Empirical Determinants of Momentum:
A Perspective Using International Data

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Abstract

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We use out-of-sample international data to consider U.S.-based empirical proxies for momentum explanations. We find that the proxy for the hypothesis that investor underreaction to information arriving in small bits rather than in large chunks results in momentum receives reliable support internationally. The market/book ratio as a proxy for valuation uncertainty, and potentially for investor overconfidence as well, receives secondary support, but we find no support for real options proxies. We confirm out-of-sample that momentum is stronger in up-markets and less-volatile markets; these market states represent high investor confidence in the original studies.

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 three to twelve months. This return pattern, uncovered by Jegadeesh and Titman (1993, JT), 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 several other explanations for momentum and empirical proxies to test these explanations.[1] Our understanding of momentum can potentially be enhanced with an out-of-sample study of these explanations, i.e., a study that uses data not used in the original papers that empirically test these explanations. Because the pattern of momentum is virtually identical in both the U.S. and internationally (momentum over six to twelve months)[2] any proxy for a robust explanation for momentum is likely to apply both in the U.S. and outside the U.S. The papers that empirically test the momentum explanations we consider mostly use U.S. data. We use an international sample for our out-of-sample investigation in this paper. To minimize subjective judgment, we use the same proxies as those used in the original studies that propose the explanations. Additionally, our tests examine all the proxies on an equal footing using the same methodology and the same (out-of-sample) dataset.

One stream of research we consider proposes behavioral theories of momentum. For example, Daniel, Hirshleifer, and Subrahmanyam (1998, DHS) present a model where investor overconfidence leads to momentum.[3] The idea here is that overconfidence builds

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

[2] See Rouwenhorst (1998), Griffin, Ji, and Martin (2003), and Asness, Moskowitz, and Pedersen (2013), for evidence that momentum strategies are profitable in many non-U.S. markets.

[3] To avoid repeating long references, we abbreviate oft-reused references by author initials. Appendix Table A1 provides a complete list of full references and their corresponding abbreviations.

as investors receive public signals that confirm their initial trading decisions but does not subside equally when they receive disconfirming ones. This leads to momentum due to continuing overreaction, on average. Daniel and Titman (1999, DT) argue that overconfidence plays a bigger role in the valuation of growth options than in that of tangible assets, and hence propose book-to-market as a proxy for the impact of overconfidence. Lee and Swaminathan (2000, LS) argue that the degree of investor overconfidence is reflected in the volume of trading[4] and hence use this quantity as a proxy for overconfidence. We test the significance of the book/market and turnover proxies with international data.

Another momentum explanation is proposed by Hong and Stein (1999, HS). In HS (1999), one category of investors condition their demands on the private information they receive but not on market prices, and another category of investors do not receive private information and they condition their demand only on market prices. HS (1999) show that information propagates in a delayed fashion, which results in momentum. HS (1999) use analyst following as a proxy for the speed of information propagation. We follow Hong, Lim, and Stein (2000, HLS) and consider the number of analysts following a stock after controlling for firm size in the international context.

The other behavioral explanations that we consider are the Da, Gurun, and Warachka (2014, DGW) frog-in-the pan (FIP) hypothesis and the anchoring hypothesis of George and Hwang (2004, GH). Under the FIP hypothesis, momentum arises because investors underreact to small bits of information due to limited attention (Hirshleifer and Teoh, 2003), but correctly react when information arrives in large chunks. DGW (2014) propose a proxy for the discreteness of information arrival and show that momentum is inversely related to this proxy. GH (2004) propose 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. They provide evidence in support of their hypothesis. We use the proxies

[4]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.

proposed by these papers to examine the robustness of their findings out-of-sample.

Next, Sagi and Seasholes (2007, SS) build on Johnson (2002) and propose a rational explanation for momentum. Johnson (2002)'s model uses the notion that prices are convex in growth rates, and hence growth rate risk is higher with higher growth rates, and is therefore higher for winners than for losers. In his model, momentum profit is the risk premium compensation for bearing the risk of the winner minus loser portfolios. Johnson (2002)'s structural model of time-varying risk and risk premiums and its extension in SS (2007) is difficult to estimate. Instead, SS (2007) use real options as the source of growth rate risk, and develop comparative statics to derive predictions about how momentum profits vary across stocks with different characteristics and test those predictions. SS (2007) use the cost of goods sold as an inverse proxy for real options.[5] 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 SS (2007)'s model, bigger sales volatility also implies bigger return volatility and SS (2007) note that momentum increases with return volatility as well. We examine the relation between momentum and return volatility.[6]

We consider the preceding proxies using Fama and MacBeth (1973) regressions. We also use regression regularization approaches (i.e., penalized regressions) to examine the relative explanatory power of the various proxies. We further conduct pairwise comparisons to examine the comparative strength of each proxy. Finally, we use a portfolio sorting approach. Across all of our tests, we find support for the FIP proxy in both emerging and non-U.S. developed markets. We find more modest support for the overconfidence hypothesis using book-to-market ratio as the proxy in some tests. We do not find any support for the other proxies.

[5] In SS (2007)'s model, firms with low costs benefit more from real options, leading to greater momentum.

[6] 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.

Our next set of tests examine time-series relations between momentum profits and market states. These relations have been motivated using time-series variations in investor confidence, so that our tests can be viewed as looking for out-of-sample confirmations of such variations. First, Cooper, Gutierrez, and Hameed (2004, CGH) find that momentum profits are higher in up markets than in down markets,[7] 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. Further, Wang and Xu (2015, WX) uncover that momentum profits are lower in high volatility states. WX (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 significant in up-markets and during less volatile periods within our international setting, thus confirming out of sample the U.S.-based evidence of CGH (2004) and WX (2015).[8]

We emphasize that throughout our work, to minimize subjective judgment calls, we use only the empirical proxies that have already been identified in the literature and we do not experiment with new proxies.[9] Also, the literature that proposes various proxies

[7]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 out of sample because sentiment measures are not available internationally.

[8]Other independent work has looked at issues similar to the one we examine. Müller and Müller (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 U.S. data, whereas our study is conducted out-of-sample (for non-U.S. data). Further, they do not consider DGW (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.

[9]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

includes a variety of tests with the U.S. data to establish the validity of the proxies for the underlying hypotheses, and we do not repeat those tests with the international data. This design choice results from the recognition that were we to come up with 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.

We also hasten to add that we do not intend in the slightest to critique any of the papers involved in our empirical work. Indeed, considerable insight has been contributed by many colleagues on the topic of why markets permit momentum. Rather than offer a test of one particular theory, our objective is to simultaneously consider the several available proxies for momentum explanations out of sample, using a common method.[10] 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 validity of the proxy for the explanation. Overall, though, we believe our work represents a reasonable step towards enhancing our understanding of the drivers of momentum.[11]

literature does not directly consider proxies for their theories, we do not address these papers.

[10]We note that there are other debates and stylized facts surrounding momentum. For example, Moskowitz, Ooi, and Pedersen (2012) find time-series momentum, where long-short portfolios are formed based on the sign of past returns rather than their cross-sectional ranks. Goyal and Jegadeesh (2018) show that because risky assets command a positive premium, the time series strategy has a bigger exposure on the long side, but otherwise both time-series and cross-sectional momentum are close to interchangeable. Asness, Moskowitz, and Pedersen (2013) show that momentum extends to asset classes beyond equities. Novy-Marx (2012) proposes that momentum profits arise because winners outperform losers over the past 7-12 months. Goyal and Wahal (2015) demonstrate that this result is due to a reversal in the second month prior to portfolio formation. Lewellen (2002) argues that momentum may be driven by return cross-autocorrelations, but Chen and Hong (2002) argue in favor of underreaction and consequently, positive autodependence in returns. Chordia and Shivakumar (2002) argue that momentum profits can be accounted for by the business cycle, but Griffin, Ji, and Martin (2003) find only modest support for this finding in international markets. 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). Our focus is more on explanations for momentum, while the above papers tend to document stylized facts about momentum.

[11]Ehsani and Linnainmaa (2022) show that factor momentum subsumes individual stock momentum (see also Kelly, Moskowitz, and Pruitt, 2021 and Arnott, Clements, Kalesnik, and Linnainmaa, 2021). Falck, Rej, and Thesmar (2020) (p. 3) indicate that "factor momentum is "spanned" by stock momentum and factor exposure, except at one-month time scale." Further, the evidence from Ehsani and Linnainmaa (2022) is that factor momentum is strongest at the one-month horizon while we have one-month return reversals for individual stocks (Jegadeesh, 1990). As such, factor and stock momentum appear to be different phenomena.

The remainder of this paper 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 robustness checks on the regressions. Section 5 uses a method based on penalized regressions. Section 6 considers pairwise comparisons across the various explanations for momentum. Section 7 considers the cross-sectional evidence using portfolio-based analyses. Section 8 revisits the FIP proxy by considering the signed versions of the proxy, and a country-by-country analysis. Section 9 presents the time-series tests on market states as proxies for investor confidence. Section 10 concludes. The Appendix to this paper contains some ancillary tables, which are prefixed with the letter 'A.'

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 are used to empirically test the cross-sectional implications of these hypotheses. Broadly, these proxies imply that the underlying phenomenon that leads to momentum falls in one of the following categories: (i) underreaction to information due to cognitive limitations, (i) overconfidence, which implies a continuing overreaction to information, and (iii) time-varying expected returns due to variations in risk. The section next presents the methodology used for conducting the out-of-sample tests that examine the robustness of these hypotheses. The actual tests appear in Section 3.

2.1 Data

We obtain data for all countries in the MSCI Developed (ex-U.S.) and the MSCI Emerging markets index. There are a total of 22 developed markets and 27 emerging markets in the MSCI indexes for which we are able to get necessary data.[12] The stock market data are from Datastream and the annual accounting data are from Worldscope. Appendix Table A2 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.[13] 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 the data cleaning procedures used by Griffin, Kelly, and Nardari (2010), Hou, Karolyi, and Kho (2011), Ince and Porter (2006), Jacobs and Müller (2020), and Lee (2011). Specifically, we proceed as follows. We download all data in U.S. dollars with five decimal places to minimize return errors stemming from currency conversions. If the gross return in any month is greater than 300% and the product of gross returns in two consecutive months is less than 50% then we set returns in both months as missing. The equivalent numbers for daily returns are 100% and 20%. We discard all daily returns exceeding 100% and all monthly returns exceeding 200%. We also exclude micro-cap stocks by including those stocks that are in the top 97% of the market capitalization of each region. For each period (day or month), we winsorize returns in each country at the 0.1% and 99.9% levels. If 90%

[12]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 United Kingdom. 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.

[13]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.

or more of stocks have zero returns in a period for a country, we set all of them to missing.

2.2 Momentum in international markets

This subsection documents momentum in our international markets sample. The momentum variable that we use is a stock's return over the previous eleven 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 in our sample from that country. 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 WML hedge portfolio, and we rebalance it monthly.

Table 1 presents the results of the WML hedge portfolio, which is the long-short portfolio formed across extreme winners and losers. The monthly hedge portfolio returns across All ex-U.S., Developed ex-U.S., and Emerging markets are, on average, 0.89%, 0.85%, and 0.74% respectively, and are of a magnitude comparable to those in JT (1993). The medians are slightly greater than the means, and momentum profits are more volatile and more negatively skewed for Developed ex-U.S. 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 and these hypotheses are tested using various empirical proxies. We examine using international data the same proxies that are used with U.S. data. While many of the original papers conduct extensive robustness checks, for parsimony, we consider the central measure, i.e., the measure that is the main focus, of each article.

We use the following cross-sectional regression:

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

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 issues; this is as per convention (Brennan, Chordia, and Subrahmanyam, 1998).[14] For convenience, we will 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 (i) we winsorize at the 0.5% and 99.5% levels, (ii) we country-neutralize by subtracting the cross-sectional mean across all stocks in our sample from that country, and (iii) we standardize across the entire sample to have zero mean and unit standard deviation. The processed variables are used in the interaction terms. To minimize concerns about transaction costs and illiquidity of some international markets, we include only non-microcap stocks. These are defined as stocks in the top 97% of the market capitalization of each region, as in Fama and French (2017).

As described in the introduction, we use proxies for momentum explanations, i.e., the X variables in Equation (1), from existing literature. Below, we describe how we construct them empirically. We discuss the underlying hypotheses in more detail within later sections.

- Book-to-market ratio (B/M): B/M is the ratio of the book value of equity to the

[14] 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.

market value. Table A2 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 HLS (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 DGW (2014), we define ID as follows:

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

  where %pos and %neg are the percentage of daily returns that are positive and negative, respectively, and PRET is the past 11-month return.

- Cost of Goods Sold (COGS): COGS is the ratio of the cost of goods sold 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%, we suspect 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-U.S., Developed ex-U.S., and Emerging markets, respectively. These coefficients are all statistically significant and confirm the evidence of momentum in Table 1. For ease of interpretation, in the tables that document the results of the tests presented below, we flip the signs on some of the X variables, so that the 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 will see in the material to follow, the variables whose signs we flip are B/M, ResAnly, 52wHi, ID, and COGS.

3.1 B/M ratio and turnover

DHS (1998) present a behavioral model to explain momentum. Investors in DHS (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. DHS (1998) show that this behavioral bias results in momentum due to a continuing overreaction.

DT (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, DT (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 as the interaction variable to test the robustness of the DT (1999) evidence outside the U.S. Column (2) of Panel A of Table 3 presents the results by regions. The interaction coefficients in All ex-U.S., Developed ex-U.S., and Emerging markets are 0.034, 0.038, and 0.043, respectively, and are of the sign predicted by DT (1999). However, the statistical significance of these interaction coefficients is small, amounting to a t-statistic of 1.3. We will revisit this 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.

LS (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. LS (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 LS (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-U.S. and -0.047 in Developed ex-U.S. The former is insignificant even at the 10% level, and the latter is significant at the 5% 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 LS (2000) find is not robust outside the U.S. Turnover by itself is significantly negatively related to returns in All ex-U.S. and Emerging markets (the respective coefficients are -0.232 and -0.398) but not in Developed ex-U.S. markets (coefficient of -0.056).

3.2 Analyst following

HS (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. Their model also assumes that information about fundamentals diffuses gradually and reaches different investors at different times. These assumptions differentiate the HS (1999) model from a rational expectations model where investors use all available information.

HLS (2000) empirically test the predictions of HS (1999). HLS (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, HLS (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 HS (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 paper, but it may be worth pursuing in future research.[15]

[15] We also find that residual analyst coverage by itself is a strong positive predictor of returns in all samples. The coefficients on residual analyst coverage are -0.242, -0.267, and -0.194 for All ex-U.S., Developed ex-U.S., and Emerging markets, respectively, all strongly statistically significant.

3.3 52-week high

GH (2004) suggest that the anchoring bias could provide 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 assessment of unknown quantities. In the context of momentum, GH (2004) suggest that investor may 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. GH (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 U.S.

The effect of the 52-week high variable is directional. Specifically, high values of this ratio imply high returns (because investors should underreact to good news in this case), and low values should imply low returns (because investors should underreact to bad news in this case). Note that the correlation between nearness to 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 GH (2004) is whether their 52-week high variable explains cross-sectional variation in returns out-of-sample, and if so, whether it supplants momentum 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, the interaction could matter if investors' perception of overvaluation when the price is higher than the 52 week high dominates their perception of undervaluation when the reverse is true. We might expect this to be the case if high values of the ratios are more salient because investors are loss averse (Coval and Shumway, 2005). For this reason, and 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% level in the Developed ex-U.S. 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. Hence, we find quite modest support for the 52-week high hypothesis as an explanation for momentum outside the U.S.

3.4 The frog-in-the-pan proxy

DGW (2014) propose a form of the slow diffusion hypothesis. They hypothesize that investors are inattentive to information that arrives gradually in small amounts (as opposed to discrete chunks), which results in underreaction to such information and, in turn, in momentum profits. This frog-in-the-pan (FIP) hypothesis predicts that momentum would be bigger for stocks with continuous information flow than for stocks with discrete information flow.

DGW (2014) observe that ID as defined in Equation (2) should be bigger when the information flow is discrete. Intuitively, returns are equally likely to be positive or negative when information flow is continuous and a large difference in the frequency of positive and negative returns suggests more concentrated information flow of the corresponding sign. DGW (2014) find bigger momentum for stocks with more continuous information.

We fit Equation (1) with ID as the interaction variable, and column (6) in Panel A of Table 3 reports the regression estimates. The interaction coefficients are 0.161 in All ex-U.S., 0.125 in Developed ex-U.S., and 0.188 in Emerging markets. All these coefficients are strongly statistically significant.[16] Therefore, the ID effect is of the right sign and

[16] 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

statistically and economically reliable.

3.5 Cost of Goods Sold

The explanations considered so far suggest that behavioral biases explain momentum. In contrast, Johnson (2002) and SS (2007) present models where the risk premium varies through time, and momentum is a compensation for the bigger risk exposures that past winners face. Intuitively, SS (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 increase and become a bigger fraction of their value. Because the firms now become riskier in totality, they command a bigger risk premium. In the SS (2007) model, the relative value of growth options is bigger for low cost of goods sold (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 SS (2007) find empirical support for this hypothesis.

We use 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-U.S. and Developed ex-U.S., and negative in Emerging markets. However, all these coefficients are statistically insignificantly different from zero.

SS (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. SS (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

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*.

for uncertainty, which he argues increases the level of underreaction. The results are in column (8) in Panel A of Table 3. We find that the interaction coefficients in All ex-U.S., Developed ex-U.S., and Emerging markets are -0.029, -0.069, and -0.077, respectively. The negative coefficients for Developed ex-U.S. 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.

4 Robustness Checks

In this section, we conduct ancillary analysis to check the robustness of our results to risk adjustment, additional cross-sectional controls, an alternative definition of momentum, and different sub-periods.

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.[17] 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

[17] 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.

returns in the following regression:

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

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-U.S. and Developed ex-U.S. markets; this evidence is consistent with DT (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.[18]

Chordia and Shivakumar (2006) propose that a factor based on earnings surprises (PMN) can capture momentum profits in the U.S. 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.[19] 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 Table A3 within the internet appendix, we find that the results are virtually unchanged after adding this factor, suggesting that our measure of earnings momentum is not related to return momentum in our out-of-sample

[18]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 A6 within the internet 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.

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

international context.[20]

4.2 Additional controls and alternative momentum returns

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

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

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), book/market, and size (market capitalization), as of a given month.[21] We process the additional Z variables on the right-hand following the same steps as those for MOM and X described after Equation (1).

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, 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-U.S. group.

In the Appendix Table A4, we present the analog of Table 3 (Panel C) using lagged returns from the second to 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).

[20] 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, Chordia, Jostova, and Philipov (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.

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

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 to 2006 while Panel B reports the results for 2007 to 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, book/market and turnover tend to be positively and negatively associated with future returns in both subperiods, for emerging markets, but this relation is less robust 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 not robust to various regions or over time.[22]

5 Multivariate Analysis with Penalized Regressions

Our tests so far analyze the 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

[22] Some countries do not exhibit significant levels of momentum. Specifically, among all countries with an average of at least 500 stocks per month with available data, the momentum variable (MOM), when included by itself, is insignificant for three countries: China, Japan, and Korea. Excluding these countries has no impact on the significance of ID as a determinant of momentum.

multivariate OLS regressions.[23] 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 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 towards zero without necessarily setting them to zero. We choose Lasso ($\rho = 0$) and Elastic net ($\rho = 0.5$) 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 Elastic net, 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 to 2006.

In Table 5, we present the coefficients using standard OLS, Lasso, and elastic nets. We find that the interaction coefficient of ID with momentum barely shrinks across the three procedures. The biggest shrinkage occurs across the interaction coefficient with residual 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

[23]See Gu, Kelly, and Xiu (2020) and Han, He, Rapach, and Zhou (2019) for other applications of these techniques to the cross-section of stock returns.

Lasso in All ex-U.S. The coefficients of B/M and Turn generally do not shrink appreciably across the three procedures.

Table A5 in the online appendix provides the FM coefficients *during the training period* for all of the predictive variables and their interactions with MOM. The appendix confirms that ID is the only robust interaction with momentum (it is 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 to 2020. We do not refit OLS, LASSO, or Elastic net 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 5 and the most recent $X_{i,t-1}$. Following Gu, Kelly, and Xiu (2020), we calculate the OOS-R^2 as

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

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 6 presents the results. We find that OOS-R^2's, MSE, and MAE are similar across the three procedures. 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 Elastic net. 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 Bilateral Tests

The previous estimations consider the statistical significance of each $MOM \times X$ variable and compare the significance to that for other variables. This statistical significance is for the null that each $MOM \times X$ equals zero, and therefore the coefficients are not directly compared to each other. We now address this issue.

Specifically, we perform a series of pairwise tests that compare the Fama-MacBeth coefficients of $MOM \times X$ across the X variables. In other words, we run a series of bilateral tests. This exercise involves running the following Fama-MacBeth cross-sectional regressions each month:

$$\begin{aligned} R_{i,t} &= \gamma_{0,t} + \gamma_{1,t} MOM_{i,t-1} + \gamma_{2,t} X1_{i,t-1} + \gamma_{3,t} MOM_{i,t-1} \times X1_{i,t-1} \\ &\quad + \gamma_{4,t} X2_{i,t-1} + \gamma_{5,t} MOM_{i,t-1} \times X2_{i,t-1} + e_{i,t}, \end{aligned}$$

where $MOM_{i,t-1}$ is the momentum return, and $X1$ and $X2$ represent each pair of the variables listed in the top row of Table 2. Note that there are 21 such pairs, given that we have seven X variables. Dropping the t subscript to denote Fama-MacBeth averages of coefficients, we test the hypothesis that $\gamma_5 > \gamma_3$ for each X pair. Such a comparison is feasible because our variables are country-neutralized and standardized. The results appear in Table 7, where $X1$ is the row variable and $X2$ is the column variable. We continue to transform the signs of some X variables so that the theoretical signs are all expected to be positive, which facilitates the pairwise comparison.

The table presents three panels for All ex-U.S., Developed-ex U.S., and Emerging markets. In each of the panels, the differences between ID and and the alternative variable are significant for every pairwise comparison.[24] The results indicate that the effect of ID generally is robust.[25] Some other pairwise comparisons do yield significance. In particular, the performance of B/M is the next best; it prevails in seven of eighteen cases.

7 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 terciles. The sorting is done every month and we hold the portfolios for the next one month.

We calculate the annualized hedge portfolio return, winners minus losers (WML) for each tercile of X, and present the results in Table 8. The table then reports the difference in WML returns, denoted ΔWML, 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 variable on momentum profits. We perform independent sorts as well as 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, so that in this case, 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

[24] As noted in Section 3.3, the X variable by itself is relevant for the case of the 52wHi variable in addition to the interaction. However, this variable by itself is not significant in Table 3. This suggests that in a bilateral test involving the X variables by themselves, the 52wHi variable would not outperform. In untabulated results, we confirm this to be the case.

[25] The comparisons of ID with COGS and RetVol have negative signs, but note that we test whether the column coefficient exceeds the row coefficient, so that these signs support that the interaction involving ID wins the boxing match.

interest.

Panel A of Table 8 reports the results for independent sorts. For $-$ID, ΔWML is statistically significantly negative at the 10% level for Developed ex-U.S. and at the 5% level for All ex-U.S. and Emerging markets. For example, in Emerging markets ΔWML equals 8.70%, which indicates that the momentum profit in the low ID tercile is 8.70% higher than that in the high ID tercile. When $-$B/M is the X variable, ΔWML is statistically significantly positive in All ex-U.S., 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 $X = -$ID, ΔWML is statistically significant in all regions at the 5% level. The magnitude of ΔWML is also economically large, at around 6% for All ex-U.S. and Developed ex-U.S. markets and at around 9% for Emerging markets, showing that high values of ID exert a large influence on explaining momentum.[26]

It can also be seen that in comparative terms, for emerging markets, the value of ΔWML in absolute terms is highest for ID amongst all of the variables. For the other cases, this value 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.[27] Overall, again, the results indicate support for ID, followed by the book-to-market ratio proxy for overconfidence.

[26] 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.

[27] 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.

8 Another Look at the FIP Proxy

In this section, we briefly consider another perspective on the FIP proxy. Specifically, we consider signed versions of ID and how they affect momentum. DGW (2014) (see their Table 4) show that these signed versions significantly explain average stock returns in the U.S. It is of interest to investigate this finding in our international setting.

The signed ID variables are defined as $ID^+ = (\%\text{pos} - \%\text{neg})$ if PRET > 0 and zero otherwise, and $ID^- = (\%\text{neg} - \%\text{pos})$ if PRET < 0 and zero otherwise. The basic idea is that positive and negative versions of ID proxy for gradual flows of positive and negative news, and these proxy for limited attention. Thus, a high ID^+ implies high (positive) future returns, and a low ID^- implies low (negative) future returns. In turn, DGW (2014) show that ID^+ and ID^- command positive and negative signs in the cross-section of average stock returns, and we expect them to reduce the economic and statistical significance of momentum.[28]

To consider the above conjectures, in the first three columns of Table 9, we include MOM by itself, and together with the signed ID variables for our samples All ex-U.S., Developed ex-U.S., and Emerging markets. We find that each of the three samples exhibits unconditional momentum. Further, both versions of the signed ID variables are strongly significant. These results confirm those of DGW (2014) in our international setting.[29]

In the other columns of Table 9, we present country-by-country results for those countries that (i) have at least 500 stocks per month on average throughout our sample period, and (ii) exhibit a significant MOM coefficient. We find that at least one of the signed ID variables is significant at the 10% level in all countries save one (the UK); however, the

[28]Note that when *unsigned* ID is high, past returns have a stronger tendency to explain future returns, so that the pertinent variable is the interaction of ID with future returns (see DGW (2014), Table 6). This is the specification in our Table 3. However, the *signed* ID variables simply proxy for the effect of past returns, and thus do not enter interactively.

[29]Grinblatt and Moskowitz (2004) propose the consistency of signed returns as an explanation for momentum, but DGW (2014) show that signed ID subsumes return consistency. In untabulated findings, we find a similar pattern in our sample; hence we do not use return consistency as an independent predictor of momentum.

negative version of ID is more consistently significant. Specifically, five of six p-values for ID^{-} are below 10% and four of six are below 5%.

9 Market States and Momentum Profits

This section provides out-of-sample evidence on the U.S.-based literature that finds predictable variations in momentum profits over time. Specifically, Cooper, Gutierrez, and Hameed (2004) (CGH) 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 DHS (1998), they argue that this implies more momentum in up-markets. Further, Wang and Xu (2015) (WX) (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 lowers momentum profits. In effect, then, our investigation using developed and emerging (non-U.S.) markets is an out-of-sample consideration of such confidence variations across the sign and volatility of market returns.

9.1 Up versus down markets

CGH (2004) show that momentum is stronger following up markets than following down markets in the U.S. 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 if the CGH (2004) results are robust out-of-sample. We examine momentum profits in up and down markets internationally using the following regression:

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

where UP is a dummy variable that equals one for an up market and zero otherwise. DOWN is defined analogously for down markets. Following CGH (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-U.S., World ex-U.S., and Emerging total return indices as the market return proxies for All ex-U.S., Developed ex-U.S., and Emerging markets, respectively. The up market and down market coefficients represent annualized momentum profits during the two states in Equation (9).

Table 10 presents the regression estimates. We find that momentum profits in up markets are significantly positive at 14.16% but marginally negative at −1.94% during down markets for the All ex-U.S. region. The momentum profits in all the other regions are also significantly positive in up markets and marginally negative in down markets. Thus, the CGH (2004) results are robust internationally.

We next examine the effect of market states on winners and losers separately. While CGH (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 10. In All ex-U.S., the difference between returns in up and down markets is −27.01% for losers and −10.92% for winners. The difference is significant for losers but not for winners. The results are similar in the Developed ex-U.S. region as well. In Emerging markets, the return difference for losers is −10.72% compared with 2.17% 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 out of sample, which is consistent with the empirical findings of CGH (2004). In a further finding, this phenomenon is stronger for losers.

9.2 High and low volatility

WX (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, WX (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.[30]

We examine the WX (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 three-year volatility because in untabulated results we find a secular decline in market volatility in all regions during our sample period. We compute 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 10 (right panel). Momentum profits are 17.69%, 15.75%, and 15.69% during low volatility periods and 1.12%, 2.99%, and −0.49% during high volatility periods in All ex-U.S., in Developed ex-U.S., and in Emerging markets, respectively. These profits during low volatility periods are significant in all regions but insignificant during high volatility periods.

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

The differences in returns across the two states for losers are 18.59% in All ex-U.S., 12.74% in Developed ex-U.S., and 11.96% in Emerging markets, compared with 2.01%, −0.02%, and −4.22% for winners. Although the return difference for losers is only significant in All ex-U.S., 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 are also driven largely by the differential performance of losers. Overall, our finding confirms the empirical conclusion of WX (2015) that momentum does well when market volatility is low, and that this phenomenon is driven by losers.[31]

In Table 11, we present the regressions of Table 10 for the two halves of the full sample. In general, the results are robust. There is a decline in significance related to the volatility states result for Developed ex-U.S. 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 out-of-sample support for CGH (2004) and WX (2015).

10 Conclusion

As Fama and French (2008) indicate, momentum is a "premier" anomaly in equity returns. Accordingly, the literature has used several U.S.-based empirical proxies to test explanations for this phenomenon. Our perspective is that our understanding of these explanations can be enhanced by considering an out-of-sample analysis. Since the same form of predictability (momentum over six to twelve month horizons) is present both in the U.S. and internationally, the proxies for robust explanations are likely to apply in both settings. Therefore, we use international data for our investigation. In order to minimize subjective judgment on our part, we use the same proxies as those used in earlier studies. Our goal is not to critique the many insights on momentum that have accumu-

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

lated, but to consider the empirical proxies using the same methodology and a common (out-of-sample) dataset.

We find reliable support for the "frog-in-the-pan" or FIP hypothesis used by Da, Gurun, and Warachka (2014), which represents when information dribbles out slowly, as opposed to in discrete chunks. Secondarily, our analysis also provides some support to the Daniel and Titman (1999) proxy for when overconfidence is more likely to operate, namely, the market/book ratio, as a cross-sectional determinant of momentum. We also find that the results of Cooper, Gutierrez, and Hameed (2004) and Wang and Xu (2015), that momentum profits are higher in up-market and low-volatility states, hold out-of-sample. The authors argue that these states proxy for investor confidence. We do not find out-of-sample support for cost of goods sold or return volatility as determinants of momentum; these have been used as real options proxies in the literature.

In closing, we reiterate that our out-of-sample tests of explanations of momentum use the empirical proxies developed in the papers that originally propose the explanations. These proxies can overlap with other rationales. For example, it is possible that FIP might represent unknown sources of risk that are reflected in momentum returns. However, we believe that our exercise, which implicitly assigns the same interpretations to the proxies as the original authors, is a reasonable step towards disentangling the underlying causes of momentum.

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Table 1: Momentum outside the U.S.

This table presents momentum profits outside the U.S. 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 hedge 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% of the market capitalization of each region). The sample period is 1993 to 2020.

	All ex-US	Developed ex-US	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 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-U.S.			
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
# stocks	7,022	7,142	10,951	10,818	10,951	6,324	10,950
				Developed ex-U.S.			
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
# 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
# stocks	3,293	3,484	4,148	4,110	4,148	3,080	4,148

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:

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

where $MOM_{i,t-1}$ is the return from month $t-12$ to $t-2$ and X represents each of 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 (i) we winsorize at the 0.5% and 99.5% levels, (ii) we country neutralize by subtracting the cross-sectional mean across all stocks in our sample from that country, and (iii) 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:

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

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:

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

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 non-microcap stocks (those in the top 97% of the market capitalization of each region). The sample period is 1993 to 2020.

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

	(1) —	(2) −B/M	(3) Turn	(4) −ResAnly	(5) −52wHi	(6) −ID	(7) −COGS	(8) RetVol
Panel C: Controls on the right-hand-side								
	All ex-U.S.							
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)
#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-U.S.							
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)
#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)
#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

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:

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

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 non-microcap stocks (those in the top 97% of the market capitalization of each region). The sample period is 1993 to 2006 in Panel A, and 2007 to 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 to 2006				
				All ex-U.S.				
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)
#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-U.S.				
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)
#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
				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)
#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

	(1) —	(2) −B/M	(3) Turn	(4) −ResAnly	(5) −52wHi	(6) −ID	(7) −COGS	(8) RetVol
Panel B: Sample period is 2007 to 2020								
All ex-U.S.								
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)
#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-U.S.								
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)
#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
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)
#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

Table 5: Penalized regressions of future returns on past momentum return and explanatory variables

We run the regression:

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

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 (i) we winsorize at the 0.5% and 99.5% levels, (ii) we country neutralize by subtracting the cross-sectional mean across all stocks in our sample from that country, and (iii) 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 non-microcap stocks (those in the top 97% of the market capitalization of each region). The sample period is 1993 to 2006.

	All ex-U.S.			Developed ex-U.S.			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

Table 6: Penalized regressions of future returns on past momentum return and explanatory variables: Out-of-sample performance

We run penalized regressions as in Table 5. Using the coefficient estimates from the training period (1993 to 2006), we calculate forecast errors for the out-of-sample period of 2007 to 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 elastic net (ENet). We calculate OOS-MSE as

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

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 out-of-sample period. The R^2 is reported in percent. The sample consists of only non-microcap stocks (those in the top 97% of the market capitalization of each region).

	All ex-U.S.			Developed ex-U.S.			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

Table 7: Fama-MacBeth regressions of future returns on past momentum return and two explanatory variables at a time

We run the following Fama-MacBeth cross-sectional regressions:

$$\begin{aligned} R_{i,t} &= \gamma_{0,t} + \gamma_{1,t} MOM_{i,t-1} + \gamma_{2,t} X1_{i,t-1} + \gamma_{3,t} MOM_{i,t-1} \times X1_{i,t-1} \\ &\quad + \gamma_{4,t} X2_{i,t-1} + \gamma_{5,t} MOM_{i,t-1} \times X2_{i,t-1} + e_{i,t}, \end{aligned}$$

where $MOM_{i,t-1}$ is the return from month $t-12$ to $t-2$ and X represent each of variables listed in the top row of Table 2. We process the variables MOM, $X1$, and $X2$ on the right-hand via the same steps as outlined in Table 3. The $X1$ variables are listed in rows and the $X2$ variables are listed in columns. 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 table reports the time-series averages of the difference in coefficient on the interaction term of MOM with $X2$ and the coefficient on the interaction term of MOM with $X1$, $\gamma_5 - \gamma_3$, together with its t-statistic in parentheses. We report these differences for all combinations of $X1$ and $X2$ variables. The sample consists of only non-microcap stocks (those in the top 97% of the market capitalization of each country). The sample period is 1993 to 2020.

	$X2$					
$X1$	Turn	−ResAnly	−52wHi	−ID	−COGS	RetVol
	All ex-U.S.					
−B/M	−0.085	−0.136	−0.039	0.144	−0.023	−0.083
	(−2.52)	(−4.69)	(−1.13)	(3.42)	(−0.71)	(−2.18)
Turn		−0.042	0.006	0.227	0.050	−0.005
		(−1.23)	(0.15)	(6.49)	(2.06)	(−0.17)
−ResAnly			0.077	0.264	0.091	0.073
			(1.96)	(5.95)	(2.44)	(1.89)
−52wHi				0.180	0.029	−0.029
				(5.43)	(0.81)	(−0.68)
−ID					−0.153	−0.166
					(−4.43)	(−5.91)
−COGS						−0.048
						(−1.59)

	$X2$					
$X1$	Turn	−ResAnly	−52wHi	−ID	−COGS	RetVol
			Developed ex-U.S.			
−B/M	−0.101	−0.108	−0.086	0.132	−0.024	−0.149
	(−2.52)	(−3.52)	(−2.20)	(2.75)	(−0.64)	(−3.55)
Turn		0.012	−0.008	0.226	0.082	−0.008
		(0.35)	(−0.21)	(5.94)	(2.94)	(−0.23)
−ResAnly			0.015	0.188	0.074	−0.006
			(0.35)	(3.70)	(1.70)	(−0.13)
−52wHi				0.196	0.101	−0.027
				(4.96)	(2.69)	(−0.59)
−ID					−0.138	−0.161
					(−3.73)	(−4.91)
−COGS						−0.113
						(−3.50)
			Emerging			
−B/M	−0.054	−0.182	−0.023	0.127	−0.041	−0.121
	(−1.12)	(−3.61)	(−0.45)	(2.09)	(−0.99)	(−2.29)
Turn		−0.116	−0.021	0.189	−0.041	−0.123
		(−2.42)	(−0.37)	(3.71)	(−1.05)	(−2.70)
−ResAnly			0.092	0.304	0.089	0.037
			(1.75)	(5.16)	(1.73)	(0.73)
−52wHi				0.224	−0.036	−0.115
				(4.75)	(−0.70)	(−1.72)
−ID					−0.182	−0.250
					(−3.62)	(−6.05)
−COGS						−0.024
						(−0.50)

Table 8: Double-sorted portfolio alphas on 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 winner minus loser (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 non-microcap stocks (those in the top 97% of the market capitalization of each region). The sample period is 1993 to 2020.

	−B/M	Turn	−ResAnly	−52wHi	−ID	−COGS	RetVol
Panel A: Independent sorts							
All ex-U.S.							
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-U.S.							
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-U.S.							
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-U.S.							
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)

Table 9: Exploring the frog-in-the-pan hypothesis with signed ID

This table presents the results of Fama-MacBeth cross-sectional regressions as in Panel A of Table 3:

$$R_{i,t} \;=\; \gamma_{0,t} + \gamma_{1,t}\, MOM_{i,t-1} + \gamma_{2,t}\, ID^{+}_{i,t-1} + \gamma_{3,t}\, ID^{-}_{i,t-1} + e_{i,t},$$

where $ID^{+} = (\%\text{pos} - \%\text{neg})$ if PRET > 0 and zero otherwise, and $ID^{-} = (\%\text{neg} - \%\text{pos})$ if PRET < 0 and zero otherwise. We run the above regressions separately for stocks in different regions and separately for those individual countries whose samples consist of more than 500 stocks per month on average, and that display momentum. The table reports the time-series averages of coefficients together with their t-statistics in parentheses. 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 non-microcap stocks (those in the top 97% of the market capitalization of each region or country). The sample period is 1993 to 2020.

	All ex-U.S.	Developed ex-U.S.	Emerging	Australia	Canada	UK	Hong Kong	India	Taiwan
				Panel A: Without signed ID					
MOM	0.217	0.277	0.135	1.042	0.993	1.167	1.089	0.927	0.874
	(3.31)	(3.59)	(2.22)	(2.21)	(3.15)	(3.15)	(3.24)	(2.15)	(2.22)
#stocks	9,780	5,987	3,972	662	835	1,115	660	615	544
Adj-R^2	1.0	1.7	0.6	2.7	3.1	3.1	0.9	2.6	2.1
				Panel B: With signed ID					
MOM	0.120	0.185	0.037	0.681	0.523	0.839	0.646	0.846	0.649
	(2.01)	(2.68)	(0.63)	(1.44)	(1.59)	(2.45)	(1.75)	(1.71)	(1.46)
ID^{+}	0.151	0.134	0.156	−8.777	2.759	−0.358	8.313	1.413	0.897
	(5.26)	(3.96)	(4.99)	(−0.85)	(1.63)	(−0.14)	(2.83)	(0.72)	(0.38)
ID^{-}	−0.162	−0.129	−0.197	−8.194	−5.863	−3.767	−5.972	−7.058	−4.377
	(−4.14)	(−2.62)	(−5.85)	(−2.11)	(−2.00)	(−1.55)	(−2.52)	(−3.39)	(−1.90)
#stocks	9,780	5,987	3,972	662	835	1,115	660	615	544
Adj-R^2	1.5	2.7	0.9	6.0	5.7	5.7	1.8	4.3	3.5

Table 10: 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 winner minus loser 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-U.S., World ex-U.S., and Emerging total return indices as the proxies for market return for All ex-U.S., Developed ex-U.S., 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-U.S., World ex-U.S., and Emerging price (not total return) indices as the market return proxies for All ex-U.S., Developed ex-U.S., 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 non-microcap stocks (those in the top 97 of the market capitalization of each country). The sample period is 1993 to 2020.

State	#obs	L	W	WML	State	#obs	L	W	WML
				All ex-U.S.					
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-U.S.					
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)

Table 11: 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 winner minus loser 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-U.S., World ex-U.S., and Emerging total return indices as the proxies for market return for All ex-U.S., Developed ex-U.S., 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-U.S., World ex-U.S., and Emerging price (not total return) indices as the market return proxies for All ex-U.S., Developed ex-U.S., 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 non-microcap stocks (those in the top 97 of the market capitalization of each country). The sample period is 1993 to 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 to 2006									
All ex-U.S.									
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-U.S.									
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 to 2020									
All ex-U.S.									
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-U.S.									
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)
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)

Appendix: Extra Tables

Table A1: References and Abbreviations

Paper	Abbreviation
Jegadeesh and Titman (1993)	JT (1993)
Daniel, Hirshleifer, and Subrahmanyam (1998)	DHS (1998)
Daniel and Titman (1999)	DT (1999)
Lee and Swaminathan (2000)	LS (2000)
Hong and Stein (1999)	HS (1999)
Hong, Lim, and Stein (2000)	HLS (2000)
George and Hwang (2004)	GH (2004)
Da, Gurun, and Warachka (2014)	DGW (2014)
Sagi and Seasholes (2007)	SS (2007)
Cooper, Gutierrez, and Hameed (2004)	CGH (2004)
Wang and Xu (2015)	WX (2015)

Table A2: Worldscope variables

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

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

Table A3: Fama-MacBeth regressions of future returns on past momentum return and explanatory variables: Risk-adjusting returns with an additional PMN factor

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

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

except that we include an additional factor on the left-hand-side to risk-adjust returns. Betas are calculated using the full-sample for each stock from a five-factor Fama and French (2017) model and a PMN factor. The PMN factor is constructed as follows. Each month we sort stocks into decile portfolios based on standardized unexpected earnings (SUE), where SUE is defined as the most recent change in quarterly earnings divided by the most recent price. The portfolios are value weighted and rebalanced monthly. We calculate the PMN factor as the return on the Decile 10 portfolio minus that on the Decile 1 portfolio. We use separate factors for developed and emerging markets and use the factor model for the stock corresponding to its region. In the regression equation, $MOM_{i,t-1}$ 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 (i) we winsorize at the 0.5% and 99.5% levels, (ii) we country neutralize by subtracting the cross-sectional mean across all stocks in our sample from that country, and (iii) 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. We run the 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 non-microcap stocks (those in the top 97% of the market capitalization of each region). The sample period is 1993 to 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	—	−B/M	Turn	−ResAnly	−52wHi	−ID	−COGS	RetVol
				All ex-U.S.				
MOM	0.171	0.214	0.220	0.177	0.273	0.143	0.172	0.239
	(4.56)	(5.34)	(5.64)	(5.10)	(9.16)	(4.06)	(4.25)	(6.52)
X	—	−0.204	−0.210	−0.182	0.113	0.028	−0.026	0.012
		(−8.07)	(−6.79)	(−4.65)	(1.93)	(1.41)	(−1.91)	(0.26)
$MOM \times X$	—	0.054	−0.032	−0.101	−0.026	0.107	0.004	−0.031
		(2.69)	(−1.98)	(−3.81)	(−1.06)	(4.83)	(0.25)	(−1.45)
#stocks	9,761	6,982	7,102	9,761	9,747	9,760	6,280	9,761
Adj-R^2	0.4	0.7	0.7	0.9	1.3	0.7	0.5	1.2
				Developed ex-U.S.				
MOM	0.220	0.266	0.282	0.223	0.354	0.207	0.229	0.321
	(5.09)	(5.44)	(6.10)	(5.89)	(10.68)	(5.20)	(4.79)	(7.88)
X	—	−0.193	−0.061	−0.185	0.122	0.047	−0.010	0.020
		(−6.98)	(−1.65)	(−3.88)	(1.86)	(2.02)	(−0.65)	(0.38)
$MOM \times X$	—	0.065	−0.049	−0.057	−0.062	0.067	0.015	−0.052
		(2.69)	(−2.77)	(−1.86)	(−2.49)	(3.03)	(0.85)	(−2.22)
#stocks	5,979	3,862	3,844	5,979	5,969	5,978	3,449	5,979
Adj-R^2	0.8	1.1	1.2	1.7	2.2	1.2	0.7	2.0
				Emerging				
MOM	0.096	0.169	0.148	0.121	0.177	0.048	0.100	0.177
	(2.16)	(3.45)	(3.40)	(2.71)	(4.55)	(1.07)	(2.02)	(3.85)
X	—	−0.288	−0.345	−0.153	0.114	−0.009	−0.080	0.020
		(−6.97)	(−7.60)	(−4.47)	(1.78)	(−0.35)	(−3.81)	(0.41)
$MOM \times X$	—	0.046	0.002	−0.116	−0.020	0.160	−0.033	−0.072
		(1.45)	(0.09)	(−3.46)	(−0.52)	(4.29)	(−1.48)	(−2.22)
#stocks	3,960	3,273	3,455	3,960	3,956	3,959	3,055	3,960
Adj-R^2	0.4	0.8	0.9	0.6	1.2	0.8	0.5	1.0

Table A4: Fama-MacBeth regressions of future returns on past 6-month momentum return and explanatory variables

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

$$\begin{aligned} R_{i,t} \quad = \quad & \gamma_{0,t} + \gamma_{1,t}\, MOM'_{i,t-1} + \gamma_{2,t}\, X_{i,t-1} + \gamma_{3,t}\, MOM'_{i,t-1} \times X_{i,t-1} \\ & + \gamma_{4,t}\, Size_{i,t-1} + \gamma_{5,t}\, MOM'_{i,t-1} \times Size_{i,t-1} + \gamma_{6,t}\, (B/M)_{i,t-1} \\ & + \gamma_{7,t}\, (GP/AT)_{i,t-1} + \gamma_{8,t}\, ATG_{i,t-1} + \gamma_{9,t}\, R_{i,t-1} + e_{i,t}, \end{aligned}$$

except that we use MOM' defined as the return from month $t-7$ to $t-2$. 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 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 non-microcap stocks (those in the top 97% of the market capitalization of each region). The sample period is 1993 to 2020.

	(1) —	(2) −B/M	(3) Turn	(4) −ResAnly	(5) −52wHi	(6) −ID	(7) −COGS	(8) RetVol
				All ex-U.S.				
MOM'	0.236	0.216	0.301	0.248	0.145	0.210	0.233	0.287
	(4.22)	(3.73)	(5.58)	(4.58)	(3.25)	(3.91)	(4.17)	(6.05)
X	—	−0.269	−0.218	−0.110	−0.250	0.030	−0.040	−0.166
		(−6.44)	(−5.81)	(−2.82)	(−2.79)	(1.35)	(−2.58)	(−2.40)
$MOM' \times X$	—	0.080	−0.050	−0.063	−0.049	0.163	−0.008	−0.040
		(3.61)	(−2.68)	(−2.41)	(−1.45)	(5.65)	(−0.52)	(−1.66)
#stocks	6,211	6,211	5,954	6,211	6,210	6,123	6,181	6,211
Adj-R^2	2.1	2.3	2.6	2.4	3.1	2.4	2.2	3.1
				Developed ex-U.S.				
MOM'	0.267	0.245	0.310	0.283	0.166	0.250	0.262	0.342
	(4.07)	(3.56)	(5.00)	(4.55)	(3.29)	(3.94)	(4.00)	(6.19)
X	—	−0.235	−0.041	−0.110	−0.289	0.051	−0.027	−0.180
		(−4.99)	(−0.82)	(−2.11)	(−2.82)	(2.13)	(−1.64)	(−2.27)
$MOM' \times X$	—	0.103	−0.036	−0.030	−0.112	0.134	0.005	−0.071
		(3.88)	(−1.87)	(−0.96)	(−3.27)	(4.72)	(0.30)	(−2.77)
#stocks	3,416	3,416	3,254	3,416	3,415	3,379	3,400	3,416
Adj-R^2	3.2	3.5	4.0	3.7	4.7	3.6	3.4	4.7
				Emerging				
MOM'	0.204	0.192	0.295	0.221	0.110	0.158	0.195	0.259
	(3.62)	(3.31)	(5.56)	(3.95)	(2.14)	(2.84)	(3.48)	(4.93)
X	—	−0.364	−0.406	−0.121	−0.226	−0.027	−0.093	−0.135
		(−7.06)	(−7.94)	(−3.09)	(−2.50)	(−0.91)	(−3.88)	(−1.94)
$MOM' \times X$	—	0.041	0.005	−0.092	−0.032	0.181	−0.060	−0.042
		(1.17)	(0.16)	(−2.26)	(−0.66)	(4.27)	(−2.42)	(−1.06)
#stocks	3,004	3,004	2,915	3,004	3,003	2,957	2,998	3,004
Adj-R^2	2.0	2.1	2.7	2.2	2.8	2.4	2.1	2.8

Table A5: Fama-MacBeth regressions of future returns on past momentum returns and a full set of explanatory variables

This table presents the results of Fama-MacBeth cross-sectional regressions.

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

where 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 (i) we winsorize at the 0.5% and 99.5% levels, (ii) we country neutralize by subtracting the cross-sectional mean across all stocks in our sample from that country, and (iii) 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. We run the regressions separately for stocks in different regions. The table reports the time-series averages of coefficients together with their t-statistics in parentheses. 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 non-microcap stocks (those in the top 97% of the market capitalization of each region). The sample period is 1993 to 2006.

	All ex-U.S.	Developed ex-U.S.	Emerging
MOM	0.512	0.639	0.403
	(7.70)	(8.84)	(3.94)
$-MOM\times$B/M	0.094	0.109	0.112
	(3.14)	(3.31)	(1.87)
$MOM\times$Turn	−0.039	−0.050	0.066
	(−1.46)	(−1.67)	(1.39)
$-MOM\times$ResAnly	−0.007	0.013	−0.077
	(−0.27)	(0.45)	(−1.09)
$-MOM\times$52wHi	−0.026	0.021	−0.039
	(−0.59)	(0.39)	(−0.51)
$-MOM\times$ID	0.143	0.094	0.202
	(3.59)	(2.28)	(2.88)
$-MOM\times$COGS	0.018	0.015	−0.020
	(0.82)	(0.63)	(−0.49)
$MOM\times$RetVol	−0.031	−0.105	−0.054
	(−0.68)	(−2.11)	(−0.59)
−B/M	−0.355	−0.335	−0.447
	(−5.83)	(−5.12)	(−6.05)
Turn	−0.136	0.011	−0.356
	(−3.55)	(0.23)	(−5.73)
−ResAnly	−0.094	−0.064	−0.132
	(−2.49)	(−1.58)	(−2.20)
−52wHi	0.110	0.190	−0.034
	(1.04)	(1.56)	(−0.29)
−ID	0.049	0.037	0.010
	(1.77)	(1.12)	(0.21)
−COGS	−0.037	−0.025	−0.135
	(−1.39)	(−0.91)	(−3.24)
RetVol	−0.193	−0.274	−0.053
	(−2.40)	(−3.22)	(−0.60)
#stocks	4,353	2,840	1,792
Adj-R^2	4.2	6.2	3.8

Table A6: Fama-MacBeth regressions of future returns on past momentum return and explanatory variables including fund flows

This table presents the results of Fama-MacBeth cross-sectional regressions as in Panel A of Table 3. We add one more X variable to these regressions, namely ΔFundFlow. This is calculated as the percentage change in the institutional fund holding (the ratio of the number of shares held by institutions to the total number of shares outstanding). The rest of the procedure remains the same. The table reports the time-series averages of coefficients together with their t-statistics in parentheses. 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 non-microcap stocks (those in the top 97% of the market capitalization of each region). The sample period is 1993 to 2020.

	—	−B/M	Turn	−ResAnly	−52wHi	−ID	−COGS	RetVol	ΔFundFlow
					All ex-U.S.				
MOM	0.217	0.290	0.268	0.217	0.308	0.165	0.216	0.304	0.191
	(3.32)	(4.72)	(4.46)	(3.75)	(6.32)	(2.70)	(3.40)	(6.06)	(2.53)
X	—	−0.283	−0.232	−0.242	0.063	−0.001	−0.048	−0.008	0.011
		(−6.73)	(−5.74)	(−3.25)	(0.60)	(−0.04)	(−3.04)	(−0.08)	(0.76)
$MOM \times X$	—	0.034	−0.028	−0.118	−0.017	0.161	0.009	−0.029	−0.014
		(1.33)	(−1.55)	(−3.55)	(−0.60)	(5.55)	(0.55)	(−1.19)	(−0.62)
#stocks	9,782	7,001	7,122	9,782	9,768	9,780	6,299	9,781	2,128
Adj-R^2	1.0	1.3	1.2	2.2	3.2	1.4	0.9	3.2	1.3
					Developed ex-U.S.				
MOM	0.277	0.351	0.341	0.271	0.397	0.230	0.285	0.415	0.240
	(3.59)	(4.57)	(4.61)	(4.21)	(7.20)	(3.22)	(3.72)	(7.24)	(2.96)
X	—	−0.261	−0.056	−0.267	0.073	0.007	−0.044	−0.008	0.004
		(−5.46)	(−1.04)	(−2.90)	(0.58)	(0.19)	(−2.39)	(−0.07)	(0.20)
$MOM \times X$	—	0.038	−0.047	−0.078	−0.058	0.125	0.018	−0.069	−0.023
		(1.22)	(−2.43)	(−2.03)	(−1.96)	(4.11)	(0.94)	(−2.56)	(−0.97)
#stocks	5,987	3,870	3,852	5,987	5,978	5,987	3,457	5,987	1,475
Adj-R^2	1.7	2.1	2.1	4.2	5.4	2.5	1.4	5.4	1.8
					Emerging				
MOM	0.135	0.231	0.191	0.163	0.214	0.077	0.136	0.234	0.081
	(2.23)	(3.88)	(3.58)	(2.77)	(4.39)	(1.30)	(2.20)	(4.37)	(0.94)
X	—	−0.369	−0.398	−0.194	0.080	−0.018	−0.084	0.028	0.007
		(−7.46)	(−7.49)	(−4.04)	(0.88)	(−0.60)	(−3.69)	(0.35)	(0.16)
$MOM \times X$	—	0.043	0.003	−0.117	−0.008	0.188	−0.023	−0.077	−0.011
		(1.26)	(0.11)	(−3.12)	(−0.20)	(4.59)	(−1.00)	(−2.22)	(−0.25)
#stocks	3,973	3,285	3,468	3,973	3,969	3,972	3,067	3,973	930
Adj-R^2	0.6	1.1	1.2	1.0	1.9	1.0	0.7	1.9	0.9