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Individualism and Momentum around the World

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ABSTRACT

This paper examines how cultural differences influence the returns of momentum strategies. Cross-country cultural differences are measured with an individualism index developed by Hofstede (2001), which is related to overconfidence and self-attribution bias. We find that individualism is positively associated with trading volume and volatility, as well as to the magnitude of momentum profits. Momentum profits are also positively related to analyst forecast dispersion, transaction costs, and the familiarity of the market to foreigners, and negatively related to firm size and volatility. However, the addition of these and other variables does not dampen the relation between individualism and momentum profits.

A SUBSTANTIAL LITERATURE EXAMINES what is generally referred to as the momentum effect—the observation that stocks that perform the best in the recent past continue to perform well in the future. For example, Jegadeesh and Titman (1993, 2001) find that stocks in the United States that realize the best (worst) returns over the past 3 to 12 months continue to perform well (poorly) over the subsequent 3 to 12 months. The profitability of momentum strategies is found in equity markets throughout the world (see, for example, Rouwenhorst (1998) for a study of momentum in Europe and Griffin, Ji, and Martin (2003)

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for a study of momentum around the world). However, there are important exceptions, most notably in Asia (e.g., Chui, Titman, and Wei (2003)).

Given the magnitude of momentum profits, about 12% per year in the United States and Europe, they are unlikely to be explained by risk-based theories. Indeed, most of the focus in the academic literature has been on behavioral explanations for this phenomenon.[1] For example, Daniel, Hirshleifer, and Subrahmanyam (DHS, 1998) show how the momentum effect can be generated by investors' overconfidence and self-attribution bias and Barberis, Shleifer, and Vishny (BSV, 1998) and Hong and Stein (1999) show how momentum can be generated by investors' initial underreaction to information.

This paper uses international data to examine the extent to which the momentum effect is generated by behavioral biases. In particular, we examine whether momentum profits are greater in those countries where investors are likely to exhibit the psychological biases discussed in the behavioral finance literature. Our focus is on what psychologists refer to as "individualism," which, according to Hofstede (2001), reflects the degree to which people focus on their internal attributes, such as their own abilities, to differentiate themselves from others. Specifically, we use an individualism index reported by Hofstede (2001) that is based on survey evidence from 50 countries.[2] Although we are not aware of this index being used in the finance literature, Hofstede's individualism index and other cultural values have become widely accepted since Hofstede published his results in 1980 (Hofstede (1980)) and they have been used by many researchers in other business disciplines.[3]

Although it does not directly measure the behavioral biases suggested in the momentum literature, we argue that individualism is likely to be correlated with overconfidence and attribution bias. To provide independent support for the idea that investors in more individualistic cultures tend to be more overconfident, we show that the individualism measure is correlated with trading volume and volatility (see Odean (1998), Gervais and Odean (2001), and Scheinkman and Xiong (2003) for models in which overconfident investors trade more and generate excess volatility).

[1]See Berk, Green, and Naik (1999), Johnson (2002), and Sagi and Seasholes (2007) for discussions of rational momentum models. While these models provide an explanation for why risk premiums can increase following positive stock return realizations, they cannot explain the magnitude of the momentum returns observed in this and other studies without assuming extreme levels of risk aversion.

[2]Hofstede (2001) classifies cultures into five dimensions: individualism, masculinity, power distance, uncertainty avoidance, and long-term orientation. In other words, cultures differ in their emphasis on these five dimensions. Among these five cultural dimensions, individualism is the most closely related to overconfidence and self-attribution bias. This index is regarded as the most comprehensive in terms of both the range of countries and the number of respondents involved (Kagitcibasi (1997)).

[3]For example, Schultz et al. (1993) and Kachelmeier and Shehata (1997) have applied Hofstede's measures of cultural values to accounting; Franke, Hofstede, and Bond (1991), Yeh and Lawrence (1995), and Weber, Shenkar, and Raveh (1996) to economics; Nakata and Sivakumar (1996) and Aaker and Williams (1998) to marketing; and Geletkanycz (1997) and Tan et al. (1998) to management.

As we show, there are significant cross-country differences in momentum profits that persist over time. In particular, countries that exhibit the most momentum in the first half of our sample period also tend to exhibit the most momentum in the second half of our sample period. Our analysis indicates that to a large extent, these differences can be explained by cross-country differences in the Hofstede individualism measure. Specifically, the average monthly returns on a zero-cost (long minus short) momentum portfolio are more than 0.6% higher in those countries with individualism indexes in the top 30% than in those countries with individualism indexes in the bottom 30%. This difference in returns is statistically very significant.

In addition to individualism, we consider a number of other variables that can plausibly be related to momentum and that can vary across countries. These include country-specific variables that proxy for information uncertainty as well as institutional variables that may be related to the development and integrity of the countries' financial markets. Our use of country-specific proxies for information uncertainty is motivated by Zhang (2006), who suggests that stocks in the United States, for which information uncertainty is higher (e.g., those with more dispersed analyst earnings forecasts), exhibit stronger momentum. Our measures of market development and integrity are motivated by the idea that these measures may be related to trading costs and the flow of information, which may in turn influence the profitability of momentum strategies.

We find that momentum profits are significantly related to some of these country-specific variables, but their inclusion does not materially affect the significance of the individualism measure. In addition, since we know that both individualism and momentum are weak in East Asian countries (indeed, this was the original motivation of the study), we examine the extent to which our results hold outside of East Asia. We find that the positive relationship between momentum profits and individualism holds even when East Asian countries are excluded from our sample.

To further examine the behavioral momentum theories we examine the long-term returns of momentum portfolios. Both DHS (1998) and Hong and Stein (1999) suggest that momentum is caused by positive feedback trading that leads to a delayed overreaction that is eventually reversed. We find that the reversals observed in the U.S. stock market also occur in most countries around the world. Although the evidence is relatively weak, we find that the magnitude of the reversals tends to be higher in countries with higher individualism, especially in the third year after portfolio formation.

The remainder of this paper is organized as follows. In Section I, we discuss the link between individualism and overconfidence as well as the self-attribution bias. In Section II, we describe the data used in the paper. In Section III, we document a positive link between individualism and trading volume as well as stock volatility. In Section IV, we report the results on momentum profits for each country as well as for portfolios of countries. Section V reports the results on the relationship between individualism and momentum profitability based on portfolio analysis. In Section VI, we test alternative explanations for the momentum effect. Section VII presents the results from robustness checks and Section VIII reports the results from long-term return reversals. Section IX concludes the paper.

I. Individualism, Overconfidence, and Self-Attribution Bias

A. The Definition and Implications of Individualism

Social psychologists distinguish between what they call individualistic and collectivistic cultures. According to Hofstede (2001), this distinction pertains to the degree to which people in a country tend to have an *independent* rather than an *interdependent self-construct*, which is a term used in psychology that relates to an individual's self-image or self-esteem. In individualistic cultures, individuals tend to view themselves as "an autonomous, independent person" (Markus and Kitayama (1991, p. 226)), while in collectivistic cultures, individuals view themselves "not as separate from the social context but as more connected and less differentiated from others" (Markus and Kitayama (1991, p. 227)). Gelfand et al. (2002, p. 835) describe individualism and collectivism as follows: "The self is served in individualistic cultures by being distinct from and better than others, in order to accomplish the culturally mandated task of being independent and standing out. By contrast, the self is served in collectivistic cultures by being accepted by others and by focusing on negative characteristics, in order to accomplish the culturally mandated task of being interdependent and blending in."[4]

B. The Link between Individualism and Overoptimism/Overconfidence and Self-Attribution Bias

The evidence in the psychology literature suggests a link between individualism and overoptimism and overconfidence.[5] For example, Markus and Kitayama (1991) argue that in individualistic cultures people think positively about themselves and focus on their own internal attributes, such as their abilities. Heine et al. (1999, pp. 769–770) argue that children in individualistic cultures "are encouraged to think about themselves positively as *stars*, as *winners*, as *above average* and as the *repositories of special qualities*," which tend to make them overestimate their abilities (i.e., they are overconfident). Indeed, in

[4]It should be noted that collective behavior is not the major concept that differentiates individualism from collectivism. As with people in collectivistic cultures, people in individualistic cultures can demonstrate collective behavior. For example, when people in individualistic cultures have overconfidence on their prior information about a firm, they can collectively underreact to the firm's recent earnings announcement. The difference between individualism and collectivism is based on the different conceptions of self.

[5]As discussed in Odean (1998), both miscalibration and overoptimism (also known as unrealistic optimism) are manifestations of overconfidence. Odean (1998) suggests that when investors overweight their own information because they are overoptimistic, they will hold posterior beliefs that are too precise (miscalibration). Furthermore, Camerer and Lovallo (1999) find that entrant failure is related to overconfidence because overconfident decision makers are overoptimistic about their success rates.

reviews of a relatively large body of evidence from cross-cultural psychological experiments and surveys, Markus and Kitayama (1991) and Heine et al. (1999) find that while people in *individualistic cultures*, such as the United States, tend to believe that their abilities are *above average*, people in collectivistic cultures, such as Japan, do not have this belief. As Van den Steen (2004) and others discuss, when individuals are overoptimistic about their abilities, they tend to overestimate the precision of their predictions, which is the notion of overconfidence discussed in DHS (1998). In contrast, since people in collectivist cultures are concerned with behaving appropriately and adapting to different social situations, they tend to have high self-monitoring (Church et al. (2006)), which means that they are cognizant of social cues and adjust their behavior to what is expected in their social environment (Biais et al. (2005)). In a recent study on trading behavior in an experimental financial market under asymmetric information, Biais et al. (2005) find that self-monitoring helps to reduce the cognitive bias caused by overconfidence.

It should be noted that the cross-cultural psychology literature discusses two types of overconfidence, overconfidence about general knowledge and peer-comparison overconfidence (e.g., Yates et al. (2002)). In a study including subjects from Taiwan, Japan, Singapore, India, and the United States, Lee et al. (1995) find that overconfidence about general knowledge is stronger in Taiwan, Singapore, and India and is weaker in Japan and the United States, but peer-comparison overconfidence is stronger in the United States than in other countries. Yates, Lee, and Shinotsuka (1996) suggest that individualism is clearly related to peer-comparison overconfidence, but is not necessarily related to overconfidence about general knowledge. As discussed in Van den Steen (2004), it is overconfidence about one's success relative to others (peer-comparison overconfidence) that causes investors to overestimate the precision of their information (i.e., miscalibration). Therefore, individualism is related to the kind of overconfidence that is discussed in the momentum literature.

There is also a link between individualistic cultures and self-attribution biases, which Zuckerman (1979, p. 245) describes as the tendency of people to "enhance or protect their self-esteem by taking credit for success and denying responsibility for failure." Markus and Kitayama (1991) and Kagitcibasi (1997) suggest that the tendency to maintain and promote self-esteem in individualistic cultures results in a pervasive self-attribution bias as well as overconfidence. Indeed, children in individualistic cultures are educated to care about their self-esteem. In a review of the studies on cross-cultural variation in the self-attribution bias, Nurmi (1992, p. 70) concludes, "this cross-cultural difference in *self-attribution bias* is typically explained by Western *individualism* and the *collectivist* orientation of Eastern cultures."[6]

[6]Italics are added to avoid confusion. After a review of the evidence from psychology, Moghaddam (1998, p. 197) concludes that "Evidence suggests that the pattern of self-serving biases found in societies more supportive of independent selves, such as the United States, is not always found in societies in which interdependent selves receive stronger encouragement, such as Japan."

C. The Relationship between Individualism and Momentum Profits, Trading Volume, as well as Volatility

Our survey of the psychology literature suggests that people in individualistic cultures are likely to be more overconfident about the precision of their information and more prone to the self-attribution bias than are people in collectivistic cultures. Hence, motivated by DHS (1998), who indicate that overconfidence and the self-attribution bias can generate momentum profits and long-term return reversals, we examine whether these return patterns are stronger in individualistic countries than in collectivistic countries. In addition, since previous studies also suggest that these behavioral biases generate excess trading volume and volatility (DHS (1998), Statman, Thorley, and Vorkink (2006), and Glaser and Weber (2009)), we also examine whether or not excess trading volume and volatility are more pronounced in individualistic countries.

II. Data Description and Summary Statistics

A. Hofstede's Individualism Index

The individualism index (*Indv*) that we use comes from a cross-country psychological survey of employee values conducted by Geert Hofstede between 1967 and 1973. The subjects of this survey were IBM employees in 72 countries and included about 88,000 respondents. Out of the 72 countries surveyed, 40 of them had more than 50 respondents.[7] The individualism index was calculated from the country mean scores on 14 questions about the employees' attitudes toward their work and private lives. Factor analysis was then used to analyze the country mean scores on the work-goal questions and two factors were produced that together explained about 46% of the variance. The individualism index is constructed from the scores on the first factor.[8]

B. Stock Market Data

With the exception of the U.S. sample that comes from CRSP, we use stock returns and trading volume from Datastream International. The data are available for 55 countries from February 1980 (for some countries) to June 2003.[9] The starting date for each country varies according to the availability of data

[7]Ten more countries were added to this sample at a later stage. Hofstede (2001) discusses the statistical method used to make the data obtained from these 10 new countries consistent with the data collected from the initial 40 countries.

[8]The first factor is highly correlated with 6 out of the 14 work-goal questions. Hofstede (2001) uses these six work-goal questions to illustrate the relationship between individualism and self-construal. These six work-goal questions are listed in the Internet Appendix. The value of the individualism index (*Indv*) for country i is calculated as $Indv_i = 50 + 25 \times Factor\ Score_i$ from the first factor. This formula helps constrain the index to a value between 0 and 100. The scores on the second factor are used to construct the index on masculinity.

[9]Before February 1980, we can obtain only limited data on select stocks in some of the countries in our sample from Datastream International.

on Datastream International.[10] We include all common stocks, both domestic and foreign, which are listed on the major stock exchange(s) in each country.[11] A cross-listed stock is included only in its home country sample.[12]

The quality of stock market data obtained from Datastream International, in particular for emerging markets, is not as good as the quality of the data from CRSP.[13] To mitigate this problem, we screen out a number of observations. As in Hong, Lee, and Swaminathan (2003), if the market capitalization of a stock is below the fifth percentile of all the stocks within a given country in any month, its return in that month is treated as missing. Our conclusion on the relationship between individualism and momentum is not affected by this screening process. For Datastream data, we set the returns that are larger (less) than 100% (–95%) equal to 100% (–95%). This procedure not only helps us to filter out suspicious stock returns, but it also ensures that the momentum effect in each country is not driven primarily by small and/or illiquid stocks.[14] To calculate the past 6-month cumulative returns on individual stocks as well as to measure the returns on the momentum portfolios, we also require each stock in our sample to have a return history of at least 8 months.

Since we need a reasonable number of stocks to form momentum portfolios, we require each country to have at least 30 stocks that meet our stock selection criteria in any month during our sample period. In addition, we require each momentum portfolio in each country to have a return history of at least 5 years. Because of these last two criteria, our sample includes only 41 countries for which there are more than 20,000 individual stocks.

[10]We calculate the stock returns adjusted for dividends from the stock return index provided by Datastream International. In months in which a stock is not traded, Datastream International carries forward its return index in the previous month to the current month. Therefore, a stock return of zero may be a result of no trading. To remedy this problem, we compute a stock's return in the current month only if the trading volume of this stock is positive in the current month as well as in the previous month. If monthly trading volume data are not available (for some countries in the early 1980s), we only calculate the return on a stock in the current month if the return index of this stock in the current month is not the same as that in the previous month. The monthly trading volume on individual stocks is also collected from Datastream International.

[11]If a stock has multiple share classes, we only include its primary class in our sample. For example, only the A-shares in the Chinese stock market and the bearer-shares in the Swiss stock market are included in our sample.

[12]We collect data on the stocks that are in the "Research" stocks list and the "Dead" stocks list. Both lists are provided by Datastream International. Including stocks from the "Dead" stocks list helps to alleviate the survival bias in our sample.

[13]As discussed by Ince and Porter (2006) and others, the data errors from Datastream International are mainly concentrated in small stocks and/or low-price stocks.

[14]We check our trimmed data from Datastream International against the data from PACAP and find that there is no material difference between these two data sources. In addition, we trim our data using two alternative screening processes. First, following Hong et al. (2003), our sample includes stock returns with values within the 1st percentile and the 99th percentile of the return distribution in each month for each country. Second, our sample excludes stocks with their market capitalization in the top or bottom 5% of the market capitalization distribution in each month for each country. Our findings do not change when we use these alternative filters. The returns on the momentum portfolios constructed from the samples using alternative screening processes are reported in the Internet Appendix.

Table I lists the countries included in our study along with their scores on the individualism index. Table I also reports the total market capitalization of their stock exchanges and the number of firms that meet our sample requirements at three different times: the first month of the sampling period, December 1996, and June 2003.[15]

In addition to the individualism index (*Indv*), we explore a large number of variables that may explain the cross-country variation in momentum profits. These variables are discussed in later sections and described in more detail in the Internet Appendix.[16]

III. Individualism, Trading Volume, and Volatility

To check the validity of Hofstede's individualism index (*Indv*) as a measure of overconfidence and self-attribution bias, we examine the extent to which cross-country differences in trading volume and volatility can be explained by this measure. Our motivation for these validity checks is the theoretical literature that suggests that these behavioral biases generate excess trading volume and volatility in stock markets (e.g., DHS (1998), Odean (1998), Gervais and Odean (2001), and Scheinkman and Xiong (2003)). The relationship between trading volume and overconfidence is quite intuitive. Overconfident investors trade more, because they overestimate the precision of their information. In addition, Odean (1998) argues that trading by overconfident investors leads to excess volatility. Previous theoretical and empirical studies also indicate that overconfidence together with the self-attribution bias generate excess trading volume and volatility (DHS (1998), Statman et al. (2006), and Glaser and Weber (2009)).

As in Griffin, Nardari, and Stulz (2007), we measure a country's trading volume as its turnover (*TN*), the ratio of the market dollar trading volume to the market capitalization of the Datastream global index for the country.[17] Similar to Bae, Chan, and Ng (2004) and Bekaert, Harvey, and Lundblad (2007), we use the squared monthly return to measure the monthly volatility of a stock. The average stock volatility in country j in month $t(V_{jt})$ is the average of the squared monthly returns on the stocks in month t in country j:

$$V_{jt} = \frac{\sum_{i=1}^{N_{jt}} R_{ijt}^2}{N_{jt}}, \tag{1}$$

[15]The sample periods used to calculate values in Table I start 12 months after the actual sample periods, since we need to use 12 observations on returns to compute the returns for momentum portfolios.

[16]An Internet Appendix for this article is online in the "Supplements and Datasets" section at http://www.afajof.org/supplements.asp.

[17]We have market turnover data for 48 countries that include the 46 countries in the study by Griffin, Nardari, and Stulz (2007). The two additional countries are Bulgaria and Romania. The dollar trading volume in Germany is inflated by about 100% because of the trading mechanism in Germany. Therefore, we divide the turnover of the Datastream global index for Germany by two. However, our finding does not change even if Germany is excluded from our sample.

Table I

Summary Statistics

Our sample consists of data on individual stocks from 41 markets around the world. We require each country in our sample to have a score on Hofstede's individualism index. Except for U.S. market data, all our data are collected from Datastream International. For the U.S. market, the data are obtained from the CRSP database. Within each country, we delete stocks whose market capitalization is below the fifth percentile of all stocks in each month. If a stock's return from Datastream is larger (smaller) than 100% (−95%), we set its return equal to 100% (−95%). Furthermore, we require each country to have at least 30 stocks with observations on market capitalization and returns in each month during our sample period and each country should have sufficient data to measure the returns on the momentum portfolios for at least 5 years. We only include common stocks (both domestic and foreign stocks) that are listed on the major exchange(s) in each country. A cross-listed stock is only included in its home country sample. This table reports the name of the major exchange(s) and the total market capitalization (in million U.S. dollars) in each country at three different times: the first month when we start to measure the returns on the momentum portfolios, December 1996, and June 2003. The first month varies across countries because data in each country available on Datastream starts on different dates. To match the data from Datastream, the first month for the U.S. market is set to February 1980. Also reported is Hofstede's individualism index (*Indv* index). The number of firms used to calculate the statistics is reported in square brackets.

Country (Stock Exchange)	*Indv* Index	Period	Market Cap (US$ million)	Start Month	Dec. 1996	June 2003
Argentina	46	199409–200306	Market cap	42,360	44,179	76,242
(Buenos Aires)			No. of firms	[61]	[57]	[58]
Australia	90	198103–200306	Market cap	35,151	254,124	401,366
(Australian)			No. of firms	[127]	[757]	[1,017]
Austria	55	198602–200306	Market cap	2,746	29,116	36,647
(Vienna)			No. of firms	[31]	[83]	[67]
Bangladesh	20	199302–200306	Market cap	205	3,443	2,062
(Dhaka)			No. of firms	[60]	[111]	[197]
Belgium	75	198103–200306	Market cap	3,316	73,058	139,203
(Brussels)			No. of firms	[43]	[114]	[150]
Brazil	38	199508–200306	Market cap	49,277	71,683	83,782
(Sao Paulo)			No. of firms	[48]	[58]	[90]
Canada	80	198102–200306	Market cap	66,478	369,828	600,917
(Toronto)			No. of firms	[260]	[789]	[847]
Chile	23	199008–200306	Market cap	7,779	50,281	52,473
(Santiago)			No. of firms	[81]	[110]	[95]
China	20	199309–200306	Market cap	24,076	82,338	470,740
(Shanghai & Shenzhen)			No. of firms	[63]	[318]	[1,096]
Denmark	74	198902–200306	Market cap	12,730	42,382	65,788
(Copenhagen)			No. of firms	[72]	[155]	[120]
Finland	63	199108–200306	Market cap	10,161	45,501	125,125
(Helsinki)			No. of firms	[38]	[75]	[118]
France	71	198103–200306	Market cap	33,382	580,130	1,063,890
(Paris)			No. of firms	[129]	[497]	[634]
Germany	67	198103–200306	Market cap	57,201	499,297	745,812
(Frankfurt)			No. of firms	[131]	[286]	[730]
Greece	35	198902–200306	Market cap	2,593	22,806	79,392
(Athens)			No. of firms	[51]	[184]	[301]

(continued)

Table I—*Continued*

Country (Stock Exchange)	*Indv* Index	Period	Market Cap (US$ million)	Start Month	Dec. 1996	June 2003
Hong Kong	25	198103–200306	Market cap	31,590	407,691	457,134
(Hong Kong)			No. of firms	[60]	[440]	[588]
India	48	199102–200306	Market cap	32,488	87,626	147,247
(Mumbai)			No. of firms	[264]	[647]	[653]
Indonesia	14	199105–200306	Market cap	16,149	84,313	37,062
(Jakarta)			No. of firms	[81]	[171]	[222]
Ireland	70	198705–200306	Market cap	6,318	27,708	58,531
(Dublin)			No. of firms	[34]	[39]	[39]
Israel	54	199212–200306	Market cap	11,224	26,206	57,528
(Tel Aviv)			No. of firms	[140]	[455]	[279]
Italy	76	198103–200306	Market cap	20,665	182,465	474,450
(Milan)			No. of firms	[72]	[172]	[245]
Japan	46	198103–200306	Market cap	352,540	3,238,767	2,323,485
(Tokyo & JASDAQ)			No. of firms	[792]	[2,374]	[2,760]
Korea	18	198508–200306	Market cap	5,933	118,586	257,263
(Korea & KOSDAQ)			No. of firms	[237]	[653]	[1,356]
Malaysia	26	198702–200306	Market cap	18,511	258,879	126,960
(Kuala Lumpur & MESDAQ)			No. of firms	[176]	[379]	[499]
Mexico	30	199204–200306	Market cap	32,759	37,407	31,140
(Mexico City)			No. of firms	[37]	[47]	[39]
Netherlands	80	198103–200306	Market cap	26,214	400,694	423,026
(Amsterdam)			No. of firms	[139]	[163]	[144]
New Zealand	79	198902–200306	Market cap	6,433	29,018	26,830
(New Zealand)			No. of firms	[50]	[93]	[108]
Norway	69	198103–200306	Market cap	2,526	48,799	67,770
(Oslo)			No. of firms	[35]	[127]	[133]
Pakistan	14	199308–200306	Market cap	4,516	7,438	11,617
(Karachi)			No. of firms	[95]	[114]	[175]
Philippines	32	199101–200306	Market cap	4,417	68,088	17,429
(Manila)			No. of firms	[41]	[152]	[105]
Poland	60	199801–200306	Market cap	7,438	n.a.	28,204
(Warsaw)			No. of firms	[57]		[176]
Portugal	27	198902–200306	Market cap	2,506	23,464	35,397
(Lisbon)			No. of firms	[45]	[84]	[51]
Singapore	20	198402–200306	Market cap	13,872	148,294	114,365
(Singapore)			No. of firms	[86]	[230]	[398]
South Africa	65	198103–200306	Market cap	28,921	146,767	116,567
(Johannesburg)			No. of firms	[54]	[336]	[279]
Spain	51	198804–200306	Market cap	50,631	183,272	410,845
(Madrid)			No. of firms	[53]	[116]	[122]
Sweden	71	198302–200306	Market cap	80,117	154,090	158,003
(Stockholm)			No. of firms	[39]	[199]	[293]
Switzerland	68	198103–200306	Market cap	15,767	82,593	43,872
(Zurich)			No. of firms	[55]	[98]	[83]
Taiwan	17	198907–200306	Market cap	119,540	251,522	274,043
(Taiwan)			No. of firms	[48]	[270]	[394]

(continued)

Table I—*Continued*

Country (Stock Exchange)	*Indv* Index	Period	Market Cap (US$ million)	Start Month	Dec. 1996	June 2003
Thailand	20	198802–200306	Market cap	7,281	87,776	56,806
(Thailand)			No. of firms	[75]	[366]	[308]
Turkey	37	198902–200306	Market cap	989	25,656	37,821
(Istanbul)			No. of firms	[38]	[179]	[263]
United Kingdom	89	198102–200306	Market cap	192,536	1,504,293	1,734,019
(London)			No. of firms	[1,619]	[1,204]	[1,407]
NYSE, (Amex & NASDAQ)	91	198102–200306	Market cap	1,265,854	7,689,812	11,391,074
			No. of firms	[4,146]	[6,732]	[4,885]

where R_{ijt} is the return on stock i in country j in month t and N_{jt} is the number of stocks in country j in month t. To calculate the average volatility of country j in month t, we require country j to have at least 30 stocks in month t.[18]

A. Individualism and Trading Volume

To investigate the relation between individualism and trading volume, we estimate the following regression:

$$\begin{aligned} LnTN_{jt} = \beta_o + \beta_1 Indv_j + \beta_2 Insider_j + \beta_3 Political_{jt} \\ + \beta_4 Fxvol_{jt} + \beta_5 Credit_{jt} + \beta_6 LnV_{jt} + \varepsilon_{jt}, \end{aligned} \tag{2}$$

where the subscripts j and t represent country j and month t, respectively. Since trading volume is highly persistent, we cluster the residuals by both country and month to compute the t-statistics on the estimated coefficients (see Petersen (2009) for a discussion of the robust t-statistics in this setting). The dependent variable is the natural logarithm of the market trading volume (*LnTN*). The independent variables include the individualism index (*Indv*) and other determinants of trading volume.

Although there is no empirical study on the determinants of cross-country trading volume, existing theoretical and cross-sectional research on stocks in the United States suggests that trading volume is likely to be related to the cost of trading, information asymmetries, and uncertainty about the aggregate economy. Based on studies that show that political risk is a determinant of liquidity costs across countries (Bekaert et al. (2007), Eleswarapu and Venkataraman (2006), and Lesmond (2005)), we include the political risk index (*Political*) from the International Country Risk Guide (ICRG) as a measure of a country's political stability. To capture the effect of asymmetric information, we control for the level of financial development with the ratio of total private credit to

[18] We compute average stock volatility for 50 countries out of the 55 countries for which we have data on stock returns from Datastream.

GDP (*Credit*) (as in Stulz and Williamson (2003)) and for the prevalence of insider trading with the insider trading index (*Insider*) obtained from La Porta, Lopez-de-Silanes, and Shleifer (2006). To measure the volatility of the overall economy we follow Du and Wei (2004) and use the volatility of the exchange rates (*Fxvol*), measured as the coefficient of variation of the monthly exchange rate calculated from the previous 5 years, as a proxy for monetary policy uncertainty. Since trading volume is affected by information flows that generate stock return volatility, we also include the natural logarithm of average stock volatility (*LnV*) as a determinant of cross-country trading volume.

Panel A in Table II reports the regression results. The estimated coefficients of *Political* and *Credit* are positive and significant, which is consistent with the idea that countries with lower liquidity costs tend to have larger trading volume.[19] The positive and significant coefficients on *Fxvol* and *LnV* indicate that trading volume is positively related to the uncertainty of monetary policies and information flow.[20] However, the estimated coefficient on *Insider* is significantly negative, indicating that higher insider trading leads to larger trading volume, which is inconsistent with our expectations. After controlling for these variables, we find that the estimated coefficient on *Indv* is significantly positive (t-statistic $= 2.13$).

To check the robustness of our result to estimation methods, we also use the Fama–MacBeth (1973) procedure to estimate equation (2). Following Chordia, Huh, and Subrahmanyam (2009), who use the Fama–MacBeth procedure to investigate cross-sectional variation in turnover in the United States' market, we use Newey–West (1994) heteroskedasticity and autocorrelation consistent estimates of standard errors to compute the t-statistics on the Fama–MacBeth coefficients.[21] The results from the Fama–MacBeth regressions are similar to those reported in Panel A of Table II except that the significance levels are much higher. We also ran a simple regression using average values of trading volume and independent variables from January 1995 to June 2003 to estimate equation (2) and the result from this OLS regression is again

[19]Liquidity costs include market depth, price impact, the number of no-trading days, and others.

[20]It is worth mentioning that trading volume also reflects investors' differences of opinion on a stock's intrinsic value as suggested by Harris and Raviv (1993), Blume, Easley, and O'Hara (1994), and Lee and Swaminathan (2000). That is, the higher the difference of opinion among investors, the greater the trading volume. However, including the dispersion of analyst forecasts (*Disp*) in the trading volume regression analysis does not change our results. More specifically, when *Disp* is included, the estimated coefficient on *Indv* is 0.009 with a t-statistic of 2.06 and the estimated coefficient on *Disp* is –0.079 with a t-statistic of –0.59.

[21]All Fama–MacBeth regression results in this paper report the time-series averages of cross-sectional OLS estimates of the coefficients. The Newey–West (1994) heteroskedasticity and autocorrelation consistent estimates of standard errors are used to compute the t-statistics on these average coefficients. As suggested by Newey and West (1994), we select the lag length (L) that equals the integer portion of $12(T/100)^{2/9}$, where T is the number of observations. As a robustness check, we also determine the lag length (L) from the autocorrelation functions of these estimates. The autocorrelation functions are computed over lag 1 to lag 24. We set $L = k$ when the autocorrelation coefficient of lag k is significant at the 5% level and the autocorrelation coefficients of higher lags are insignificant. Our results do not change if we use the second method to determine the lag length.

Table II
Individualism, Stock Market Trading Volume, and Average Stock Volatility

Panel A reports the OLS estimates of the coefficients related to market trading volume. The market trading volume (*TN*) of country *j* in month *t* is measured as the market dollar trading volume of the Datastream Global Index of this country divided by this index's market capitalization in month *t*. The natural logarithm of monthly market trading volume (*LnTN*) is regressed on Hofstede's individualism index (*Indv*), the insider index (*Insider*), the political risk index (*Political*), the volatility of the exchange rate (*Fxvol*), the total private credit expressed as a ratio of GDP (*Credit*), and the natural logarithm of market volatility (*LnV*). Panel B reports the OLS estimates of the coefficients related to average stock volatility. The monthly average stock volatility is computed as the average of the monthly squared stock returns. The natural logarithm of monthly average stock volatility (*LnV*) is regressed on Hofstede's individualism index (*Indv*), the insider index (*Insider*), the total private credit expressed as a ratio of GDP (*Credit*), the volatility of real GDP per capita growth rates (*Gwvol*88), the volatility of the exchange rate (*Fxvol*), the ratio between the monthly market value of the S&P-IFC market index and the monthly market value of the S&P-IFC investable index (*Open*), the debt ratio (*Debt*), and the market value expressed as a ratio of GDP (*MCap*). While *Indv, Insider,* and *Gwvol*88 are constant over time, all other variables are updated monthly or annually. The definitions of these variables are described in the Internet Appendix. The sample period is from January 1988 to June 2003. We use the Petersen (2009) procedure to compute the standard errors clustered by country and month. Robust *t*-statistics are in parentheses.

Panel A: Market Trading Volume		Panel B: Average Stock Volatility	
Intercept	−2.588	Intercept	5.378
	(−4.80)		(11.44)
Indv	0.010	*Indv*	0.009
	(2.13)		(2.62)
Insider	−0.351	*Insider*	−0.325
	(−2.30)		(−3.88)
Fxvol	0.017	*Fxvol*	0.015
	(2.17)		(5.18)
Credit	0.932	*Credit*	0.149
	(4.28)		(0.89)
Political	0.027	*Gwvol*88	0.125
	(3.09)		(2.83)
LnV	0.300	*Open*	−0.181
	(4.46)		(−0.56)
		Debt	1.016
			(1.68)
		MCap	0.002
			(2.84)
Min. no. of countries	13		12
Max. no. of countries	38		36
Median no. of countries	34		31

similar to our result from the panel regression. The results on the volume regressions from alternative estimation methods are reported in the Internet Appendix.

In summary, we find evidence of a strong and robust positive relationship between individualism and cross-country trading volume even after controlling for variables that potentially explain the normal level of trading volume.

B. Individualism and Volatility

In a cross-country study, Du and Wei (2004) document that market volatility is negatively related to the degree of financial market development, and positively related to the volatility of real GDP growth rates, the volatility of exchange rates (*Fxvol*), the country's debt ratio (*Debt*), and the prevalence of insider trading (*Insider*). In a study of emerging market volatility, Bekaert and Harvey (1997) find that cross-country volatility is also negatively related to the ratio of market capitalization to GDP (*MCap*) and the openness of the capital market (*Open*). Bae et al. (2004) report that volatility in emerging markets is positively related to the investability of the stocks in these markets. We use the ratio of total private credit to GDP (*Credit*) as a measure of financial market development. The volatility of real GDP growth is computed as the standard deviation of the real GDP growth rates from 1988 to 2003 (*Gwvol88*) or from 1995 to 2003 (*Gwvol95*). As in Bekaert et al. (2007), we use the investability index in each country as a measure of stock market openness (*Open*). The country's debt ratio (*Debt*) is the average leverage ratio of firms.

Panel B of Table II provides estimates of the following volatility regression with standard errors clustered by country and month:

$$LnV_{jt} = \beta_o + \beta_1 Indv_j + \beta_2 Insider_j + \beta_3 Credit_{jt} + \beta_4 Gwvol88_j + \beta_5 Fxvol_{jt} + \beta_6 Open_{jt} + \beta_7 Debt_{jt} + \beta_8 MCap_{jt} + \varepsilon_{jt}. \quad (3)$$

Consistent with Du and Wei (2004), we find that *Insider* has a negative effect on stock volatility and the volatility of real GDP growth rates (*Gwvol*88) has a positive effect on stock volatility. Similar to Bekaert and Harvey (1997), we find that the volatility of exchange rates (*Fxvol*) has a positive effect on stock volatility. In contrast to their finding, we find that the ratio of market capitalization to GDP (*MCap*) has a strong positive effect on stock volatility. One should note, however, that their finding pertains to emerging markets, while our sample includes both developed and emerging markets. More importantly, we find that the estimated coefficient on *Indv* is positive and significant (t-statistic = 2.62). The estimated coefficients on other variables are not significant.[22]

To investigate whether the positive relationship between individualism and volatility is robust to estimation methods, we use the Fama–MacBeth (1973) procedure, with Newey–West (1994) heteroskedasticity and autocorrelation consistent estimates of standard errors, to estimate equation (3). We also run a

[22]Du and Wei (2004) use the natural logarithm of real GDP (*LnGdppc*) as a measure of financial market development. By replacing the ratio of total credit to GDP (*Credit*) with *LnGdppc* in our regression analysis of volatility, we find that the estimated coefficient on individualism (*Indv*) is still significantly positive (t-statistic = 2.36), while the estimated coefficient on *LnGdppc* is significantly negative.

simple regression using average values of volatility and independent variables from January 1995 to June 2003 to estimate equation (3). The results, in the Internet Appendix, indicate that the estimated coefficient on *Indv* is positive and significant for all specifications and, with a few exceptions, the coefficient estimates of the other variables are similar to those estimated by the OLS regression.

IV. Returns on Momentum Portfolios

This section reports, for each country, the profitability of momentum strategies that form portfolios based on stocks' past 6-month returns and that hold the stocks for 6 months. For each market, stocks with performance in the bottom one-third during the formation period are assigned to the loser (L) portfolio, while those in the top one-third are assigned to the winner (W) portfolio. These portfolios are equally weighted and are not rebalanced over the 6-month holding period.[23] We use the top and the bottom one-third rather than the 10% cutoffs used by Jegadeesh and Titman (1993) because of the smaller sample sizes in most countries. In addition, to minimize the effect of the bid-ask bounce and the lead-lag effect, we skip 1 month between the ranking period and the holding period.[24] The returns are all measured in U.S. dollars. However, our findings are virtually identical if we measure returns in local currencies.

As in Jegadeesh and Titman (1993) we construct overlapping momentum portfolios; for example, the winner portfolio formed in January is the equally weighted combination of those stocks with cumulative returns in the top one-third over the previous June-to-November period (the W portfolio in November), over the previous May-to-October period (the W portfolio in October), and so on up to the previous January-to-June period (the W portfolio in June). If a stock has a missing return during the holding period, we replace it with the corresponding value-weighted market return. If a stock is delisted, we rebalance the portfolio at the end of the delisting month.[25]

Panel A of Table III presents the average U.S. dollar monthly returns (%) of the winner portfolio, the loser portfolio, and the winner-minus-loser portfolio for each of the 41 countries. The results in Table III indicate that all

[23] We equal-weight rather than value-weight portfolios to put more weight on the smaller stocks, because psychological biases are more important for individual domestic investors and small stocks are mainly traded by this type of investor.

[24] A number of stocks in our sample, particularly those from the emerging markets, are thinly traded. The illiquidity of these stocks may generate negative serial correlation in the returns that can swamp any underlying positive serial correlations in the returns. In addition, the data errors in stock prices that occur in month t usually will be corrected in month $t + 1$. This correction in data errors will also generate a negative serial correlation in returns. Having a 1-month gap between the portfolio formation period and the holding period helps remedy this problem.

[25] Returns on these W/L portfolios in month t are computed as [(the average cumulative returns of the stocks in these portfolios in month t divided by the average cumulative returns of these stocks in month $t - 1$) – 1] times 100%. We effectively compute the buy-and-hold returns on these portfolios. The portfolios are rebalanced only at the end of the 6-month holding period.

Table III

Momentum Profits by Country

At the end of each month, all stocks in each country are ranked in ascending order based on the past 6-month cumulative returns. Stocks in the bottom one-third are assigned to the "L" portfolio and those in the top one-third to the "W" portfolio. These equally weighted portfolios are held for 6 months. To increase the power of the tests, overlapping portfolios are constructed. The winner (loser) portfolio is an overlapping portfolio that consists of "W" ("L") portfolios in the previous 6 ranking months. Returns on these portfolios are measured 1 month after ranking. Returns on these portfolios in month t are computed as (average cumulative returns of the stocks in these portfolios in month t divided by average cumulative returns of these stocks in month $(t - 1) - 1$). Returns on the winner and loser portfolios are the simple average of the returns on the six "W" and the six "L" portfolios, respectively. If a stock has a missing return during the holding period, it is replaced by the corresponding value-weighted market return. If a stock is delisted, we rebalance the portfolio at the end of the delisting month. The momentum portfolio (W – L) is a zero-cost, winner-minus-loser portfolio. Panel A reports the average monthly returns (%) on these portfolios in U.S. dollars for each country. The country-average portfolio is a portfolio that puts equal weight on each country-specific momentum portfolio in this portfolio. The formation of the composite portfolio is similar to that of the momentum portfolio in each country. Specifically, at the end of each month, all stocks in each country are ranked in ascending order based on the past 6-month cumulative returns. Stocks in the top one-third of past returns in each country are assigned to the "W" portfolio and the bottom one-third stocks are assigned to the "L" portfolio. The minimum number of countries in each portfolio in our sample at any point in time must be at least two. These equally weighted portfolios are held for 6 months. Similar to the country-specific momentum portfolio, the composite portfolio is an overlapping portfolio. The average monthly returns (%) on these country-average and composite portfolios in U.S. dollars are reported in Panel B. Corresponding t-statistics are in parentheses.

Panel A: By Country

Country	Winner (W)	Loser (L)	W Minus L
Argentina	0.559 (0.66)	0.483 (0.42)	0.076 (0.12)
Australia	1.639 (3.60)	0.564 (1.18)	1.075 (4.76)
Austria	1.126 (2.84)	0.501 (1.27)	0.625 (2.70)
Bangladesh	3.171 (2.81)	1.494 (1.57)	1.677 (2.75)
Belgium	1.723 (5.90)	0.830 (2.82)	0.893 (5.50)
Brazil	1.548 (1.43)	1.088 (0.84)	0.459 (0.96)
Canada	1.823 (5.10)	0.478 (1.18)	1.345 (6.29)
Chile	2.129 (3.76)	1.136 (2.00)	0.993 (3.60)
China	1.233 (0.98)	0.976 (0.80)	0.257 (0.92)
Denmark	1.235 (3.87)	0.273 (0.79)	0.962 (4.29)
Finland	1.457 (2.58)	0.480 (0.68)	0.977 (2.62)
France	1.819 (4.91)	0.877 (2.20)	0.942 (4.68)
Germany	1.218 (3.93)	0.225 (0.59)	0.993 (4.41)
Greece	2.352 (2.50)	1.767 (1.88)	0.585 (1.49)
Hong Kong	1.583 (2.65)	0.811 (1.24)	0.772 (3.18)
India	1.957 (2.18)	0.819 (0.84)	1.138 (2.91)
Indonesia	0.917 (0.76)	0.781 (0.54)	0.136 (0.30)
Ireland	1.342 (3.13)	0.458 (0.98)	0.884 (3.06)
Israel	0.851 (1.03)	0.531 (0.63)	0.320 (1.19)
Italy	1.309 (3.06)	0.405 (0.89)	0.904 (4.47)
Japan	0.883 (2.04)	0.922 (1.91)	−0.039 (−0.18)
Korea	1.257 (1.65)	1.594 (1.83)	−0.337 (−0.81)
Malaysia	1.427 (1.75)	1.329 (1.37)	0.098 (0.26)
Mexico	1.181 (1.67)	0.488 (0.62)	0.693 (2.00)

(continued)

Table III—*Continued*

Panel A: By Country

Country	Winner (W)	Loser (L)	W Minus L
Netherlands	1.759 (5.56)	0.928 (2.63)	0.831 (4.40)
New Zealand	2.148 (4.52)	0.566 (1.05)	1.582 (5.01)
Norway	2.121 (4.90)	1.075 (2.27)	1.046 (3.77)
Pakistan	1.189 (1.38)	0.729 (0.72)	0.461 (1.05)
Philippines	0.823 (0.96)	0.450 (0.43)	0.372 (0.68)
Poland	1.141 (1.16)	−0.623 (−0.60)	1.764 (3.33)
Portugal	0.806 (1.94)	0.498 (1.00)	0.308 (0.93)
Singapore	1.064 (1.81)	0.921 (1.25)	0.143 (0.47)
South Africa	1.540 (3.15)	0.604 (1.15)	0.936 (3.29)
Spain	1.035 (2.44)	0.410 (0.80)	0.625 (2.24)
Sweden	1.499 (3.60)	0.787 (1.48)	0.711 (2.27)
Switzerland	1.285 (4.06)	0.465 (1.45)	0.819 (4.39)
Taiwan	0.347 (0.39)	0.549 (0.57)	−0.202 (−0.48)
Thailand	1.739 (2.19)	1.260 (1.36)	0.479 (1.10)
Turkey	3.044 (2.18)	3.458 (2.43)	−0.414 (−0.96)
United Kingdom	1.708 (4.92)	0.576 (1.56)	1.132 (7.08)
United States	1.523 (4.36)	0.735 (1.78)	0.788 (3.44)
Average	1.476 (16.38)	0.798 (8.58)	0.678 (8.54)

Panel B: All Countries

Portfolio Formed Method	Period	Winner (W)	Loser (L)	W Minus L
Country-average	1984:02–2003:06	1.680 (5.84)	0.955 (3.06)	0.725 (7.35)
Composite	1984:02–2003:06	1.371 (4.72)	0.851 (2.46)	0.519 (3.49)

but four countries (Japan, Korea, Taiwan, and Turkey) exhibit positive momentum profits. The profits in 25 of the countries are statistically significant. The highest momentum profits are in Poland (1.764% per month), Bangladesh (1.677% per month), New Zealand (1.582% per month), and Canada (1.345% per month).[26]

To test whether the cross-country differences in momentum profits are persistent, we divide the whole sample into two subsamples: the first half (February 1984 to June 1993) and the second half (July 1993 to June 2003). For the 36 countries that are in both subperiods, the Spearman rank correlation between their momentum profit ranks in these two subsamples is 0.33 (p-value = 0.05). For the 22 countries that have at least 60 monthly observations on momentum profits in each subsample the Spearman rank correlation increases to 0.50 (p-value = 0.02).

Panel B of Table III reports momentum profits from portfolio strategies that exploit the momentum strategy around the world. We refer to the first as the country-average momentum portfolio and the second as the composite momentum portfolio.[27] The country-average portfolio equally weights each

[26] However, the results for Poland are based on a return history of only 5 years.

[27] We also consider the momentum strategy that classifies winners and losers based on the past 6-month returns on *all* stocks in our sample. This momentum strategy yields larger profits

country-specific momentum portfolio. The composite momentum portfolio is weighted more toward the countries with more stocks. More specifically, at the end of each month, all stocks in the "W" portfolio in each country are assigned to the "global W" portfolio and all stocks in the "L" portfolio in each country are assigned to the "global L" portfolio. The minimum number of countries in each portfolio in our sample at any point in time must be at least two and the sample period starts in February 1984 and ends in June 2003.[28]

The result in Panel B of Table III indicates that the average monthly return on the country-average portfolio over the period from February 1984 to June 2003 is 0.72% per month (t-statistic = 7.35). The average monthly momentum profit on the composite portfolio is 0.52% per month with a t-statistic of 3.49. The magnitude of these returns is similar to what we observe for momentum portfolios in the United States. However, the t-statistics are much larger because the international momentum portfolio is much more diversified.[29]

V. Individualism and the Profitability of Momentum Strategies: Portfolio Analysis

In this section, we investigate the relation between individualism and the profitability of momentum strategies across countries. We classify countries into three groups, from low (bottom 30%) to high (top 30%), based on their scores on the individualism index (*Indv*). Country-average and composite portfolios are formed in each *Indv*-sorted group of countries.

In Table IV we report the average monthly returns on *Indv*-sorted momentum portfolios. These results reveal that momentum profits monotonically increase with the score of the individualism index. The average return on the high-*Indv* country-average portfolio is 1.04% per month with a t-statistic of 7.93, and the spread in the average returns between the high-*Indv* and the low-*Indv* country-average portfolios is 0.65% per month, which is highly significant with

than the country-average or the composite portfolios. In particular, the average monthly return on this strategy over the period from February 1981 to June 2003 is 0.93% per month (t-statistic = 5.73). In contrast to our country-average and composite momentum portfolios, this portfolio is not country-neutral.

[28]To be consistent with the sample period of the individualism-sorted momentum portfolios, the sample periods for the country-average and composite portfolios start in February 1984. Over the period from February 1981 to June 2003, the average monthly return on the country-average portfolio is 0.68% per month (t-statistic = 7.67) and that on the composite portfolio is 0.51% per month (t-statistic = 3.79).

[29]Our sample includes the 38 countries included in Griffin, Ji, and Martin (2003). The correlation between the average cross-country momentum profits in this study and in Griffin et al. (2003) is 0.67 (p-value = 0.00). The correlation between the average cross-country momentum profits in Griffin et al. (2003) and the individualism index is 0.49 (p-value = 0.00). However, our findings are not directly comparable since Griffin et al. (2003) classify the top (bottom) 20% of stock returns as winners (losers), while our study uses the top and bottom one-third designations. Furthermore, our sample ends in June 2003, while their sample ends in December 2000.

Table IV

Momentum Profits and Individualism

This table reports average monthly momentum profits (%) in U.S. dollars for country-average portfolios (Panel A) and composite portfolios (Panel B) classified by Hofstede's individualism index. The country-average portfolio is a portfolio that puts equal weight on each country-specific momentum portfolio in this portfolio. The formation of the composite portfolio is similar to that of the momentum portfolio in each country. See Table III for the detailed description of the constructions of the country-average and composite portfolios. At the end of each month, all countries in our sample are allocated into three groups, from low (bottom 30%) to high (top 30%), based on their scores on the individualism index. Country-average (or composite) portfolios are formed in each individualism-sorted group. The test period is from February 1984 to June 2003. The corresponding t-statistics are in parentheses.

Portfolio Formed Method	Index on Individualism	Winner (W)	Loser (L)	W Minus L
	Panel A: Country-Average Portfolios			
Country-average	Low	1.628	1.241	0.387
		(4.30)	(2.96)	(2.80)
	2	1.693	1.004	0.689
		(5.22)	(2.90)	(5.91)
	High	1.748	0.707	1.041
		(6.14)	(2.27)	(7.93)
	High minus low	0.120	−0.534	0.654
		(0.39)	(−1.53)	(4.30)
	Panel B: Composite Portfolios			
Composite	Low	1.465	1.343	0.122
		(3.60)	(2.89)	(0.74)
	2	1.266	1.028	0.238
		(3.61)	(2.69)	(1.58)
	High	1.538	0.837	0.701
		(4.90)	(2.12)	(3.29)
	High minus low	0.073	−0.507	0.579
		(0.21)	(−1.28)	(2.61)

a t-statistic of 4.30. Similarly, the spread in average returns between the high-*Indv* and the low-*Indv* composite portfolios is 0.58% per month with a t-statistic of 2.61.

We also compute the annual spread in average returns between the high-*Indv* and the low-*Indv* country-average portfolios by calendar year over the period from 1984 to 2002 and find positive annual spreads in 14 out of 19 years.[30] The average annual spread is 8.57% and it is significantly positive (t-statistic = 3.37). The median, minimum, and maximum annual spreads are 7.02%, –9.75%, and 26.56%, respectively.

[30]There are 11 monthly spreads (February to December) in 1984. Since we only have six monthly spreads in 2003, we exclude 2003 from this analysis.

VI. Other Determinants of Cross-Country Momentum: Regression Analysis

In this section, we examine other possible cross-country determinants of momentum. To do so, we regress momentum profits on the individualism index and other potential determinants:[31]

$$Mom_{jt} = \alpha_o + \beta_1 Indv_j + F_j\gamma_1 + A_{jy}\gamma_2 + M_{jt}\gamma_3 + \varepsilon_{jt}, \tag{4}$$

where Mom_{jt} is the return on the momentum portfolio in country j in month t and $Indv_j$ is the individualism index of country j. While F_j is a vector of explanatory variables that are constant over time, A_{jy} and M_{jt} are vectors of explanatory variables that are updated annually and monthly, respectively. The Internet Appendix provides more information about these explanatory variables. The ε_{jt} is an error term. We use the Fama–MacBeth (1973) procedure to estimate equation (4). The t-statistics of the averages of the time-series estimates from these month-by-month, cross-sectional regressions are adjusted for heteroskedasticity and autocorrelation using the Newey and West (1994) method.

A. Firm Characteristics Suggested by Behavioral Research

A number of studies examine the extent to which stocks in the United States with different firm characteristics suggested by behavioral research exhibit more or less momentum. In this section we describe some of these cross-sectional determinants and examine the extent to which cross-country differences in the average values of these characteristics explain differences in momentum profits across countries.

The variables that we consider have previously been used to proxy for the speed of information flow and information uncertainty. These variables include turnover (examined in Lee and Swaminathan (2000) and Verardo (2009)), firm size (examined in Jegadeesh and Titman (1993), Daniel and Titman (1999), Hong, Lim, and Stein (2000) and Zhang (2006)), analyst coverage (examined in Hong, et al. (2000), Zhang (2006), and Verardo (2009)), cash flow volatility (examined in Zhang (2006)), dispersion in analyst forecasts (examined in Zhang (2006) and Verardo (2009)), and return volatility (examined in Zhang (2006) and Verardo (2009)). Following this earlier work we include the following variables: market trading volume (*TN*), average dispersion in analyst forecasts in a country (*Disp*), the average volatility of the individual stocks in a market (*V*), the volatility of the growth of cash flows (*Cfvol*) computed from each country's cash flow component of the Datastream global index, the median firm size in a country (*SZ*), and the average number of analysts following each stock in a country (*Ana*).[32]

[31] When momentum profits are regressed on individualism (*Indv*) only, the estimated coefficient on *Indv* is significantly positive (t-statistic = 4.84).

[32] Daniel and Titman (1999) also find that book-to-market ratios and momentum profits are negatively related. In regressions reported in the Internet Appendix, we include the natural logarithm of the book-to-market ratio based on the Datastream global index. The estimated coefficient on *LnBM* is insignificant and none of the other coefficients change materially.

The results from the Fama–MacBeth (1973) regressions reported in Panel A of Table V reveal that the coefficient on *Indv* is positive and quite significant after controlling for these other potential determinants of momentum profits. Among the other explanatory variables, only the estimated coefficients on *LnSZ, LnDisp*, and *LnV* are significant. Consistent with Zhang (2006) and Hong et al. (2000), cross-country differences in momentum are positively related to dispersion in analyst forecasts (*LnDisp*), but are negatively related to firm size (*LnSZ*). In contrast to Zhang (2006) and Verardo (2009), the estimated coefficient on stock market volatility (*LnV*) is negative. Based on joint *F*-tests, we conclude that the coefficients on this group of variables are reliably different from zero both with and without the individualism variable.[33]

B. Financial Market Development and Institutional Quality

The informational efficiency of a country's financial markets may be related to the development and integrity of the financial markets. The idea is that better developed stock markets with greater integrity facilitate the flow of information and reduce trading costs.

As suggested by Stulz and Williamson (2003), we use the ratio of total private credit to GDP (*Credit*) as a measure of financial market development. To measure the extent to which foreign institutions can invest in the market, we use an index on capital flow restrictions (*Control*, where a higher value indicates more restrictions), the average common language dummy variable (*Lang*, where a higher score indicates more common languages) used by Chan, Covrig, and Ng (2005), and, following Bekaert et al. (2007), the ratio of the market capitalization of the stocks comprising the S&P-IFC investable index to the market capitalization of the stocks comprising the S&P-IFC global index in each country as a measure of stock market openness (*Open*).

Our regression results from Panel B of Table V indicate that individualism is still significantly positive when these variables are included in the regression.[34] However, of the financial development variables included, only language (*Lang*) is statistically significant, and the *F-test* measuring the significance of the

[33]We also regress momentum profits on *Indv* and each of the explanatory variables listed in Table V one at a time. In these bivariate regressions, only the estimated coefficients on the natural logarithm of market trading volume (*LnTN*), the natural logarithm of market volatility (*LnV*), the natural logarithm of firm size (*LnSZ*), the natural logarithm of the transaction cost index (*LnTran*), and the average common language dummy variable (*Lang*) are significant. The signs of these coefficients are the same as those reported in Table V. However, the estimated coefficient on *LnTN* becomes insignificant in Panel A of Table V. Moreover, this coefficient is insignificant when *LnTN* is the only explanatory variable in the regression (i.e., a univariate regression). On the other hand, the estimated coefficients on *Indv* are always significantly positive in all the bivariate regressions. These findings indicate that the insignificant coefficients in Table V are unlikely due to multicollinearity problems.

[34]To be consistent with the sample period of the comprehensive model, the sample periods for the tests related to financial market development and market integrity start in January 1987. The results from tests covering the sample period from February 1984 to June 2003 are quite similar and are reported in the Internet Appendix.

Table V

Determinants of Momentum Profits across Countries: Results from the Fama–MacBeth Regressions

Monthly returns on country-specific momentum portfolios are regressed on Hofstede's individualism index (*Indv*) and different sets of explanatory variables. Panel A reports the results related to a set of variables that are suggested by behavioral momentum models. These variables include the natural logarithm of market trading volume (*LnTN*), the natural logarithm of analyst coverage (*LnAna*), the natural logarithm of the dispersion of analyst forecasts (*LnDisp*), the logarithm of stock market volatility (*LnV*), the cash flows growth rate volatility (*Cfvol*), and the logarithm of median firm size (*LnSZ*). Panel B shows the results related to a set of proxies for the financial market development. These proxies are the total private credit expressed as a ratio of GDP (*Credit*), the average common language dummy variable (*Lang*), the ratio between the monthly market value of the S&P-IFC market index and the monthly market value of the S&P-IFC investable index (*Open*), and an index on control of capital flows (*Control*). Panel C reports the results related to a set of variables related to institutional quality. This set of variables includes the insider index (*Insider*, a higher score indicates that insider trading is less prevalent), the ICRG corruption index (*Crp*, a higher value indicates a lower corruption level), the ICRG political risk index (*Political*), the natural logarithm of the transaction cost index (*LnTran*), and the investor protection index (*Protection*). Panel D reports the results from the comprehensive model. The descriptions of all the variables are listed in the Internet Appendix. The row "*Starting date*" shows the starting month for the test in each panel and all the tests end in June 2003. This table reports the time-series averages of cross-sectional OLS estimates of the coefficients. The t-statistics are in parentheses. The Newey–West (1994) heteroskedasticity and autocorrelation consistent estimates of standard errors are used to compute these t-statistics. F_1 (an F-statistic) is used to test the hypothesis that all the estimated slope coefficients except the coefficient on *Indv* are jointly equal to zero. F_2 (an F-statistic) is used to test the hypothesis that all the estimated slope coefficients are jointly equal to zero. The p-values are in parentheses.

	Panel A: Behavioral Models	Panel B: Market Development	Panel C: Institutional Quality	Panel D: Comprehensive
Intercept	5.974 (4.95)	0.385 (1.41)	−1.891 (−1.96)	3.501 (2.90)
Indv	0.015 (4.29)	0.014 (5.24)	0.019 (6.24)	0.015 (4.44)
LnTN	−0.158 (−1.01)			
LnDisp	0.181 (1.64)			0.205 (1.94)
LnV	−0.839 (−4.60)			−0.651 (−3.97)
Cfvol	−0.005 (−0.52)			
LnSZ	−0.305 (−2.69)			−0.260 (−3.97)
LnAna	0.163 (1.22)			
Credit		−0.162 (−0.93)		
Lang		1.330 (1.92)		1.944 (2.65)
Open		−0.412 (−1.05)		
Control		−0.008 (−0.30)		
Insider			−0.099 (−0.54)	
Crp			0.066 (0.65)	
Political			0.003 (0.18)	
LnTran			0.405 (3.16)	0.295 (2.33)
Protection			−0.070 (−0.28)	
F_1	6.10 (0.00)	2.03 (0.09)	2.09 (0.07)	8.40 (0.00)
F_2	8.55 (0.00)	5.97 (0.00)	8.24 (0.00)	12.64 (0.00)
Min. no. of countries	28	15	17	17
Max. no. of countries	39	37	33	36
Med. no. of countries	36	34	32	35
Starting date	January 1992	January 1987	January 1987	January 1987

variables other than individualism fails to reject the null hypothesis that the coefficients of these variables are all equal to zero.

To measure market integrity we include the prevalence of insider trading (*Insider*, where a higher score indicates that insider trading is less common), and investor protection (*Protection*, where a higher score indicates a higher level of protection). These variables were considered previously by La Porta et al. (2006). We also include the corruption index (*Crp*, where a higher score indicates a lower level of corruption) and the political risk index (*Political*, where a higher scores indicates a lower risk level). These indexes, from the ICRG, have been shown to be related to liquidity across countries (Lesmond (2005) and Eleswarapu and Venkataraman (2006)). In addition, we include the estimate of transaction costs (*Tran*, where a higher value indicates a higher trading cost) used by Chan et al. (2005) as the measure for the cost of trading stocks in each country.

Panel C of Table V reports the results from the Fama–MacBeth (1973) regressions that contain these variables.[35] Again, we find that the estimated coefficient of *Indv* remains significantly positive after the inclusion of these variables. In addition, the coefficient of the natural logarithm of the transaction cost index (*LnTran*) is positive and significant, but the estimated coefficients of the other integrity variables are insignificant and the F-test fails to reject the null hypothesis that the coefficients of the variables other than individualism are all equal to zero.

C. *Rational Momentum Models*

This section examines the extent to which the cross-country differences in momentum profits can be explained by variables suggested in the rational momentum literature. First, as discussed in Jegadeesh and Titman (1993) and Conrad and Kaul (1998), momentum profits can be partially attributed to the cross-sectional variation in expected stock returns. In addition, Johnson (2002) and Sagi and Seasholes (2007) suggest that momentum profits are higher for firms with better growth options.

To measure the variation in expected stock returns in each country, we use the standard deviation of beta estimates (*StdBeta)*. To measure the availability of growth options, we use the Bekaert et al. (2007) measure of the average local growth opportunities (*LGO*) of a country. We also investigate whether variation in momentum profits across countries is related to earnings growth volatility (*Eavol*) and dividend growth volatility (*Divvol*). We compute these volatilities from the earnings and dividends of the Datastream global index of each country.

The results from the Fama–MacBeth regressions reported in the Internet Appendix suggest that when these variables are included in our regressions,

[35]In tests reported in the Internet Appendix, we also include the concentration of ownership obtained from La Porta et al. (2006), the ICRG law, and order index and a dummy variable for common law countries in the regressions. Similar to the reported findings, only the estimated coefficients on *Indv* and *LnTran* are significant and positive. In addition, replacing *LnTran* with *Tran* in our regressions does not change our findings.

the estimated coefficient on *Indv* remains significantly positive. However, the estimated coefficients on the rational momentum variables are insignificant. Indeed, the *F*-test fails to reject the null hypothesis that the coefficients of the variables other than individualism are all equal to zero at conventional significance levels.

D. A Comprehensive Model

It would be of interest to include all the variables in equation (4) instead of estimating the coefficients in groups. However, since our cross-country sample has a relatively limited number of countries (41 at a maximum), we have limited degrees of freedom.

In this subsection we present regressions that include only those variables that are significant at the 10% level or better in Table V. These regressions include the common language dummy variable (*Lang*), the natural logarithm of the transaction cost index (*LnTran*), the natural logarithm of median firm size (*LnSZ*), the natural logarithm of dispersion in analyst forecasts (*LnDisp*), and the natural logarithm of stock market volatility (*LnV*). The coefficient estimates from this Fama–MacBeth regression, reported in Panel D of Table V, are all significant and have the same signs as those in previous regressions.[36]

VII. Robustness Checks

A. Additional Variables

The results in the previous section indicate that individualism is significantly related to momentum profits in various specifications that include a substantial number of variables that can conceivably explain the cross-country pattern of momentum profits. In tests reported in the Internet Appendix, we consider additional explanatory variables that include the macroeconomic risk factors suggested by Chordia and Shivakumar (2002). We find that none of these variables are significant.[37] In short, we were unable to come up with plausible determinants of momentum profits that subsume the effect of individualism.

[36]We also perform a bootstrap test to investigate the statistical significance of the cross-sectional relation between individualism and momentum profits. This test is carried out in a balanced sample with 35 countries over the period from January 1995 to June 2003. Specifically, we generate data by sequentially selecting the individualism score along with other variables in our comprehensive model and randomly assign them to one of the 35 countries in our sample without replacement. We generate 1,000 random assignments, and for each random assignment, we repeat the multivariate regression specified in equation (4). The findings on *Indv, LnDisp, LnV*, and *LnSZ* are similar to those obtained from the Fama–MacBeth regressions and confirm that the positive relation between individualism and momentum profitability is not likely to be due to chance. This finding is reported in the Internet Appendix.

[37]The macroeconomic variables we considered include the real per capita GDP growth rates (*Gdppcgw*), the change in exchange rates (*Cfx*), and the dividend yield (*DY*). The regression result related to macroeconomic factors is reported in the Internet Appendix.

In addition, since the motivation of this study is based in part on the fact that momentum profits are weak in East Asian countries (Chui et al. (2003)), and given these countries have low scores on the individualism index, it is important to perform an out-of-sample test that does not include the East Asian countries. We therefore remove the 10 East Asian countries from our sample and rank the remaining 31 countries, from low (bottom 30%) to high (top 30%) according to their scores on the individualism index. We construct three *Indv*-sorted country-average portfolios from this reduced sample. We find that the average monthly returns on the low-*Indv*, medium-*Indv*, and high-*Indv* country-average portfolios are 0.72%, 0.94%, and 1.14%, respectively.[38] The spread in average monthly returns between the high-*Indv* and the low-*Indv* portfolios is 0.42%, which is significant at the 5% level (t-statistic = 2.15). As an additional test, we include a dummy variable for East Asian countries (*EAsia*) in our comprehensive model as specified in equation (4). As shown in the Internet Appendix, the inclusion of *EAsia* has little effect on the regression (it reduces the t-statistic of the estimated coefficient on the individualism index (*Indv*) from 4.44 to 3.25), and its coefficient is negative but insignificant. These results suggest that the positive relation between individualism and momentum is not driven by East Asian countries.[39]

B. An Alternative Individualism Index

To investigate the robustness of our results, we consider an alternative measure of individualism that comes from the GLOBE (Global Leadership and Organizational Behavior Effectiveness) project. We use the country scores from GLOBE's institutional collectivism index from House et al. (2004). A detailed discussion of GLOBE is in the Internet Appendix. We are able to find scores from GLOBE's institutional collectivism index for 33 of the countries in our sample. Using $Indv_{GLOBE}$ instead of Hofstede's individualism index (*Indv*), we re-estimate the Fama–MacBeth regressions specified in equation (4). Consistent with our previous results, the results in the Internet Appendix show that the estimated coefficient on $Indv_{GLOBE}$ is positive and significant (t-statistic = 1.90).

[38]Since we require each country-average portfolio to have at least two countries, the average returns on these country-average portfolios are calculated from the period between February 1989 and June 2003.

[39]We also estimate our comprehensive model using the reduced sample of non-East Asia countries over the period from January 1987 to June 2003. The results from the Fama–MacBeth regression show that the estimated coefficient on *Indv* is 0.017 with a t-statistic of 2.43. For robustness checks, we also use the Petersen (2009) panel regression procedure clustered by country and month as well as the simple OLS regression model based on time-series means from 1995 to 2004 to reestimate the comprehensive model with and without *EAsia*. The findings from these robustness tests are reported in the Internet Appendix. We find that the results are similar to those reported in Table V.

C. Additional Culture Variables

In addition to examining Hofstede's individualism index, we also consider Hofstede's other culture indexes: masculinity (*MAS*), power distance (*PDI*), and uncertainty avoidance (*UAV*). Although the link between these cultural attributes and the behavioral biases, described in the finance literature, are somewhat tenuous, there are plausible links that can be explored. The results in the Internet Appendix indicate that including these additional culture variables in our simple regression models or comprehensive model does not change our findings.[40] While the estimated coefficient of the individualism index (*Indv*) is significantly positive, the estimated coefficients of the other culture variables are insignificant.

D. Do Small Firms Affect Our Results?

Since smaller stocks tend to generate greater momentum profits, it is possible that the positive relation between momentum and individualism is driven by a relation between average firm size and momentum. To investigate this possibility, we remove all stocks with a market capitalization less than US$100 million from our sample.[41] This requirement forces us to reduce the number of countries in our sample to 37 and to change the sample starting period from February 1984 to February 1987. Based on this reduced sample, we find that the average monthly returns on the high-*Indv*, medium-*Indv*, and low-*Indv* country-average portfolios are 0.88%, 0.53%, and 0.29%, respectively. The spread in average returns between the high-*Indv* and the low-*Indv* country-average portfolios is 0.59% per month (t-statistic = 3.01), which is very close to the spread of 0.65% reported in Table IV. Similar findings are obtained using composite portfolios. Hence, the positive relationship between individualism and momentum does not seem to be driven by the small firms in our sample.

We also examine a sample that excludes the largest stocks in each market, since these stocks may be influenced by the trades of foreign institutions and thus may be less influenced by the cultures within the individual countries. Specifically, we remove all stocks with a market capitalization larger than the median of all the stocks within a given country in any month in our sample.[42] Using the monthly profits of the momentum portfolio constructed in each

[40] Since only 18 countries in our sample have scores on the cultural value of long-term orientation, including this variable in our test, reduces our sample size by 50%. Therefore, we exclude this variable from our analysis.

[41] Over the period from December 1983 to June 2003, the average (median) monthly 30$^{\text{th}}$ percentile NYSE/Amex breakpoint of market capitalization was US$92 million (US$84 million). The maximum 20$^{\text{th}}$ percentile NYSE/Amex breakpoint of market capitalization was US$91 million. Removing small firms from our sample can also help improve our data quality, since data errors for Datastream International are mainly concentrated in small firms.

[42] After we remove stocks with a market capitalization larger than the median of all the stocks within a given country in any month, the momentum profits for all *Indv*-sorted country groups become stronger. The momentum profits in the high-*Indv* group exceed those in the low-*Indv* group by about 0.66% per month with a t-statistic of 3.67.

country with this smaller sample, we re-estimate the Fama–MacBeth (1973) regression specified in equation (4) and find that the estimated coefficient on *Indv* is 0.016 with a *t*-statistic of 4.00. When the dummy variable for East Asian countries (*EAsia*) is included in the comprehensive model, the coefficient on *Indv* is still significantly positive. The results from the Fama–MacBeth regressions using the small stock sample with and without *EAsia* are reported in the Internet Appendix.

E. Limiting Our Sample to Developed Markets

There are a number of relatively undeveloped financial markets in our sample. The stocks in these countries have very low market capitalization, they are often illiquid, and the data may be of lower quality. For this reason, we replicate our tests on a sample of 26 countries that are classified as advanced economies by the International Monetary Fund (IMF). These countries are mainly those countries in the EURO region, the United Kingdom, the United States, Japan, Hong Kong, Korea, Taiwan, and Singapore. Among these advanced economies, 5 are classified as low-*Indv*, 9 are classified as medium-*Indv*, and 12 are classified as high-*Indv*. The spread in momentum profits between the high-*Indv* countries and the low-*Indv* countries in this smaller sample is 0.84% per month with a *t*-statistic of 4.98.

VIII. Post-holding Period Returns

Behavioral momentum models suggest that, over longer horizons, the momentum effect is subsequently reversed. In this section we examine the post-holding period returns of the momentum portfolios and test whether these returns are indeed more negative in countries with higher scores on the individualism index.

Table VI reports the average monthly returns for the *Indv*-sorted country-average and composite portfolios for the 3 years subsequent to the formation date. Consistent with our previous results, during the first year after formation, the average monthly profits on these momentum portfolios are positive and increase with the degree of individualism. However, in the 24 subsequent months, the momentum portfolios exhibit negative returns, which is consistent with the findings of Jegadeesh and Titman (2001) for firms in the United States.

During the second year after portfolio formation, the magnitude of the return reversals is significantly higher in high individualism countries than in low individualism countries (difference = −0.32% per month with a *t*-statistic of −2.06) only for the composite momentum portfolio.[43] In contrast, during the

[43] The major reason for the difference in return reversals between the country-average and the composite momentum portfolios in the second year after portfolio formation is that the United States and Japan have a much greater weight in the composite portfolio. When we exclude the United States and Japan from our sample, we still find a positive relation between the magnitude of return reversals and individualism; however, the effect is no longer significant.

Table VI
Individualism and Post-holding Period Returns on Momentum Portfolios

This table presents average monthly momentum profits (%) in U.S. dollars for country-average portfolios (Panel A) and composite portfolios (Panel B) classified by Hofstede's individualism index (a lower score indicates a lower degree of individualism). The construction of these portfolios is discussed in Table III. The average monthly momentum profits are calculated over different post-holding periods. There is a 1-month gap between the portfolio formation period and the holding period. The test period is from February 1984 to June 2003. All t-statistics are in parentheses. The Newey–West (1994) heteroskedasticity and autocorrelation consistent estimates of standard errors are used to compute these t-statistics.

Individualism Rank	Months 1–12	Months 13–24	Months 25–36	Months 13–36
Panel A: Country-Average Portfolios				
Indv-low	0.065	−0.274	0.010	−0.145
	(0.42)	(−2.16)	(0.07)	(−1.29)
Indv-2	0.562	−0.021	−0.123	−0.090
	(4.59)	(−0.17)	(−1.18)	(−0.95)
Indv-high	0.740	−0.146	−0.296	−0.222
	(4.90)	(−1.35)	(−2.77)	(−2.60)
High minus low	0.675	0.128	−0.306	−0.078
	(3.82)	(0.88)	(−1.82)	(−0.61)
Panel B: Composite Portfolios				
Indv-low	−0.122	−0.326	−0.232	−0.305
	(−0.78)	(−3.65)	(−2.60)	(−5.25)
Indv-2	0.119	−0.302	−0.269	−0.299
	(1.23)	(−3.05)	(−3.22)	(−4.46)
Indv-high	0.367	−0.646	−0.543	−0.604
	(2.80)	(−4.47)	(−3.78)	(−5.16)
High minus low	0.489	−0.320	−0.311	−0.299
	(3.68)	(−2.06)	(−1.79)	(−2.25)

third year after portfolio formation, the difference in the return reversals between high- and low-individualism countries is statistically significant at the 10% level for both country-average and composite momentum portfolios.

In the Internet Appendix we show that the extent of the return reversals is stronger when we limit our analysis to a sample of smaller stocks with a market capitalization below the median of all the stocks within a given country in any month in our sample. Within this sample of smaller stocks we do find that, indeed, the extent of the long-term return reversals is significantly stronger in high individualism countries than in low individualism countries for both country-average and composite momentum portfolios.

IX. Conclusion

It is always interesting to compare the profitability of investment strategies across international markets. In addition to providing a robustness check on results generated from excessively mined U.S. data, a cross-country study can potentially provide evidence on how cultural differences as well as institutional differences affect the efficiency of financial markets.

The Jegadeesh and Titman (1993) momentum effect provides a major challenge to the efficient market hypothesis. Looking just at U.S. data, one might conclude that the momentum effect is both too persistent (i.e., it generates positive returns in all post-war decades) and too strong (i.e., it generates implausibly high Sharpe ratios) to be explained by risk. As our analysis demonstrates, the momentum strategies generated with global data provide even higher Sharpe ratios and thus provide an even greater challenge to traditional finance theories.

The cross-country differences in momentum profits described in this paper provide a challenge to behavioral as well as traditional risk-based theories. Although the risk-based theorists must explain why momentum returns are risky in the United States and Europe but not in Japan and in most East Asian countries, the behavioral theorists must explain why individuals in some, but not all countries, are subject to the psychological biases that cause momentum.

The evidence in this paper indicates that culture can have an important effect on stock return patterns, which is consistent with the idea that investors in different cultures interpret information in different ways and are subject to different biases. One interpretation of our results on the relation between momentum profits and cultural differences is that in less individualistic cultures investors put less weight on information that they come up with on their own and more weight on the consensus of their peers. In other words, individuals in less individualistic cultures act less like the overconfident/self-attribution biased investors described by Daniel et al. (1998), and thus tend not to make investment choices that generate momentum profits.

Of course, there are a number of competing theories of momentum and our evidence in support of a behavioral theory should be viewed more as circumstantial than definitive. By identifying a cross-country relationship between momentum profits and individualism we hope that this study can help motivate future research on how cultural differences influence stock returns. For example, since Hong et al. (2003) find that earnings momentum is stronger in Western countries than in East Asian countries, it might make sense to examine the cross-country relation between earnings momentum and individualism. Another possibility worth considering is that investors in less individualistic cultures place too much credence on consensus opinions, and may thus exhibit herd-like overreaction to the conventional wisdom.[44]

[44]To briefly follow up on this idea, we evaluate the returns of high and low book-to-market (*BM*) portfolios, which are available for 22 countries from Ken French's website. These portfolio returns over the period from January 1984 to December 2003 are sorted into three groups, from low (bottom 30%) to high (top 30%), based on their scores on the Hofstede's individualism index (*Indv*). The average monthly *BM* effect for the low-*Indv*, the medium-*Indv*, and the high-*Indv* groups are 0.530%, 0.438%, and 0.099%, respectively. The difference in the *BM* effect between the low-*Indv* and the high-*Indv* groups is 0.431% per month with a t-statistic of 1.87.

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