 percent and 99.5 percent levels, (2) we country neutralize by subtracting the cross-sectional mean across all stocks in our sample from that country, and (3) we standardize across the entire sample to have zero mean and unit standard deviation. The processed variables are used in the interaction terms. We reverse the signs of some of the X variables so that the interaction term with MOM of all variables is expected to be positive based on the original study's motivations. Panel B runs the regression:

$$R_{i,t} - \beta_i' F_t = \gamma_{0,t} + \gamma_{1,t}\, MOM_{i,t-1} + \gamma_{2,t}\, X_{i,t-1} + \gamma_{3,t}\, MOM_{i,t-1} \times X_{i,t-1} + e_{i,t},$$

where the betas on the left-hand side are calculated using the full sample for each stock from a five-factor Fama and French (2017) model. We use separate factors for developed and emerging markets and use the factor model for the stock corresponding to its region. Panel C runs the regression:

$$\begin{aligned} R_{i,t} = {} & \gamma_{0,t} + \gamma_{1,t} MOM_{i,t-1} + \gamma_{2,t} X_{i,t-1} + \gamma_{3,t} MOM_{i,t-1} \times X_{i,t-1} \\ & + \gamma_{4,t} Size_{i,t-1} + \gamma_{5,t} MOM_{i,t-1} \times Size_{i,t-1} + \gamma_{6,t} (B/M)_{i,t-1} \\ & + \gamma_{7,t} (GP/AT)_{i,t-1} + \gamma_{8,t} ATG_{i,t-1} + \gamma_{9,t} R_{i,t-1} + e_{i,t}, \end{aligned}$$

with additional controls on the right-hand side. We then run the above regressions separately for stocks in different regions. The table reports the time-series averages of coefficients together with their t-statistics in parentheses. We omit the coefficients on the control variables in Panel C for brevity. The last two rows in each subpanel report the average number of stocks and the average adjusted-R^2 in percent. The sample consists of only nonmicrocap stocks (those in the top 97 percent of the market capitalization of each region). The sample period is 1993–2020.

	(1) —	(2) –B/M	(3) Turn	(4) –ResAnly	(5) –52wHi	(6) –ID	(7) –COGS	(8) RetVol
Panel A: No controls								
				All ex-USA				
MOM	0.217 (3.32)	0.290 (4.72)	0.268 (4.46)	0.217 (3.75)	0.308 (6.32)	0.165 (2.70)	0.216 (3.40)	0.304 (6.06)

(continued)

Table 3. (continued)

	(1) —	(2) −B/M	(3) Turn	(4) −ResAnly	(5) −52wHi	(6) −ID	(7) −COGS	(8) RetVol
X	—	−0.283	−0.232	−0.242	0.063	−0.001	−0.048	−0.008
		(−6.73)	(−5.74)	(−3.25)	(0.60)	(−0.04)	(−3.04)	(−0.08)
$MOM \times X$	—	0.034	−0.028	−0.118	−0.017	0.161	0.009	−0.029
		(1.33)	(−1.55)	(−3.55)	(−0.60)	(5.55)	(0.55)	(−1.19)
No. of stocks	9,782	7,001	7,122	9,782	9,768	9,780	6,299	9,781
Adj-R^2	1.0	1.3	1.2	2.2	3.2	1.4	0.9	3.2
				Developed ex-USA				
MOM	0.277	0.351	0.341	0.271	0.397	0.230	0.285	0.415
	(3.59)	(4.57)	(4.61)	(4.21)	(7.20)	(3.22)	(3.72)	(7.24)
X	—	−0.261	−0.056	−0.267	0.073	0.007	−0.044	−0.008
		(−5.46)	(−1.04)	(−2.90)	(0.58)	(0.19)	(−2.39)	(−0.07)
$MOM \times X$	—	0.038	−0.047	−0.078	−0.058	0.125	0.018	−0.069
		(1.22)	(−2.43)	(−2.03)	(−1.96)	(4.11)	(0.94)	(−2.56)
No. of stocks	5,987	3,870	3,852	5,987	5,978	5,987	3,457	5,987
Adj-R^2	1.7	2.1	2.1	4.2	5.4	2.5	1.4	5.4
				Emerging				
MOM	0.135	0.231	0.191	0.163	0.214	0.077	0.136	0.234
	(2.23)	(3.88)	(3.58)	(2.77)	(4.39)	(1.30)	(2.20)	(4.37)
X	—	−0.369	−0.398	−0.194	0.080	−0.018	−0.084	0.028
		(−7.46)	(−7.49)	(−4.04)	(0.88)	(−0.60)	(−3.69)	(0.35)
$MOM \times X$	—	0.043	0.003	−0.117	−0.008	0.188	−0.023	−0.077
		(1.26)	(0.11)	(−3.12)	(−0.20)	(4.59)	(−1.00)	(−2.22)
No. of stocks	3,973	3,285	3,468	3,973	3,969	3,972	3,067	3,973
Adj-R^2	0.6	1.1	1.2	1.0	1.9	1.0	0.7	1.9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	—	−B/M	Turn	−ResAnly	−52wHi	−ID	−COGS	RetVol
Panel B: Risk-adjusted returns on the left-hand side								
				All ex-USA				
MOM	0.169	0.214	0.218	0.175	0.271	0.141	0.169	0.239
	(4.48)	(5.32)	(5.58)	(5.01)	(8.98)	(3.95)	(4.17)	(6.50)

(continued)

Table 3. (continued)

	(1) —	(2) −B/M	(3) Turn	(4) −ResAnly	(5) −52wHi	(6) −ID	(7) −COGS	(8) RetVol
X	—	−0.206	−0.211	−0.181	0.110	0.028	−0.026	0.010
		(−8.10)	(−6.84)	(−4.63)	(1.88)	(1.43)	(−1.84)	(0.20)
$MOM \times X$	—	0.053	−0.033	−0.102	−0.026	0.108	0.004	−0.032
		(2.64)	(−2.05)	(−3.83)	(−1.09)	(4.84)	(0.25)	(−1.48)
No. of stocks	9,761	6,982	7,102	9,761	9,747	9,760	6,281	9,761
Adj-R^2	0.4	0.7	0.7	0.9	1.3	0.7	0.5	1.2
				Developed ex-USA				
MOM	0.218	0.268	0.281	0.221	0.352	0.204	0.227	0.320
	(5.04)	(5.48)	(6.09)	(5.83)	(10.52)	(5.12)	(4.75)	(7.87)
X	—	−0.197	−0.063	−0.184	0.120	0.047	−0.009	0.017
		(−7.06)	(−1.71)	(−3.87)	(1.82)	(2.03)	(−0.59)	(0.31)
$MOM \times X$	—	0.062	−0.050	−0.059	−0.061	0.068	0.015	−0.051
		(2.60)	(−2.78)	(−1.90)	(−2.47)	(3.13)	(0.87)	(−2.19)
No. of stocks	5,979	3,862	3,844	5,979	5,970	5,979	3,450	5,979
Adj-R^2	0.8	1.1	1.2	1.7	2.2	1.2	0.8	2.0
				Emerging				
MOM	0.092	0.163	0.145	0.118	0.172	0.045	0.099	0.176
	(2.06)	(3.32)	(3.29)	(2.61)	(4.40)	(0.99)	(1.99)	(3.81)
X	—	−0.284	−0.345	−0.155	0.112	−0.008	−0.080	0.019
		(−6.88)	(−7.60)	(−4.53)	(1.75)	(−0.31)	(−3.80)	(0.38)
$MOM \times X$	—	0.046	−0.003	−0.117	−0.024	0.157	−0.033	−0.076
		(1.46)	(−0.10)	(−3.51)	(−0.61)	(4.21)	(−1.46)	(−2.34)
No. of stocks	3,960	3,273	3,455	3,960	3,956	3,959	3,055	3,960
Adj-R^2	0.4	0.8	1.0	0.6	1.2	0.8	0.5	1.0
Panel C: Controls on the right-hand side								
				All ex-USA				
MOM	0.283	0.259	0.342	0.301	0.255	0.242	0.280	0.367
	(5.16)	(4.30)	(6.49)	(5.62)	(6.08)	(4.56)	(5.13)	(7.75)
X	—	−0.302	−0.206	−0.118	−0.180	0.029	−0.038	−0.171
		(−7.68)	(−5.40)	(−2.99)	(−2.02)	(1.31)	(−2.43)	(−2.44)
$MOM \times X$	—	0.057	−0.042	−0.072	−0.055	0.164	0.004	−0.037
		(2.23)	(−2.35)	(−2.53)	(−1.58)	(5.37)	(0.23)	(−1.40)

(continued)

Table 3. (continued)

	(1) —	(2) −B/M	(3) Turn	(4) −ResAnly	(5) −52wHi	(6) −ID	(7) −COGS	(8) RetVol
No. of stocks	6,102	6,102	5,849	6,102	6,101	6,102	6,073	6,102
Adj-R^2	2.1	2.3	2.6	2.4	3.2	2.5	2.2	3.2
	Developed ex-USA							
MOM	0.332	0.315	0.389	0.355	0.304	0.294	0.331	0.459
	(5.21)	(4.30)	(6.43)	(5.80)	(6.45)	(4.69)	(5.17)	(8.74)
X	—	−0.287	−0.032	−0.134	−0.178	0.051	−0.025	−0.170
		(−6.48)	(−0.64)	(−2.59)	(−1.71)	(2.23)	(−1.51)	(−2.15)
$MOM \times X$	—	0.061	−0.046	−0.047	−0.114	0.149	0.014	−0.086
		(1.96)	(−2.30)	(−1.43)	(−3.16)	(4.84)	(0.77)	(−3.03)
No. of stocks	3,370	3,370	3,209	3,370	3,369	3,370	3,354	3,370
Adj-R^2	3.2	3.5	4.0	3.7	4.7	3.6	3.4	4.8
	Emerging							
MOM	0.236	0.226	0.310	0.266	0.209	0.189	0.230	0.327
	(4.15)	(3.69)	(5.89)	(4.62)	(4.22)	(3.30)	(4.03)	(5.95)
X	—	−0.384	−0.390	−0.120	−0.173	−0.018	−0.083	−0.156
		(−7.50)	(−7.56)	(−3.06)	(−1.95)	(−0.58)	(−3.45)	(−2.21)
$MOM \times X$	—	0.027	0.012	−0.098	−0.001	0.169	−0.029	−0.036
		(0.71)	(0.43)	(−2.19)	(−0.03)	(3.56)	(−1.13)	(−0.90)
No. of stocks	2,944	2,944	2,850	2,944	2,944	2,944	2,931	2,944
Adj-R^2	2.0	2.2	2.6	2.3	2.9	2.4	2.1	2.8

issue when we risk-adjust returns in Section 4.1. The coefficient on B/M is significantly positive in all regions. Therefore, consistent with the evidence in Fama and French (1992), B/M strongly explains cross-sectional differences in returns.

Lee and Swaminathan (2000) document a positive relation between momentum and turnover. They note that many of the characteristics of high-turnover stocks are similar to those of growth stocks, and those of low-turnover stocks are similar to those of value stocks. Lee and Swaminathan (2000) suggest that turnover could also be a proxy for overconfidence, based on Odean (1998). We fit equation (1) with turnover as the interaction variable to test the robustness of Lee and Swaminathan's (2000) evidence. Column (3) in Panel A of Table 3 presents the regression estimates. The negative relation between returns and turnover is consistent with the evidence in Datar, Naik, and Radcliffe (1998). The interaction coefficient is −0.028 in All ex-USA and −0.047 in Developed ex-USA. The former is insignificant even at the 10 percent level, and the latter is significant at the 5 percent level. The interaction coefficient is economically small (close to zero) and statistically insignificant in Emerging markets. These estimates indicate that the positive relation between momentum and turnover that Lee and Swaminathan (2000) find does not extend readily to the international context. Turnover by itself is significantly negatively related to returns in All ex-US and Emerging markets (the respective coefficients are −0.232 and −0.398) but not in Developed ex-US markets (coefficient of −0.056).

3.2 Analyst following

Hong and Stein (1999) present a model which assumes that investors process only a limited set of information. Investors in one cohort use only the price history to compute a stock's intrinsic value and in another use information about the stock's fundamentals but overlook its price history. In their model, information gradually disseminates between the two investor cohorts and results in momentum. These assumptions differentiate the Hong and Stein (1999) model from a rational expectations model where investors contemporaneously use all available information.

Hong, Lim, and Stein (2000) empirically test the predictions of Hong and Stein (1999). Hong, Lim, and Stein (2000) hypothesize that the speed of information diffusion would be related to the extent of analyst coverage of a firm. Because more analysts cover large firms than small firms, Hong, Lim, and Stein (2000) regress analyst coverage against firm size and use the residual number of analysts as the proxy for speed of information diffusion. They report that momentum is stronger for firms with smaller residual analyst coverage, which is consistent with the prediction of Hong and Stein (1999).

We fit equation (1) with ResAnly as the interaction variable and column (4) in Panel A of Table 3 presents the results. The interaction coefficients indicate that higher residual analyst following tends to be associated with higher momentum, a finding that is at odds with the idea that low analyst following implies slower diffusion speed. We find this result puzzling. A full investigation of this finding is beyond the scope of our article, but it may be worth pursuing in future research.[13]

3.3 52-week high

George and Hwang (2004) propose that an anchoring bias could be an explanation for momentum. They note that results in experimental economics research that are surveyed in Kahneman, Slovic, and Tversky (1982) find that subjects tend to use anchors to guide their

13 We find that residual analyst coverage by itself is a strong positive predictor of returns in all samples. The absolute coefficients on residual analyst coverage are 0.242, 0.267, and 0.194 for All ex-USA, Developed ex-USA, and Emerging markets, respectively, all strongly statistically significant. Given the opposite sign for this variable relative to the original study of Hong, Lim, and Stein (2000), we also perform a portfolio procedure where we sort firms into terciles by momentum, and then by residual analysts' following. Both for the USA and internationally, we find the spread in momentum profits across the extreme analyst terciles to be insignificant at the 5% level.

assessment of unknown quantities. In the context of momentum, George and Hwang (2004) hypothesize that investors use the 52-week high price for a stock as their anchor and, therefore, perceive stocks with prices near 52-week highs as expensive relative to stocks with prices farther away. Such a behavioral bias would lead to an undervaluation of near 52-week high stocks and overvaluation of away from 52-week high ones. George and Hwang (2004) use the ratio of the price at the end of the previous month and the high price over the past 52 weeks as a measure of nearness to the 52-week high. They report that this measure explains a large portion of momentum in the USA.

Under the anchoring bias hypothesis, George and Hwang (2004) suggest the variable 52wHi would better capture this bias than past returns. Note that the correlation between nearness to the 52-week high and *MOM* is likely to be large because past winners are likely to be closer to the 52-week high and past losers are likely to be farther away. So the key test of George and Hwang (2004) is whether 52wHi explains cross-sectional variation in returns internationally, and if so, whether it supplants *MOM* appreciably. As such, it is the coefficient of X, and how much its inclusion attenuates the effect of *MOM*, that are of greater interest here than the interaction term $MOM \times X$. However, for consistency, we include the interaction term as well.

Column (5) in Panel A of Table 3 reports the regression results. We find that the interaction term is significant at the 5 percent level in the Developed ex-US region (coefficient of −0.058) but insignificant in the other regions. The coefficient on nearness to the 52-week high by itself is small and statistically insignificant in all regions. The coefficient on return momentum is barely changed in the presence of the 52-week high variable. In unreported analysis, the coefficient of the 52-week high remains insignificant when the interaction term is omitted (coefficient = 0.023, t-statistic = 1.06). Thus, we find limited evidence for the anchoring proxy in the international context.

3.4 The FIP proxy

The intuition that momentum arises as a consequence of underreaction to news has a long history (Chan, Jegadeesh, and Lakonishok 1996). Along this line of thought, Da, Gurun, and Warachka (2014) propose that due to limited attention, investors underreact to information that arrives gradually, but react correctly when it arrives discretely. They refer to this explanation as the FIP hypothesis, and predict that momentum would be bigger for stocks with continuous rather than discrete information flow.

The proxy for FIP used by Da, Gurun, and Warachka (2014) is ID, as defined in equation (2). Intuitively, ID is simply the sign of the momentum return, multiplied by the difference between the proportions of daily returns over the momentum period that are negative and positive. Therefore ID is high in two scenarios: when the stock has risen on very few positive returns relative to negative ones, and when the stock has fallen on very few negative returns relative to positive ones.

Based on the intuition above, Da, Gurun, and Warachka (2014) propose that ID should be bigger when the information flow is discrete. The idea is that if the frequency of negative daily returns exceeds that of positive ones on a rising stock (high ID), it suggests concentrated positive information flow. Similarly, if the frequency of positive daily returns exceeds that of negative ones on a falling stock (again, high ID), it suggests concentrated negative information flow. Hence Da, Gurun, and Warachka (2014) perform a large number of tests to consistently find stronger momentum for stocks with more continuous information (i.e., those with low ID).

We fit equation (1) with ID as the interaction variable, and column (6) in Panel A of Table 3 reports the regression estimates for our three samples. The interaction coefficients are 0.161 in All ex-USA, 0.125 in Developed ex-USA, and 0.188 in Emerging markets. All these coefficients are remarkably significant. Indeed, the absolute value of the t-statistic for the interaction of *MOM* with ID is at least 50 percent larger than its next greatest counterpart for any other interaction variable.[14] The adjusted R^2 for the regression involving ID also takes on the highest value among all of the X variables we consider.

Thus, overall, we find that the ID effect is of the right sign and statistically and economically reliable. The result strongly suggests that slow news diffusion plays a material role in explaining international momentum.

3.5 Cost of goods sold

Johnson (2002) and Sagi and Seasholes (2007) present models where the risk premium varies through time, and momentum is compensation for the bigger risk exposures that past winners face. Intuitively, Sagi and Seasholes (2007) consider firms with safe assets and growth options, and the firm value is a sum of these two parts. Firms become winners when the value of their growth options increases and becomes a bigger fraction of their value. Because the firms now become riskier in totality, they command a bigger risk premium. In the Sagi and Seasholes (2007) model, the relative value of growth options is bigger for low-COGS firms than for high-COGS firms because their operational leverage is bigger. Therefore, the growth options hypothesis predicts that momentum would be bigger for low-COGS firms and Sagi and Seasholes (2007) find empirical support for this hypothesis.

Sagi and Seasholes (2007) also suggest that revenue volatility is a proxy for growth options. Because we need a reasonable number of data quarters to compute revenue volatility, the sample size of firms for which we are able to compute this variable is too small for any meaningful power of the tests. Instead, we use daily return volatility computed over the last 12 months. Sagi and Seasholes (2007) note that in their model, momentum also increases in return volatility. This latter variable is also used by Zhang (2006) in a different context: as a proxy for uncertainty, which he argues increases the level of underreaction. We note here that if COGS proxies for operational leverage, it may also proxy for uncertainty.

We now discuss the use of COGS as the interaction variable in equation (1). Column (7) in Panel A of Table 3 presents the regression results. We find that the interaction coefficient is positive in All ex-USA and Developed ex-USA, and negative in Emerging markets. However, all these coefficients are statistically insignificantly different from zero.

The results for return volatility are in column (8) in Panel A of Table 3. We find that the interaction coefficients in All ex-USA, Developed ex-USA, and Emerging markets are -0.029, -0.069, and -0.077, respectively. The negative coefficients for Developed ex-USA and Emerging markets are both statistically significantly different from zero. These results suggest that return volatility interacts negatively with momentum, which is the reverse of the expected sign of the interaction.

To reiterate, the arguments of Sagi and Seasholes (2007) and Zhang (2006) indicate that uncertainty proxies, via their impact on growth options, or the level of underreaction, positively influence momentum profits. In our international context, we find limited evidence that these variables help explain momentum in the hypothesized direction. We emphasize that we only examine specific proxies for real options values and uncertainty, and cannot rule out that there are as-yet unexplored proxies for these phenomena that might provide better explanations for momentum in an international context.

[14] A proxy for a hypothesis to explain momentum does not necessarily attenuate the momentum coefficient. To illustrate this point, suppose such a proxy is independent of MOM. In this case, the slope coefficient on the interaction term would be significant, but the coefficient on MOM would be the same as in the univariate regression. The addition of ID, however, attenuates the coefficient on MOM to varying degrees relative to that in the corresponding univariate regressions. The extent of attenuation reflects the correlation between MOM and ID in each international subsample, and not the explanatory power of ID per se.

4 Further analysis

In this section, we conduct additional tests to check the robustness of our results to risk adjustment, additional cross-sectional controls, an alternative definition of momentum, different sub-periods, excluding countries known to not exhibit momentum, and the US evidence on momentum in the period for which we have international data.

4.1 Risk-adjusted returns

Our baseline FM regressions do not include any controls for risk. We now risk-adjust returns and check their relation to the variables of interest. Specifically, we use the Brennan, Chordia, and Subrahmanyam (1998) procedure for the risk-adjustment. We compute the month t factor loadings for each stock with the following time-series regression:

$$R_{i,s} = a + b'_{i,t} f_s + e_{i,s}, \quad \text{for } s = t-36 \text{ to } t-1, \tag{3}$$

where f_s is the month s realization of the five factors in the Fama and French (2017) five-factor model.[15] We then compute risk-adjusted returns $R_{i,t} - \hat{b}'_{i,t} f_t$ where $\hat{b}_{i,t}$ is the factor sensitivity estimate vector from the time-series equation (3) and use these risk-adjusted returns in the following regression:

$$R_{i,t} - \hat{b}'_{i,t} f_t = \gamma_{0,t} + \gamma_{1,t} MOM_{i,t-1} + \gamma_{2,t} X_{i,t-1} + \gamma_{3,t} X_{i,t-1} \times MOM_{i,t-1} + e_{i,t}, \tag{4}$$

Panel B of Table 3 reports the regression estimates of equation (4). The results in Panel B are similar to the corresponding results in Panel A with a few exceptions. The most prominent difference is that the interaction coefficient with B/M becomes negative and statistically significant for All ex-US and Developed ex-US markets; this evidence is consistent with Daniel and Titman (1999). All other conclusions from Section 3 are largely unchanged. In particular, ID continues to significantly explain cross-sectional differences in momentum as the interaction coefficient on ID in column (6) of Panel B of Table 3 is negative and statistically significant for all regions.[16]

Chordia and Shivakumar (2006) propose that a factor based on earnings surprises (PMN) can capture momentum profits in the USA. We therefore add PMN computed from international data as an additional factor when risk-adjusting returns. We construct PMN as follows. We first compute standardized unexpected earnings (SUE) as the most recent change in quarterly earnings scaled by the most recent market price.[17] We then sort stocks into value-weighted decile portfolios based on. We calculate the PMN factor as the difference in returns across the extreme deciles. In Supplementary Appendix Table IA.1, we find that the results are

[15] We use separate factors for developed and emerging markets and use the factor model for the stock corresponding to its region. These factors are obtained from Ken French's website (http://tinyurl.com/bdfn35ze). An alternative set of factors are provided in Hou, Xue, and Zhang (2015). These latter factors are not available at the international level (see also Novy-Marx 2015), so we use the ones in Fama and French (2017) instead.

[16] The flows hypothesis of Vayanos and Woolley (2013) and Lou (2012) suggests that momentum profits are due to institutional funds flowing into individual stocks. We do not have high quality fund flows data at the monthly horizon within our international context. Note, however, that if informed institutions play a role in explaining momentum, then this explanation should be subsumed by another already considered X variable that represents underreaction to news, such as ID or analyst following. Nonetheless, in Table IA.4 within the Supplementary Appendix, we compute quarterly changes in institutional holdings as an additional X variable using FactSet (we also present the coefficients for other X variables and their interactions for comparison). The coverage from FactSet is not comprehensive, leading to a substantial reduction in sample size. In this smaller sample, while the role for holdings changes in explaining momentum is limited, the significance of ID continues to prevail.

[17] This approach is similar to that of Livnat and Mendenhall (2006).

virtually unchanged after adding this factor, suggesting that our measure of earnings momentum is not related to return momentum in our international context.[18]

4.2 Additional controls and alternative momentum returns

We now modify equation (1) to include additional controls:

$$R_{i,t} = \gamma_{0,t} + \gamma_{1,t} MOM_{i,t-1} + \gamma_{2,t} X_{i,t-1} + \gamma_{3,t} X_{i,t-1} \times MOM_{i,t-1} + \gamma_{4,t} Z_{i,t-1} + e_{i,t}, \quad (5)$$

where Z's are new controls. These include asset growth (Cooper, Gulen, and Schill 2008), gross profitability (Novy-Marx 2013), one-month reversal (Jegadeesh 1990), B/M, and size (market capitalization), as of a given month.[19] We process the additional Z variables on the right hand following the same steps as those for MOM and X described after equation (1). We also include market capitalization interacted with MOM as an additional control. This is because larger firms may have less momentum because they are easier to arbitrage, and controlling for this possibility is desirable.

Panel C of Table 3 reports results with additional controls. We do not tabulate the coefficients on control variables for brevity. Compared to Panel A, we lose about one-third of the stocks for which we do not have sufficient accounting data to calculate control variables. Nevertheless, the results in Panel C are similar to those in Panel A. Once again the robust result that emerges is that of the ID variable, and as in Panel B, growth stocks have more momentum in the All ex-US group.

In Supplementary Appendix Table IA.2, we present the analog of Table 3 (Panel C) using lagged returns from the second to the seventh month, MOM', to measure momentum instead of MOM. We find that the results are materially unchanged (other panels of Table 3 yield similar results).

4.3 Subsample results

Our sample period includes the tech bubble, the 2008 financial crisis, and the beginnings of the COVID crisis. To assess whether our results are affected by such outlier events, we examine the results in two equal subsamples, 1993–2006 and 2007–2020. We present the results for equation (5) in Table 4. Panel A reports results for 1993–2006, while Panel B reports the results for 2007–2020.

Since this exercise cuts the number of time-series observations in each subperiod in half, we expect the coefficients to be less precisely estimated in Table 4. Nevertheless, in every one of the six cases (three regions and two subsamples), the coefficient of ID interacted with momentum is negative and significant, pointing to the robustness of this explanatory variable.

Among other results for the subsamples, B/M and turnover tend to be positively and negatively associated with future returns in both subperiods, for emerging markets, but this relation is less prominent for the other regions. The interaction of B/M with momentum is statistically significant in the first half of the subsample but not so in the second half. Patterns in the other interaction coefficients are consistent across regions or over time.

[18] We also use SUE as an independent control variable on the right-hand-side (see the next Section 4.2 for details on the approach) instead of risk-adjusting returns using PMN on the left-hand-side. We find virtually no impact on the interaction coefficients. Avramov et al. (2007) relate distress risk to momentum returns. Because we do not have international bond ratings data, we use the annual bankruptcy predictor developed by Campbell, Hilscher, and Szilagyi (2008) (which in turn, is based on Altman 1968) as an additional X variable and find that it plays no role in explaining momentum. Results are available upon request.

[19] We include B/M only in the specifications that do not already include it as an X variable.

Table 4. Fama–MacBeth regressions of future returns on past momentum returns and explanatory variables: Subsamples.
This table presents the results of Fama–MacBeth cross-sectional regressions similar to those in Panel C of Table 3:

$$R_{i,t} = \gamma_{0,t} + \gamma_{1,t} MOM_{i,t-1} + \gamma_{2,t} X_{i,t-1} + \gamma_{3,t} MOM_{i,t-1} \times X_{i,t-1} + \gamma_{4,t}\, Size_{i,t-1} + \gamma_{5,t}\, MOM_{i,t-1} \times Size_{i,t-1} + \gamma_{6,t}\,(B/M)_{i,t-1} + \gamma_{7,t}\,(GP/AT)_{i,t-1} + \gamma_{8,t}\, ATG_{i,t-1} + \gamma_{9,t}\, R_{i,t-1} + e_{i,t}.$$

We run the above regressions separately for stocks in different regions. The table reports the time-series averages of coefficients together with their *t*-statistics in parentheses. We omit the coefficients on the control variables for brevity. The last two rows in each subpanel report the average number of stocks and the average adjusted-R^2 in percent. The sample consists of only nonmicrocap stocks (those in the top 97 percent of the market capitalization of each region). The sample period is 1993–2006 in Panel A, and 2007–2020 in Panel B.

	(1) —	(2) – B/M	(3) Turn	(4) – ResAnly	(5) – 52wHi	(6) – ID	(7) – COGS	(8) RetVol
Panel A: Sample period is 1993–2006								
				All ex-USA				
MOM	0.402	0.347	0.433	0.424	0.395	0.375	0.398	0.480
	(5.61)	(4.51)	(6.25)	(6.13)	(6.58)	(5.68)	(5.58)	(8.56)
X	—	−0.440	−0.138	−0.124	−0.129	0.088	−0.038	−0.144
		(−7.14)	(−2.60)	(−2.61)	(−1.01)	(2.62)	(−1.53)	(−1.38)
$MOM \times X$	—	0.129	−0.035	−0.022	−0.084	0.174	−0.010	−0.041
		(3.68)	(−1.26)	(−0.65)	(−1.76)	(4.24)	(−0.40)	(−0.99)
No. of stocks	4,411	4,411	4,160	4,411	4,410	4,411	4,385	4,411
Adj-R^2	2.4	2.6	2.9	2.7	3.5	2.7	2.5	3.6
				Developed ex-USA				
MOM	0.396	0.357	0.446	0.418	0.399	0.370	0.394	0.515
	(4.56)	(3.73)	(5.38)	(5.01)	(5.86)	(4.58)	(4.52)	(7.72)
X	—	−0.404	−0.018	−0.115	−0.140	0.098	−0.016	−0.158
		(−5.95)	(−0.27)	(−2.12)	(−0.98)	(2.46)	(−0.63)	(−1.43)
$MOM \times X$	—	0.110	−0.056	− 0.025	−0.090	0.192	−0.006	−0.079
		(2.72)	(−1.65)	(−0.69)	(−1.66)	(4.19)	(−0.24)	(−1.70)
No. of stocks	2,977	2,977	2,777	2,977	2,977	2,977	2,960	2,977
Adj-R^2	3.6	3.9	4.5	4.0	5.2	4.2	3.8	5.2

(continued)

Table 4. (continued)

	(1) —	(2) − B/M	(3) Turn	(4) − ResAnly	(5) − 52wHi	(6) − ID	(7) − COGS	(8) RetVol
					Emerging			
MOM	0.409	0.358	0.415	0.456	0.366	0.376	0.398	0.477
	(5.13)	(4.07)	(5.69)	(5.71)	(4.81)	(4.67)	(4.92)	(6.38)
X	—	−0.591	−0.326	−0.130	−0.107	0.008	−0.133	−0.115
		(−6.88)	(−4.17)	(−2.09)	(−0.78)	(0.17)	(−3.07)	(−1.01)
$MOM \times X$	—	0.114	0.068	−0.035	−0.048	0.189	−0.061	−0.038
		(1.66)	(1.36)	(−0.44)	(−0.62)	(2.56)	(−1.34)	(−0.52)
No. of stocks	1,677	1,677	1,630	1,677	1,676	1,677	1,668	1,677
Adj-R^2	1.8	2.0	2.4	2.1	2.7	2.2	2.0	2.7
Panel B: Sample period is 2007–2020								
					All ex-USA			
MOM	0.164	0.172	0.252	0.179	0.116	0.110	0.163	0.255
	(2.01)	(1.86)	(3.20)	(2.22)	(2.05)	(1.35)	(2.00)	(3.39)
X	—	−0.167	−0.274	−0.113	−0.232	−0.030	−0.037	−0.198
		(−3.54)	(−5.01)	(−1.79)	(−1.83)	(−1.08)	(−1.99)	(−2.09)
$MOM \times X$	—	−0.014	−0.048	−0.121	−0.025	0.155	0.017	−0.033
		(−0.38)	(−2.18)	(−2.66)	(−0.51)	(3.40)	(0.86)	(−1.01)
No. of stocks	7,773	7,773	7,518	7,773	7,771	7,773	7,741	7,773
Adj-R^2	1.8	2.0	2.3	2.2	2.8	2.2	1.9	2.8
					Developed ex-USA			
MOM	0.270	0.273	0.332	0.293	0.211	0.220	0.268	0.404
	(2.89)	(2.46)	(3.77)	(3.27)	(3.26)	(2.29)	(2.87)	(4.99)
X	—	−0.170	−0.046	−0.153	−0.215	0.004	−0.035	−0.182
		(−3.06)	(−0.61)	(−1.73)	(−1.41)	(0.20)	(−1.55)	(−1.61)
$MOM \times X$	—	0.012	−0.037	−0.070	−0.137	0.106	0.034	−0.092
		(0.26)	(−1.67)	(−1.26)	(−2.88)	(2.59)	(1.33)	(−2.84)
No. of stocks	3,758	3,758	3,636	3,758	3,757	3,758	3,743	3,758
Adj-R^2	2.8	3.1	3.5	3.5	4.2	3.1	3.0	4.3

(continued)

Table 4. (continued)

	(1) —	(2) − B/M	(3) Turn	(4) − ResAnly	(5) − 52wHi	(6) − ID	(7) − COGS	(8) RetVol
	Emerging							
MOM	0.083	0.109	0.216	0.097	0.070	0.024	0.081	0.194
	(1.05)	(1.29)	(2.90)	(1.21)	(1.11)	(0.30)	(1.02)	(2.47)
X	—	−0.201	−0.447	−0.112	−0.231	−0.040	−0.038	−0.193
		(−3.59)	(−6.54)	(−2.24)	(−2.00)	(−1.00)	(−1.62)	(−2.20)
$MOM \times X$	—	−0.051	−0.037	−0.154	0.040	0.151	0.000	−0.034
		(−1.46)	(−1.18)	(−3.25)	(0.63)	(2.46)	(0.00)	(−0.88)
No. of stocks	4,068	4,068	3,932	4,068	4,067	4,068	4,051	4,068
Adj-R^2	2.1	2.3	2.8	2.4	3.0	2.6	2.2	3.0

4.4 Excluding countries without momentum

It is well known that some countries in Asia have no momentum; see, for example, Chui, Titman, and Wei (2010).[20] Indeed, in untabulated results, we find that, among all countries in our sample with an average of at least 500 stocks per month, the momentum variable (*MOM*), when included by itself, is insignificant for three countries: China, Japan, and Korea. We therefore run our baseline regression of Table 3 while excluding these three countries from our analysis. We find that the interaction of ID with momentum attains t-statistics of 4.08, 2.49, and 3.92 across the three samples All ex-USA, Developed ex-USA, and Emerging markets, respectively. The only other robust interaction (which is significant at the 5 percent level in all cases) is with return volatility, which, however, is of a sign contradictory to the real options and uncertainty arguments, as in Table 3.

4.5 US evidence

We also fit equation (5) with the US data. Given that the international data are only available in 1993 and onwards, for comparability, we perform the analysis in two subsamples: 1963–1992 and 1993–2020. The results appear in Table 5. We find that the momentum strategy is not profitable during the 1993–2020 sample period,[21] but highly profitable during the earlier (1963–1992) period. For instance, with *MOM* as the only independent variable in this regression, the slope coefficient is 0.454 (t-statistic = 6.73) in the first subperiod, but falls to 0.138 (t-statistic = 1.38) in the second. In the first subperiod, B/M and ID are the two most significant interactive variables and the coefficients are of the correct sign. The interactive variable involving COGS is also marginally significant. Since momentum itself is not significant in the second subperiod, we do not interpret the interactions further. Overall, the results are mostly in line with the international results.

5. Multivariate analysis with penalized regressions

Our tests so far analyze X variables one at a time. We next check the marginal explanatory power of these variables and their interactions in a kitchen sink regression. Since the dangers of overfitting loom large, we now employ penalized regressions, in addition to multivariate OLS regressions.[22] Our regression setup is

$$R_{i,t} = \gamma_0 + \gamma_1\, MOM_{i,t-1} + \gamma_2'\, X_{i,t-1} + \gamma_3'\, MOM_{i,t-1} \times X_{i,t-1} + e_{i,t}, \tag{6}$$

where X is now the vector of all standardized explanatory variables. We use Lasso and Elastic net (ENet) to run equation (6). These regressions take the general form of minimizing the following loss function

$$\mathcal{L}(\gamma, \lambda, \rho) = \sum_{i,t} (y_{i,t} - \gamma' x_{i,t-1})^2 + \lambda(1-\rho)\sum_j \gamma_j + 0.5\lambda\rho \sum_j \gamma_j^2, \tag{7}$$

where λ and ρ are additional hyperparameters. $\rho = 0$ corresponds to Lasso and $\rho = 1$ corresponds to ridge regressions (see Hastie, Tibshirani, and Friedman 2009). As Lasso imposes a penalty related to the absolute values of the coefficients, it tends to completely eliminate some variables from the model, allowing for sparse selection of variables. On the other hand, ridge regression shrinks coefficients toward zero without necessarily setting them to

[20] Chui, Titman, and Wei (2010) relate variation in momentum across countries to culture (specifically, overconfidence caused by individualism).

[21] This finding is consistent with Chordia, Subrahmanyam, and Tong (2014) and McLean and Pontiff (2016), who respectively argue that trading cost reductions and academic publication of anomalies in recent years have reduced their profitability.

[22] See Gu, Kelly, and Xiu (2020) and Han et al. (2019) for other applications of these techniques to the cross-section of stock returns.

Table 5. Fama–MacBeth regressions of future returns on past momentum returns and explanatory variables: USA.

This table presents the results of Fama–MacBeth cross-sectional regressions similar to those in Panel C of Table 3:

$$R_{i,t} = \gamma_{0,t} + \gamma_{1,t} MOM_{i,t-1} + \gamma_{2,t} X_{i,t-1} + \gamma_{3,t} MOM_{i,t-1} \times X_{i,t-1} + \gamma_{4,t} Size_{i,t-1} + \gamma_{5,t} MOM_{i,t-1} \times Size_{i,t-1} + \gamma_{6,t} (B/M)_{i,t-1} + \gamma_{7,t} (GP/AT)_{i,t-1} + \gamma_{8,t} ATG_{i,t-1} + \gamma_{9,t} R_{i,t-1} + e_{i,t}.$$

We run the above regressions for stocks in the USA. The table reports the time-series averages of coefficients together with their *t*-statistics in parentheses. We omit the coefficients on the control variables for brevity. The last two rows in each subpanel report the average number of stocks and the average adjusted-R^2 in percentage. The sample consists of only nonmicrocap stocks (those in the top 97 percent of the market capitalization). The sample period is 1963–1992 in Panel A, and 1993–2020 in Panel B.

	(1) —	(2) – B/M	(3) Turn	(4) – ResAnly	(5) – 52wHi	(6) – ID	(7) – COGS	(8) RetVol
Panel A: Sample period is 1963–1992								
MOM	0.454	0.426	0.463	0.508	0.389	0.425	0.454	0.449
	(6.73)	(5.84)	(6.70)	(6.90)	(5.55)	(6.26)	(6.74)	(7.16)
X	—	–0.264	0.006	–0.078	–0.136	0.007	–0.011	–0.205
		(–4.70)	(0.10)	(–1.66)	(–1.46)	(0.26)	(–0.42)	(–2.35)
$MOM \times X$	—	0.058	–0.002	–0.049	–0.029	0.066	0.052	0.009
		(2.20)	(–0.08)	(–1.79)	(–1.00)	(2.31)	(2.16)	(0.31)
No. of stocks	1,471	1,471	1,345	1,814	1,471	1,471	1,471	1,471
Adj-R^2	6.9	7.2	8.3	5.8	8.1	7.2	7.1	9.1
Panel B: Sample period is 1993–2020								
MOM	0.138	0.145	0.156	0.157	0.147	0.133	0.136	0.155
	(1.38)	(1.26)	(1.65)	(1.60)	(1.70)	(1.38)	(1.35)	(1.74)
X	—	–0.049	–0.011	–0.098	–0.059	0.021	0.034	–0.124
		(–0.67)	(–0.12)	(–2.30)	(–0.43)	(0.63)	(0.92)	(–0.91)
$MOM \times X$	—	0.036	–0.023	–0.010	–0.080	–0.026	0.074	–0.023
		(0.76)	(–0.78)	(–0.23)	(–1.73)	(–0.58)	(2.34)	(–0.64)
No. of stocks	1,670	1,670	1,670	1,670	1,670	1,670	1,670	1,670
Adj-R^2	6.6	7.2	8.1	7.0	8.5	7.0	7.0	9.2

zero. We choose Lasso ($\rho = 0$) and ENet ($\rho = 0.5$) for our specifications. These two techniques are the simplest and most parsimonious amongst commonly used machine learning techniques. We choose the hyperparameter λ via ten-fold cross-validation. To ensure comparability with Lasso and ENet, in using OLS, we use panel regressions instead of FM. The model is fit over the training sample that is the first half of the sample period, viz. 1993–2006.

In Table 6, we present the coefficients using standard OLS, Lasso, and ENets. We find that the interaction coefficient of ID with momentum barely shrinks across the three procedures. Shrinkage is prominent for the interaction coefficient with analyst coverage. The interactive coefficient with the 52-week high also shrinks and is not included by Lasso in one case. The interactive coefficient with RetVol is not included by Lasso in All ex-USA. The coefficients of B/M and Turn generally do not shrink appreciably across the three procedures.

Supplementary Appendix Table IA.3 provides the FM coefficients *during the training period* for all of the predictive variables and their interactions with *MOM*. The appendix confirms that ID has the most prominently significant interaction with momentum (it is

Table 6. Penalized regressions of future returns on past momentum return and explanatory variables. We run the regression:

$$R_{i,t} = \gamma_0 + \gamma_1 MOM_{i,t-1} + \gamma_2 X_{i,t-1} + \gamma_3 MOM_{i,t-1} \times X_{i,t-1} + e_{i,t},$$

where $MOM_{i,t-1}$ is the return from month $t-12$ to $t-2$ and X represents each of variables listed in the top row of Table 2. We process the variables MOM and X on the right hand through the following steps every month (1) we winsorize at the 0.5 percent and 99.5 percent levels, (2) we country neutralize by subtracting the cross-sectional mean across all stocks in our sample from that country, and (3) we standardize across the entire sample to have zero mean and unit standard deviation. The processed variables are used in the interaction terms. We reverse the signs of some of the X variables so that the interaction term with MOM of all variables is expected to be positive based on the original study's motivations. The column "OLS" runs panel regressions. The column "LASSO" runs LASSO regressions and the column "ENet" runs elastic net regressions (with $\rho = 0.5$). We use 10-fold cross-validation for LASSO and ENet. Coefficients selected to be zero by LASSO or ENet are represented by "0.000." We then run the above regressions separately for stocks in different regions. The sample consists of only nonmicrocap stocks (those in the top 97 percent of the market capitalization of each region). The sample period is 1993–2006.

	All ex-USA			Developed ex-USA			Emerging		
	OLS	LASSO	ENet	OLS	LASSO	ENet	OLS	LASSO	ENet
MOM	0.410	0.403	0.401	0.460	0.454	0.431	0.424	0.397	0.404
$-MOM \times$ B/M	0.096	0.094	0.094	0.130	0.127	0.117	0.001	0.000	0.000
$MOM \times$ Turn	−0.078	−0.075	−0.074	−0.108	−0.107	−0.102	0.007	0.000	0.000
$-MOM \times$ ResAnly	0.005	0.000	0.000	0.018	0.014	0.000	−0.069	−0.048	−0.054
$-MOM \times$ 52wHi	−0.034	−0.029	−0.028	0.015	0.010	0.000	−0.056	−0.046	−0.049
$-MOM \times$ ID	0.241	0.238	0.237	0.248	0.248	0.245	0.251	0.243	0.245
$-MOM \times$ COGS	0.024	0.019	0.017	0.037	0.034	0.022	−0.017	−0.006	−0.009
$MOM \times$ RetVol	0.000	0.000	0.000	−0.046	−0.041	−0.025	−0.014	−0.004	−0.005
− B/M	−0.449	−0.440	−0.438	−0.432	−0.428	−0.412	−0.533	−0.507	−0.513
Turn	−0.107	−0.102	−0.101	0.027	0.023	0.007	−0.327	−0.314	−0.317
− ResAnly	−0.122	−0.112	−0.109	−0.095	−0.091	−0.076	−0.201	−0.175	−0.181
− 52wHi	−0.078	−0.073	−0.072	−0.006	−0.007	−0.006	−0.100	−0.088	−0.091
− ID	0.091	0.085	0.084	0.094	0.091	0.078	0.069	0.056	0.059
− COGS	−0.061	−0.055	−0.054	−0.051	−0.048	−0.036	−0.125	−0.111	−0.114
RetVol	−0.146	−0.144	−0.143	−0.223	−0.220	−0.207	−0.013	−0.008	−0.009
Intercept	0.771	0.774	0.775	0.853	0.852	0.850	0.804	0.806	0.806

significant across all three regions). The interaction of *MOM* with BM is not significant for emerging markets, but is significant for the other two regions.

We next analyze the predictive power of the three procedures in an out-of-sample (OOS) setting. Our forecasting period is the second half of the sample period, viz. 2007–2020. We do not refit OLS, LASSO, or ENet on a rolling or an expanding window basis. Therefore, the OOS period is a true testing period. For each of the procedures and for each region, we obtain a forecast of the returns as $\hat{R}_{i,t}$ using coefficients from Table 6 and the most recent $X_{i,t-1}$. Following Gu, Kelly, and Xiu (2020), we calculate the OOS-R^2 as

$$\text{OOS} - R^2 = 1 - \frac{\sum_{(i,t)} (R_{i,t} - \hat{R}_{i,t})^2}{\sum_{(i,t)} R_{i,t}^2}, \tag{8}$$

where we take forecast errors over all stocks over the entire OOS period in the numerator and raw (not demeaned) returns as the denominator. We also present the mean-squared error (MSE) and the mean absolute error (MAE) for the three samples. Table 7 presents the results. We find that OOS-R^2's, MSE, and MAE are similar across the three procedures.

Table 7. Penalized regressions of future returns on past momentum return and explanatory variables: OOS performance.

We run penalized regressions as in Table 6. Using the coefficient estimates from the training period (1993–2006), we calculate forecast errors for the OOS period of 2007–2020. We calculate OOS-R^2 as:

$$\text{OOS} - R^2 = 1 - \frac{\sum_{(i,t)} \left(R_{i,t} - \hat{R}_{i,t}\right)^2}{\sum_{(i,t)} R_{i,t}^2},$$

where $R_{i,t}$ is the realized return and $\hat{R}_{i,t}$ is the forecasted return using OLS, LASSO, or ENet. We calculate OOS-MSE as

$$\text{OOS-MSE} = \frac{1}{T}\sum_t \frac{1}{N_t}\sum_i (R_{i,t} - \hat{R}_{i,t})^2.$$

We calculate OOS-MAE as

$$\text{OOS-MAE} = \frac{1}{T}\sum_t \frac{1}{N_t}\sum_i |R_{i,t} - \hat{R}_{i,t}|.$$

In each case, the coefficient estimates are not updated over the OOS period. The R^2 is reported in percent. The sample consists of only nonmicrocap stocks (those in the top 97 percent of the market capitalization of each region).

	All ex-USA			Developed ex-USA			Emerging		
	OLS	LASSO	ENet	OLS	LASSO	ENet	OLS	LASSO	ENet
OOS- R^2	0.363	0.368	0.370	0.189	0.191	0.198	0.580	0.592	0.590
OOS-MSE	0.017	0.017	0.017	0.015	0.015	0.015	0.020	0.020	0.020
OOS-MAE	0.090	0.090	0.090	0.083	0.083	0.083	0.098	0.098	0.098

Using the Diebold and Mariano (1995) test, we are unable to reject the hypothesis that the OOS-R^2's are different from each other.

Overall, the conclusion from Section 3 is that the slow diffusion FIP proxy (represented by ID) continues to receive support when other explanatory variables for momentum are included, and the coefficient on this interactive variable is stable when we use $\mathcal{L}_1$ and $\mathcal{L}_2$ penalties via Lasso and ENet. To a lesser extent, our results also support the B/M ratio as explaining cross-sectional variations in momentum, although, from Table 4, this proxy is less intertemporally stable than ID.

6. Portfolio returns

To investigate the economic significance of the cross-sectional explanatory power of the relation between momentum and the variables that we examine, we calculate profits for double-sorted portfolios. These sorts also lend perspective to the issue of how the explanatory proxies affect the profitability of momentum strategies. Specifically, we sort by X and by the momentum variable MOM into 3×3 terciles. The sorting is done every month and we hold the portfolios for the next 1 month.

We now calculate the annualized WML portfolio returns (across the extreme terciles of MOM) for each tercile of X and present the results in Table 8. The table presents ΔWML, which is the difference in WML returns, across the high and low X terciles. Because WML is the momentum profit in each of the X terciles, ΔWML is the incremental effect of the X

Table 8. Returns on portfolios double-sorted by past momentum return and explanatory variables.
Each month we sort stocks into tercile portfolios based on last 11-month returns skipping the most recent month, *MOM*, and an *X* variable. The stocks are independently sorted in Panel B and sequentially sorted in Panel B (where we first sort on *X* and then on *MOM*). The portfolios are value-weighted and rebalanced monthly. For all sorts, we country neutralize by subtracting the cross-sectional country (not regional) mean of that variable. We calculate the WML portfolio for each tercile of *X*. The table reports the difference in WML returns, ΔWML, across high and low *X* terciles. The returns are annualized and *t*-statistics are reported in parentheses below the returns. The sample consists of only nonmicrocap stocks (those in the top 97 percent of the market capitalization of each region). The sample period is 1993–2020.

	– B/M	Turn	– ResAnly	– 52wHi	– ID	– COGS	RetVol
Panel A: Independent sorts							
				All ex-USA			
ΔWML	4.76	– 1.31	– 1.17	0.80	4.93	0.33	3.85
	(2.03)	(– 0.56)	(– 0.52)	(0.28)	(2.22)	(0.20)	(1.27)
				Developed ex-USA			
ΔWML	3.60	– 2.81	– 0.06	1.41	4.10	– 0.18	4.19
	(1.47)	(– 1.18)	(– 0.02)	(0.48)	(1.71)	(– 0.09)	(1.16)
				Emerging			
ΔWML	3.26	– 0.14	– 4.08	5.59	8.70	– 2.23	3.29
	(1.00)	(– 0.05)	(– 1.41)	(1.35)	(2.48)	(– 0.80)	(0.86)
Panel B: Sequential sorts							
				All ex-USA			
ΔWML	4.31	– 2.09	– 3.39	0.69	5.94	0.01	7.75
	(1.63)	(– 0.83)	(– 1.56)	(0.28)	(2.64)	(0.00)	(2.45)
				Developed ex-USA			
ΔWML	4.37	– 2.82	– 2.64	0.69	4.90	– 0.35	6.60
	(1.62)	(– 1.10)	(– 1.03)	(0.24)	(1.98)	(– 0.19)	(1.92)
				Emerging			
ΔWML	5.52	0.46	– 4.59	4.92	9.39	– 1.67	6.15
	(1.67)	(0.15)	(– 1.58)	(1.48)	(2.82)	(– 0.56)	(1.61)

variable on momentum profits. We perform independent sorts and sequential sorts (where we sort first on X and then on momentum return). While both kinds of sorts examine momentum while controlling for the X variable, the method of controlling is different. Independent sorts effectively consider unconditional relations, and hence ΔWML is the difference in unconditional momentum returns across high and low X terciles. This method is close in spirit to our earlier FM regressions. Sequential sorts consider conditional momentum, controlling for values of X, and thus are of equal interest. Note that unlike the FM coefficients, the portfolio returns, being the result of quantile sorts, are not pure plays on the relevant $MOM \times X$ variable, as we do not linearly control for other explanatory variables MOM and X, which is required for the factor play interpretation (Back, Kapadia, and Ostdiek 2015). Therefore, we do not expect a complete mapping from the FM results of Section 3 onto this section's results.

Panel A of Table 8 reports the results for independent sorts. For −ID, ΔWML is statistically significantly positive at the 10 percent level for Developed ex-USA and at the 5 percent level for All ex-USA and Emerging markets. For example, in Emerging markets ΔWML equals 8.70 percent, which indicates that the momentum profit in the low ID tercile is 8.70 percent higher than that in the high ID tercile. When—B/M is the X variable, Δ

WML is statistically significantly positive in All ex-USA, indicating that momentum is more profitable for growth stocks than for value stocks. However, ΔWML is statistically insignificant for the other regions, and when X represents any of the other variables.

Panel B of Table 8 presents the results for sequential sorts. For $X = -\text{ID}$, ΔWML is statistically significant in all regions at the 5 percent level. The magnitude of ΔWML is also economically large, at around 6 percent for All ex-USA and Developed ex-US markets and at around 9 percent for Emerging markets, showing that low values of ID exert a large influence on explaining momentum.[23]

The absolute value of the coefficient on ΔWML is highest for ID amongst all of the variables for emerging markets. For the other regions, it is either the highest or the second highest. These observations suggest that the spread in ID across the extreme terciles has consistent economic and statistical explanatory power for momentum returns.[24] Overall, again, the results indicate support for ID, followed by the B/M ratio proxy for overconfidence.

7. Market states and momentum profits

This section provides international evidence regarding time-series variation in momentum that has previously been documented using US data. Specifically, Cooper, Gutierrez, and Hameed (2004) find that aggregate momentum profits depend on the sign of market returns. These authors propose that investor confidence is higher in up-markets. Based on Daniel, Hirshleifer, and Subrahmanyam (1998), they argue that this implies more momentum in up-markets. Furthermore, Wang and Xu (2015) (see also Daniel and Moskowitz 2016) show that momentum profits are lower in high-volatility states. They propose that investors are less confident (more fearful) in high market volatility states and oversell losers, and the subsequent reversals of these losers lower momentum profits.

7.1 Up versus down markets

Cooper, Gutierrez, and Hameed (2004) show that momentum is stronger following up markets than following down markets in the USA. They attribute this finding to the notion that confidence is higher in rising markets. The idea is that investors are net long in markets and are likely to have received a sequence of positive signals confirming their long positions in up markets, thus building their confidence.

We investigate whether the results of Cooper, Gutierrez, and Hameed (2004) hold internationally. We examine momentum profits in up and down markets using the following regression:

$$\text{WML}_t = \gamma_1 \,\text{UP}_{t-1} + \gamma_2 \,\text{DOWN}_{t-1} + e_t, \tag{9}$$

where UP is a dummy variable that equals one for an up-market and zero otherwise. DOWN is defined analogously for down markets. Following Cooper, Gutierrez, and Hameed (2004), UP equals unity if the market return over the previous 36 months is positive and DOWN equals unity if this return is negative. We use the MSCI All-Country ex-USA, World ex-USA, and Emerging total return indices as the market return proxies for All ex-USA, Developed ex-USA, and Emerging markets, respectively. The up-market and

23 As we note in Section 3.3, in the case of 52wHi, it is the X variable that is of at least equal interest relative to the interaction of momentum with X. We have verified that extreme sorts on this X variable alone do not yield a significant return spread.

24 In an important paper, Bandarchuk and Hilscher (2013) argue that sequential sorts on characteristics, and then on momentum, simply sort on extreme realizations of past returns, and therefore have challenges in isolating the effect of characteristics on momentum. Their observation applies to sequential sorts, as opposed to independent sorts or regressions. We get similar results with all three methods, so that our overall conclusions are robust to the bias that they discuss.

Table 9. Time-series determinants of momentum.
This table describes the results of the time series:

$$R_t = \gamma_1\, State1_{t-1} + \gamma_2\, State2_{t-1} + e_t,$$

where *R* is the loser, or winner, or WML portfolio constructed by sorting on last 11 month returns (excluding the most recent month) and State are dummy variables indicating macroeconomic state in the previous month. UP (DOWN) is equal to one if the market return over the last 36 months is positive (negative), and zero otherwise. We use MSCI All-Country ex-USA, World ex-USA, and Emerging total return indices as the proxies for market return for All ex-USA, Developed ex-USA, and Emerging markets, respectively. HIVOL (LOVOL) is equal to one if the market volatility over the last 12 months is higher (lower) than the market volatility over the past 36 months, and zero otherwise. Market volatility is calculated using daily data. We use MSCI All-Country ex-USA, World ex-USA, and Emerging price (not total return) indices as the market return proxies for All ex-USA, Developed ex-USA, and Emerging markets, respectively. The table reports the annualized slopes (in percent) from the above regression together with their *t*-statistics. The sample consists of only nonmicrocap stocks (those in the top ninety-seven of the market capitalization of each country). The sample period is 1993–2020.

State	#obs	L	W	WML	State	#obs	L	W	WML
All ex-USA									
UP	262	−3.88	10.27	14.16	HIVOL	140	12.65	13.77	1.12
		(−0.79)	(2.57)	(3.52)			(1.87)	(2.51)	(0.20)
DOWN	71	23.12	21.19	−1.94	LOVOL	193	−5.94	11.75	17.69
		(2.44)	(2.76)	(−0.25)			(−1.03)	(2.52)	(3.79)
DIFF		−27.01	−10.92	16.09	DIFF		18.59	2.01	−16.58
		(−2.52)	(−1.26)	(1.85)			(2.09)	(0.28)	(−2.30)
Developed ex-USA									
UP	258	−4.37	10.22	14.59	HIVOL	141	9.02	12.02	2.99
		(−0.84)	(2.67)	(3.21)			(1.27)	(2.32)	(0.49)
DOWN	75	22.47	18.25	−4.22	LOVOL	192	−3.72	12.04	15.75
		(2.33)	(2.57)	(−0.50)			(−0.61)	(2.71)	(2.98)
DIFF		−26.84	−8.03	18.81	DIFF		12.74	−0.02	−12.76
		(−2.45)	(−1.00)	(1.96)			(1.36)	(−0.00)	(−1.57)
Emerging									
UP	237	0.48	13.03	12.56	HIVOL	141	10.46	9.98	−0.49
		(0.09)	(2.49)	(3.15)			(1.52)	(1.47)	(−0.09)
DOWN	96	11.20	10.87	−0.33	LOVOL	192	−1.50	14.19	15.69
		(1.34)	(1.32)	(−0.05)			(−0.25)	(2.44)	(3.56)
DIFF		−10.72	2.17	12.89	DIFF		11.96	−4.22	−16.18
		(−1.08)	(0.22)	(1.74)			(1.32)	(−0.47)	(−2.39)

down-market coefficients represent annualized momentum profits during the two states in equation (9).

Table 9 presents the regression estimates. We find that momentum profits in up markets are significantly positive at 14.16 percent but marginally negative at −1.94 percent during down markets for the All ex-US region. The momentum profits in all the other regions are also significantly positive in up markets and marginally negative in down markets. Thus, the results of Cooper, Gutierrez, and Hameed (2004) are robust internationally.

We next examine the effect of market states on winners and losers separately. While Cooper, Gutierrez, and Hameed (2004) do not make any predictions on this issue, nonetheless, to gain additional empirical insight, we replace the dependent variable WML in equation (9) with returns on winner and loser portfolios separately. We report the regression estimates within additional columns in Table 9. In All ex-USA, the difference between returns in up and down markets is −27.01 percent for losers and −10.92 percent for winners. The difference is significant for losers but not for winners. The results are similar in the Developed ex-US region as well. In Emerging markets, the return difference for losers is −10.72 percent compared with 2.17 percent for winners. Although the point estimate of the difference is bigger in magnitude for losers than for winners, they are both insignificant. Overall, we confirm that the momentum strategy is profitable in up markets, but not in down markets OOS, which is consistent with the empirical findings of Cooper, Gutierrez, and Hameed (2004). In a further finding, this phenomenon is stronger for losers.

7.2 High and low volatility

Wang and Xu (2015) find that momentum profits are bigger when market volatility is low than when it is high. They find that the relation between momentum profits and market volatility is mainly due to the asymmetric performance of loser stocks. As we mentioned earlier, Wang and Xu (2015) argue that there is "overselling" of losers because investors are more fearful in high-volatility states, and the subsequent price recovery of these losers results in low-momentum profits.[25]

We examine the Wang and Xu's (2015) finding internationally by estimating the following regression:

$$\mathrm{WML}_t = \gamma_1\,\mathrm{HIVOL}_{t-1} + \gamma_2\,\mathrm{LOVOL}_{t-1} + e_t, \tag{10}$$

where HIVOL is a dummy variable that equals one if the market is in high-volatility state, and LOVOL is analogously defined for low-volatility states. We classify a market as being in a high-volatility state if the standard deviation of daily market returns over the previous 12 months is greater than that over the previous 36 months and as in a low-volatility state otherwise. We classify the volatility state based on 12-month market volatility relative to the past 3-year volatility because, in untabulated results, we find a secular decline in market volatility in all regions during our sample period. We compute the market standard deviation for each region using daily return data for the corresponding MSCI index.

We fit Equation (10) separately with WML_t, annualized winner returns and loser returns as dependent variables, and present the results in Table 9 (right panel). Momentum profits are 17.69 percent, 15.75 percent, and 15.69 percent during low volatility periods and 1.12 percent, 2.99 percent, and −0.49 percent during high-volatility periods in All ex-USA, in Developed ex-USA, and in Emerging markets, respectively. These profits during low-volatility periods are significant in all regions but insignificant during high-volatility periods.

The differences in returns across the two states for losers are 18.59 percent in All ex-USA, 12.74 percent in Developed ex-USA, and 11.96 percent in Emerging markets, compared with 2.01 percent, −0.02 percent, and −4.22 percent, respectively, for the winners. Although the return difference for losers is only significant in All ex-USA, the point estimates of the differences are bigger for losers than winners in all regions. Therefore, the difference between the performance of momentum in high- and low-volatility states is also driven largely by the differential performance of losers. Overall, our finding confirms the empirical conclusion of Wang and Xu (2015) that momentum profits are higher when market volatility is low. Further, this phenomenon is driven largely by losers.[26]

In Table 10, we present the regressions of Table 9 for the two halves of the full sample. In general, the results are robust. There is a decline in significance related to the volatility

[25] Stivers and Sun (2010) find that cross-sectional return dispersion explains the time-series of momentum profits; Wang and Xu (2015) find that market volatility is able to capture this effect.

[26] Daniel and Moskowitz (2016) also find that momentum is negatively related to volatility in continental Europe, but they do not consider emerging markets.

Table 10. Time-series determinants of momentum: subsamples.
This table describes the results of the time series:

$$R_t = \gamma_1\, State1_{t-1} + \gamma_2\, State2_{t-1} + e_t,$$

where R is the loser, or winner, or WML portfolio constructed by sorting on last 11 month returns (excluding the most recent month) and State are dummy variables indicating the state of the market in the previous month. UP (DOWN) is equal to one if the market return over the last 36 months is positive (negative), and zero otherwise. We use MSCI All-Country ex-USA, World ex-USA, and Emerging total return indices as the proxies for market return for All ex-USA, Developed ex-USA, and Emerging markets, respectively. HIVOL (LOVOL) is equal to one if the market volatility over the last 12 months is higher (lower) than the market volatility over the past 36 months, and zero otherwise. Market volatility is calculated using daily data. We use MSCI All-Country ex-USA, World ex-USA, and Emerging price (not total return) indices as the market return proxies for All ex-USA, Developed ex-USA, and Emerging markets, respectively. The table reports the annualized slopes (in percent) from the above regression together with their t-statistics. The sample consists of only nonmicrocap stocks (those in the top ninety-seven of the market capitalization of each country). The sample period is 1993–2006 in Panel A and from 2007 to 2020 in Panel B.

State	#obs	L	W	WML	State	#obs	L	W	WML
Panel A: Sample period is 1993–2006									
All ex-USA									
UP	**133**	–2.72	14.64	17.36	**HIVOL**	**58**	10.96	19.53	8.57
		(–0.45)	(2.75)	(2.87)			(1.19)	(2.41)	(0.94)
DOWN	**32**	13.78	26.76	12.98	**LOVOL**	**107**	–5.20	15.62	20.82
		(1.11)	(2.46)	(1.05)			(–0.77)	(2.62)	(3.09)
DIFF		–16.50	–12.12	4.38	**DIFF**		16.16	3.92	–12.25
		(–1.19)	(–1.00)	(0.32)			(1.41)	(0.39)	(–1.08)
Developed ex-USA									
UP	**133**	0.18	14.16	13.98	**HIVOL**	**59**	12.11	17.31	5.20
		(0.03)	(2.60)	(2.05)			(1.23)	(2.12)	(0.51)
DOWN	**32**	11.31	23.23	11.93	**LOVOL**	**106**	–3.10	15.14	18.24
		(0.85)	(2.09)	(0.86)			(–0.42)	(2.48)	(2.39)
DIFF		–11.12	–9.07	2.05	**DIFF**		15.20	2.17	–13.04
		(–0.75)	(–0.73)	(0.13)			(1.24)	(0.21)	(–1.02)
Emerging									
UP	**108**	6.58	19.58	13.00	**HIVOL**	**59**	12.65	15.00	2.35
		(0.93)	(2.65)	(2.12)			(1.33)	(1.50)	(0.28)
DOWN	**57**	0.67	9.04	8.36	**LOVOL**	**106**	0.03	16.46	16.43
		(0.07)	(0.89)	(0.99)			(0.00)	(2.20)	(2.67)
DIFF		5.91	10.55	4.64	**DIFF**		12.62	–1.46	–14.09
		(0.49)	(0.84)	(0.44)			(1.06)	(–0.12)	(–1.37)
State	**#obs**	**L**	**W**	**WML**	**State**	**#obs**	**L**	**W**	**WML**
Panel B: Sample period is 2007–2020									
All ex-USA									
UP	128	–5.49	5.59	11.08	HIVOL	81	13.43	9.45	–3.97
		(–0.70)	(0.93)	(2.10)			(1.35)	(1.25)	(–0.60)
DOWN	39	30.79	16.62	–14.17	LOVOL	86	–6.86	6.95	13.81
		(2.16)	(1.53)	(–1.48)			(–0.71)	(0.95)	(2.13)
DIFF		–36.28	–11.03	25.25	DIFF		20.29	2.51	–17.78
		(–2.23)	(–0.89)	(2.31)			(1.46)	(0.24)	(–1.91)
Developed ex-USA									
UP	124	–9.50	6.00	15.50	HIVOL	81	6.56	8.19	1.63
		(–1.16)	(1.10)	(2.57)			(0.64)	(1.21)	(0.22)

(continued)

Table 10. (continued)

State	#obs	L	W	WML	State	#obs	L	W	WML
Panel B: Sample period is 2007–2020									
DOWN	43	30.78	14.54	−16.24	LOVOL	86	−4.48	8.20	12.68
		(2.22)	(1.57)	(−1.59)			(−0.45)	(1.25)	(1.72)
DIFF		−40.28	−8.55	31.74	DIFF		11.04	−0.01	−11.05
		(−2.50)	(−0.80)	(2.67)			(0.77)	(−0.00)	(−1.05)
Emerging									
UP	128	−4.96	7.02	11.98	HIVOL	81	8.55	5.52	−3.04
		(−0.63)	(0.94)	(2.30)			(0.85)	(0.59)	(−0.46)
DOWN	39	26.58	13.54	−13.04	LOVOL	86	−3.38	11.40	14.78
		(1.86)	(1.00)	(−1.38)			(−0.35)	(1.25)	(2.32)
DIFF		−31.54	−6.52	25.02	DIFF		11.93	−5.88	−17.81
		(−1.93)	(−0.42)	(2.32)			(0.85)	(−0.45)	(−1.95)

states result for Developed ex-USA in the second half, but significance remains in all other cases. Thus, the two central momentum results on market states based on direction and volatility are generally robust across regions and across time. The results therefore provide international support for Cooper, Gutierrez, and Hameed (2004) and Wang and Xu (2015).[27]

8. Conclusion

As Fama and French (2008) indicate, momentum is a "premier" anomaly in equity returns. Accordingly, the literature proposes several hypotheses to explain this phenomenon and tests them with US data. Because similar momentum is observed in markets outside the USA as well, it is worthwhile to investigate the extent to which the US-based momentum explanations extend internationally. This is the subject of our focus, and in order to minimize subjective judgment on our part, we use the same proxies for momentum explanations as those used in studies using US data.

Overall, we find support for the "frog-in-the-pan" explanation for momentum proposed by Da, Gurun, and Warachka (2014), which posits that because of investors' limited attention, markets underreact to information when it arrives gradually as opposed to in discrete chunks. The evidence supporting FIP holds consistently across developed and emerging markets. We also find some evidence for the overconfidence hypothesis that Daniel and Titman (1999) test with the market/book ratio as the empirical proxy.

In time-series tests, we find that the US results of Cooper, Gutierrez, and Hameed (2004) and Wang and Xu (2015) hold internationally. Specifically, momentum profits are higher in up-market and low-volatility states in all regions. The difference in returns for losers between market states is greater than that for winners, which is also consistent with the US evidence. These pieces of evidence are consistent with the arguments of Cooper, Gutierrez, and Hameed (2004) that overconfidence, and, in turn, momentum, are higher in rising markets. They also accord with Wang and Xu (2015), who argue that "overselling" of losers in high-volatility states and their subsequent price recovery cause momentum profits to attenuate.

27 Using the five factor Fama and French (2017) model alphas in place of raw portfolio returns in Tables 9 and 10 preserves the general thrust of the results.

Although we do find support for the notion that international momentum arises from slow diffusion of news, we caution the reader that this conclusion is based on the proxy for diffusion used in Da, Gurun, and Warachka (2014). More generally, it is possible that proxies we borrow from the literature are consistent with multiple hypotheses; however, we interpret them as in the papers that originally propose and test them with the US data. It is possible that the FIP proxy might represent unknown sources of risk that are reflected in momentum returns, or that an as-yet unexplored proxy for a rational explanation might explain momentum even better. These lines of investigation are left for future research.

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Supplementary material

Supplementary material is available at *Review of Finance* online.

Data availability

The data underlying this article were provided under license by Datastream/Worldscope, CRSP, and Compustat. The datasets were purchased through our institutions. Scrambled/randomly deleted data and code are provided at Harvard Datavserse.

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Appendix

Table A1. Worldscope variables.
In general, we do not replace missing values with zero. However, if a variable is starred in the list below, then it is set to zero if missing.

Code	Name
WC01001	Sales
WC01051	COGS
WC02999	Total assets
WC03063	Income taxes payable
WC03263	Deferred taxes
WC03351	Total liabilities
WC03451	Preferred stock
WC03501	Common equity
WC03995	Shareholder equity
Book equity	[(Shareholder equity) or (Common equity + Preferred stock*) or (Total assets − Total liabilities)] + (Deferred Taxes* − Preferred stock*)
Gross profit	Sales − COGS

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