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Student ID number: 1 3 0 0 8 2 5 6

Student's name: The Hung Nguyen

Student's signature:

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Return Predictability and Complicated Countries

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The Hung Nguyen

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Return Predictability and Complicated Countries

Abstract

Prices should instantly reflect information according to the efficient markets hypothesis (EMH). Hong and Stein (1999), however, suggest that the information processing environment will affect price discovery because of the gradual diffusion of information. This paper investigates the roles of information processing complexity in the price discovery process across countries. We hypothesise that the same piece of relevant macroeconomic information can be incorporated into stock prices at different speeds, depending on the complication of information environment in each country. The results show that returns for less complicated countries can predict future returns for more complicated countries with the out-of-sample R^2's ranging from 3% to 14%. We find that the predictability induced by the complications in information processing is consistent at both group level and country level. Moreover, our results prevail after we control for regional effects.

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1. Introduction

Prices should instantly reflect information under the efficient market hypothesis (EMH). Hong and Stein (1999), however, suggest that the information processing environment will affect price discovery because of the gradual diffusion of information. In this paper, we confirm the roles of information processing complexity in the price discovery process across different countries. We hypothesise that the same piece of relevant macroeconomic information can be incorporated into stock prices at different speeds, depending on the complication of information environment in each country. The results show that returns from less complicated countries predict future returns for more complicated countries[1] with the out-of-sample R^2's ranging from 3% to 14%. Our results are consistent with previous literature that documents the roles of information asymmetry in return predictability. Cohen and Lou (2012), for instance, show that complexity in information processing generates a return predictability from easy-to-analyse firms to conglomerate firms. Our findings are also consistent with financial news media stories, which often suggest that some countries (e.g. the United States (US)) are affected by the macroeconomic news earlier than other countries[2]. Analysts cite the speed of information delivery as the crucial indicator to understand the changes in market price[3]. Motivated by a strand of literature that suggests the important roles of country and industry effects in understanding financial markets[4], we examine the findings of Cohen and Lou (2012) for a large sample of countries and focus on two sets of countries with substantial differences in information processing quality.

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[1] Sample countries are classified into less or more complicated groups depending on the consistency in the rankings of their indices. Details of our classifications are provided in later sections.

[2] For instance: regarding news on the warning of a global recession in 2015, Economist David Levy suggested that "*When the US sneezes, the rest of the world catches a cold*" (Cordon, 2014). Retrieved from: http://www.independent.co.uk/news/business/analysis-and-features/doom-and-gloom-2015-global-recession-warning-from-financial-seers-of-the-century-9624700.html

[3] For example, Metreveli (2012) notes that "*the effects of news on price changes strongly depend on the speed of data delivery*".

[4] For instance, Moskowitz and Grinblatt (1999) show a strong link between industry effects and the momentum phenomenon. Nijman, Swinkels, and Verbeek (2004) find the significant roles of country and industry effects in momentum strategy.

Viswanathan and Childers (1996) and Kozup, Howlett, and Pagano (2008) point out that the key to effective processing of information lies in how easily the information conveys meanings in an information processing context. We study information processing complexity across countries, since it is important in three ways. First, different countries are different in their trading mechanisms and information processing channels, leading to different incorporation speeds of information into asset prices. The variations in information processing across countries, therefore, create opportunities and challenges for mutual funds and multinational corporations. Since mutual funds and multinational firms could serve as a channel connecting one country with other nations, understanding the country's information processing contributes to understanding global financial markets. Second, a strand of literature documents the impacts of the level of capital market development on market quality and price efficiency (Madhavan, 1996; Bloomfield & O'Hara, 1999; Bessembinder, Maxwell, & Venkataraman, 2006; De la Torre, Gozzi, & Schmukler, 2007), and on information collection and processing capacity (Perotti & Von Thadden, 2003; Cornand & Heinemann, 2008). Some studies suggest that several regions and countries have a higher level of market transparency and information disclosure than others (Patel, Balic, & Bwakira, 2002; La Porta, Lopez-de-Silanes, & Shleifer, 2006; Edwards, Harris, & Piwowar, 2007). Based on these findings, we may infer that investors from higher-transparency and disclosure countries may have better access to information and thus, have better information processing, since information in such countries is supposed to flow more freely and more frequently. The complexity in country information processing, therefore, has asset pricing implications from an international perspective. Finally, the diversification in information processing capacity across countries provides a setting for further research to investigate how a country's unique characteristics, for instance, language, culture, social norms, and other geographic factors, influence investors' information collecting and processing capacity (Huang, 2012). All things considered, the complication in country information processing requires thorough and comprehensive research; our paper takes a step in this direction.

This paper contributes to a growing strand of literature on the effects of information asymmetry on return predictability. To the best of our knowledge, this is the first study that investigates the return predictability induced by complications in country information processing for a large sample of countries. This research is also a pioneer study on the return effects between two groups of countries with substantially different information processing capacities.

To be specific, we employ the country indices from a survey of La Porta et al. (2006) as a benchmark to assess each country's information processing environment. As they note, the country indices are based on the answers of attorneys, in a sample of 49 countries with the largest stock market capitalisation in 1993 (La Porta, Lopez-de-Silanes, Shleifer, & Vishny, 1998). The selected indices in La Porta's survey provide a comprehensive assessment for the information processing environment in different countries. Inspired by existing studies that show the positive relationship between the level of country transparency[5] and the holdings of international investors (Diamond & Verrechia, 1991; Gelos & Wei, 2005), we rank these indices for all countries in the sample and assess the consistency of the rankings. We find that some countries exhibit a fairly consistent trend in ranking indices while others witness an immense complication[6] in rankings. While it is often straightforward to make an investment decision in countries with relatively consistent ranking indices (e.g., the US, Canada), it requires more complex analyses to invest in countries with complicated information processing (e.g., Colombia, Korea). The variations in the speed of information incorporation into asset prices across countries, therefore, may lead to a return predictability. To test how the return predictability can be induced by the complications in country information processing, we define two extreme groups of countries that exhibit substantial differences in the ranking indices of the information processing quality, and investigate the relation between returns for these two groups. We find that returns for a group with less-

[5] Galos and Wei (2005) document that transparency can be regarded as a channel to appeal capital and reduce capital market volatility and an increase transparency results in an increase in investment flows in a certain country.

[6] When rankings are too complex for users to fully incorporate, these rankings create the complications in processing.

complicated information processing (hereafter the *Less-Com* group) is a strong predictor for future stock returns for a peer group with more complicated information process (hereafter the *More-Com* group).

We further analyse the return predictability for individual countries in the *More-Com* group. If the information barriers among countries really matter and there exists a significant predictability for the whole *More-Com* group, we would expect a considerable return predictability for individual countries in the *More-Com* group. We find that returns for the *Less-Com* group can predict future returns for eight over ten individual countries in the *More-Com* group. Our findings, therefore, are consistent at both group level and country level.

Inspired by a growing body of literature that shows that several regions and countries have a higher level of market transparency and information disclosure (Patel et al., 2002; La Porta et al., 2006; Edwards et al., 2007), and thus, may take better advantages of information processing than other regions and nations, we study the return predictability for the *More-Com* group in each region. To test the regional effects, we classify countries in the *More-Com* group and *Less-Com* group into each region, and then compute return for each group in that region. We find that not only can the *Less-Com* group for the whole sample, but also the *Less-Com* group in each region, predict the return for the *More-Com* group in that region. Again, these results are consistent at both group level and country level.

We provide evidence for the economic linkage between the complications in country information processing and stock return predictability. Information barriers among countries seem to be the cause of gradual diffusion of information. Hong and Stein (1999) and Hong, Torous, and Valkanov (2007) suggest that if investors have limited information processing capacity, information will gradually be incorporated into stock prices. The under-reaction of asset prices to relevant information, as a result, may lead to a noticeable return predictability in financial markets (Cohen & Lou, 2012; Bakshi, Panayotov, & Skoulakis, 2014). Since information is diffused gradually due to the complications in country information processing, it takes more time to incorporate the same piece of macroeconomic information into stock prices for a set of countries with the more complicated information processing, than for a set of countries with the less complicated process. In other words, stock returns for the *Less-Com* group have predictive power for future stock returns for the *More-Com* group.

We show that the predictability of the *Less-Com* group is closely related to its ability to predict stock return components, both cash flows and discount rates components. We also find a positive relation between the ability to predict future stock returns and ability to predict economics fundamental for return. Thus, the return predictability induced by the complications in information processing gains its support from both cash flow channels and discount rates channels. We also investigate whether return predictability is driven by time-varying risk premiums. Accordingly, if there exists a significantly positive relation between returns for the *Less-Com* group and expected volatility in stock returns for the *More-Com* group, the returns for the *Less-Com* group can capture expected risk premium, and hence, help forecast stock returns for the *More-Com* group. Our results do not support this argument. We finally examine the learning theory that suggests that as time goes by, investors start paying more attention to new predictors, and hence, predictability tends to diminish over time. Our results support the learning theory for group level prediction but not for country level prediction.

Our results are robust and consistent. The return predictability induced by the complications in country information processing is significant not only at group level but also at country level. We also conduct several robustness tests. First, the out-of-sample R^2's, which range from 3% to 14% for group return prediction, and from 2.6% to 15.8% for individual country return prediction, indicate strong out-of-sample predictability for stock return compared to established predictors in previous literature[7]. In addition, the bootstrapping critical value out-of-sample R^2's are highly statistically significant. Second, we examine the reversed relationship to test if the returns for the *More-Com* group can predict future stock returns for the *Less-Com* group. This relationship, if it exists, will cast doubt on the return predictability generated from country information processing capacities. We find no evidence to support this reversed relationship, at either group or country level. Third, we consider the predictive ability of the *Less-Com* group with and without controlling for a country's economic variables, proxied by the three-month Treasury bill rate and log of dividend yields. In both cases, the results consistently indicate the predictive power of the *Less-Com* group. Finally, we test the predictability by using different sources of return indices. The results from different sources are relatively consistent in supporting our findings.

The return predictability induced by the complexity in information processing is closely related to the disagreement about an asset's value and investors' irrationality. Academic studies suggest that differences of opinion, which can be induced by asymmetric information, significantly affect an asset's price discovery process (Diether, Malloy, & Scherbina, 2002). At the country level, the variations in the information processing environment which are induced by asymmetric information, resemble the differences of opinion across these countries, and hence, provide a setting for cross-country asset prediction. Furthermore, behavioural finance, which is described as "the application of psychology to financial decisions" (Shefrin, 2010, p. 1), provides a framework to understand the market anomalies and return predictability. Daniel Kahneman, the winner of the Nobel Prize in Economics in 2002, introduces in his book "Thinking, Fast and Slow" (2011) two thinking systems that generate a human's decision and actions: the fast

[7] Goyal and Welch (2008) document that a number of well-known predictors, such as dividend yield, book-to-market, or nominal interest rate, display a poor out-of-sample prediction for equity premium with out-of-sample R^2 hovering around zero. Rapach, Strauss, and Zhou (2009) show that combining 15 individual forecasts generate out-of-sample R^2 from 1% to 3.58%. More recently, Jacobsen, Marshall, and Visaltanachoti (2014) suggest a new return predictability using price movements in industrial metals that generates out-of-sample R^2 from 3% to 9%. More impressively, Kelly and Pruitt (2013) show that a single factor created from cross-section book-to-market ratios strongly forecasts returns for the US market by generating an out-of-sample R^2 of 13%.

thinking system and the slow thinking system. An example of the fast thinking system is survival instinct: when we face dangerous situations, we act quickly and instinctively to save ourselves. Conversely, the slow thinking system facilitates our analytical functions with limited information, or too much information in a complex world, such as deciding which markets to invest in, or which stocks to buy. Expert analysis also points out the predominant role of the slow thinking system in the world of complex choices.[8] In the world of uncertainty, given the information barriers across countries and the complications in country information processing environments, an investor's irrational actions (either over-reaction or under-reaction) to relevant macroeconomic information creates the sources for cross-country return predictability.

The rest of this paper is structured as follows. Section 2 discusses the back ground and hypotheses. Section 3 reports data description and methodology. Section 4 discusses the predictive results for the group return, while Section 5 discusses results for the country return. Section 6 provides further discussion and Section 7 concludes the paper.

2. Background and Hypotheses

There is an intensive body of literature that documents the effects of information asymmetry to market performances and corporate activities. For example, some literature documents the impact of incomplete information on capital market development (Merton, 1987; Healy & Palepu, 2001); a number of studies investigate the roles of information asymmetry in corporate financing (Easley & O'Hara, 2004; Carpenter & Petersen, 2002); a different strand of literature addresses the impacts of information asymmetry on corporate governances (e.g., Aboody & Lev, 2000; Kanagaretnam, Lobo, & Whalen, 2007); and an emerging strand of literature examines the roles of information asymmetry in return predictability (Cohen & Lou, 2012; Rapach, Strauss, & Zhou, 2013). There is also a growing body of literature that documents the impacts of country

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[8] Eric Bonabeau, the chief scientist of Icosystem- a strategy consulting firm in Massachusetts points out that "*The more options you have to evaluate, the more data you have to weigh, and the more unprecedented the challenges you face, the less you should rely on instinct and the more on reason and analysis*" (Bonabeau, 2003, p.117).

transparency on investment decisions. For instance, Gelos and Wei (2005) find a positive relationship between country transparency and international investment flows into a certain country; Diamond and Verrechia (1991) show that a reduction in information asymmetry reduces a firm's cost of capital; Ferreira and Matos (2008) find that institutional investors have a preference for the stocks in countries with strong disclosure standards; and Bhattacharya, Daouk, and Welker (2003) document that earning opacity increases asymmetric information in a broad set of countries, and the information risks caused by earning opacity affects equity markets around the world.

Our paper is closely related to the strand of literature that investigates predictive ability generated from information processing complexity. Specifically, at firm level, Cohen and Lou (2012) find that the complexity in processing information among different types of firms allows a significant return predictability from easy-to-analyze firms to conglomerate firms. At the country level, Rapach et al. (2013) document the leading role of the US return in forecasting stock returns for some industrialised countries by showing that information tends to slowly diffuse from the US market to its trading partners. However, their research, on one hand, studies a small set of countries in which the US is their largest trading partner; on the other hand, they investigate a set of developed countries in which there are no noticeable differences in information processing capacities. Motivated by research that suggests the important roles of country and industry effects in understanding assets pricing, we examine the findings of Cohen and Lou for a large sample of countries and focus on two sets of countries with substantial differences in information processing. This makes our study stand out from existing literature.

Theoretical frameworks suggest that information barriers among countries could be a natural candidate for gradual diffusion of information- a striking feature of financial markets. The basic theme of information diffusion theory, according to Hong and Stein (1999) and Hong et al. (2007), is that if investors have limited resources and information processing capacity, information is gradually incorporated into stock prices. Given an investor's limited attention, slow information diffusion may prevent the expected stock returns from being fully explained by traditional asset pricing models[9]. The under-reaction of asset prices to relevant information, as a result, may lead to a pronounced return predictability in financial markets (Hong & Stein, 2007; Cohen & Lou, 2012; Bakshi et al., 2014).

Academic studies also document that the impact of gradual diffusion of information on stock prices varies among different types of information and industries. For instance, Ellison and Mullin (2001) find that information about health care reform is gradually incorporated into pharmaceutical stock prices; Hong and Stein (2000) show the relationship between firm-specific information diffusion and the profitability of momentum strategies; DellaVigna and Pollet (2007) point out the effects of demographic shifts on forecasted demand changes; Cohen, Diether, and Malloy (2013) and Hirshleifer, Hsu, and Li (2013) find an impact of gradual information flow on corporate innovation; and Egelhoff (1991) and Huang (2012) show that the operations information of multinational firms can help forecast future stock returns.

Our paper contributes to current literature on gradual-diffusion information at the country level, while also filling the gaps in existing literature on stock return predictability generated from country information processing.

We hypothesise that, given the same piece of relevant macroeconomic information, if the information is diffused gradually as a result of the complications in country information processing, it will take more time to incorporate that information into stock prices for the *More-Com* group than for the *Less-Com* group. In other words, stock returns for the *Less-Com* group have predictive power for future stock returns for the *More-Com* group[10]. This is the first and main hypothesis for this paper, in its alternative form it is as follows:

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[9] The traditional asset pricing models, pioneered by Sharpe (1964) and Lintner (1965), are widely used to measure the relationship between expected return and risk (Fama & French, 2004).

[10] The definition and classification of the *More-Com* and *Less-Com* group are described in details in Section 3: Data and Methodology. In brief, *Less-Com* countries are countries that exhibit the less variation in information environment assessments; whereas; *More-Com* countries exhibit the more complexity in information processing.

Hypothesis 1: The stock returns for the less complicated group can predict stock returns for the more complicated group.

To make a deeper analysis on the predictive power for future stock returns, we consider three additional tests. *First*, we study the stock return predictability for individual countries in the *More-Com* group. We hypothesise that, if the information barriers among countries really matter, the gradual diffusion information gains strong support, and thus, future stock return predictability is supposed to be strong for the whole *More-Com* group, as well as for individual countries in the *More-Com* group. We also examine whether stock returns for the *Less-Com* group can predict stock returns for individual countries in the *More-Com* group.

Second, to further assess the predictability generated from country information processing, we study the return predictability for the *More-Com* group in each region. Existing literature shows that several regions and countries have higher levels of market transparency and information disclosure (e.g., Patel et al., 2002; La Porta et al. 2006; Edwards et al., 2007), and thus, may take better advantages of gradual diffusion information processes than other regions and nations. Regarding regional effects, we examine whether the stock returns for the *Less-Com* group in each region can predict future stock returns for the *More-Com* group in that region. Furthermore, regarding information barriers among countries, we also consider whether the stock returns for the *Less-Com* group in each region can predict stock returns for individual countries in the *More-Com* group in that region.

The thrust of this paper is to not only examine country information processing and its effect on future return predictability, but also to understand the underlying economic rationales for the predictability within the *Less-Com* countries, if evidence for that predictability can be significantly proved. Supposing that information barriers among countries actually exist and there is significant evidence for return predictability generated from gradual diffusion information, in search for an economic interpretation for return predictability, we examine the three following hypotheses.

First, theoretical frameworks and literature point out the two main predictability channels for stock returns: the cash flow channel and the discount rates channel. Those in favor of cash flow predictability channels argue that predictors, by forecast dividend growth or log dividend yield, help forecast next period stock returns (Menzly, Santos, & Veronesi, 2004; Campbell & Vuolteenaho, 2004; Campbell, Polk, & Vuolteenaho, 2010; Bakshi et al., 2014). On the other hand, those supporting the second strand of literature claim that some predictors can predict future stock returns by predicting the discount rate components in returns (Campbell & Vuolteenaho, 2004; Cochrane, 2011; Bakshi et al., 2014). Considering the sources of predictability, we propose the second hypothesis as follows:

Hypothesis 2: Cash flows and Discount rate are the sources of return predictability

We use two approaches to clarify the possible sources of return predictability. In the first approach, we adapt the framework of Bakshi et al. (2014) to study economic interpretation regarding return predictability. Specifically, they argue that the ability to predict return components (either cash flow or discount rate components) is attributed to the ability to predict news related to either cash flow channels, or discount rate channels, or both. Inspired by this argument, we consider whether the stock returns for the *Less-Com* group can predict news related to cash flows, or news related to discount rates, in future stock returns for the *More-Com* group.

In the second approach, we examine the relation between ability to predict stock returns and ability to predict economic fundamentals. We hypothesise that, if information barriers among countries exist, the gradual information diffusion, according to Hong and Stein (1999) and Hong et al. (2007), would become noticeable, since the stock market gradually incorporates information about economic fundamentals. The under-reaction of stock prices to information about economic fundamentals may lead to a return predictability in stock markets. Accordingly, the ability to predict stock returns should be positively related to its ability to predict economic fundamentals. This leads to our next consideration of whether the ability to predict stock returns for the *More-Com* group is significantly positively related to its ability to predict the fundamentals of these returns.

In the third hypothesis, we examine the relation between returns for the *Less-Com* group and volatility-based measures of risk for the *More-Com* group. A growing body of literature attempts to capture the relation between predictability of return and risk premium (French, Schwert, & Stambaugh, 1987; Harvey, 1995; Bollerslev, Tauchen, & Zhou, 2009). Bakshi et al. (2014), especially, argue that a predictor can predict future stock returns by capturing variation in risk premiums, as measured by volatility. Accordingly, if there exists a significantly positive relation between a predictor and expected volatility in stock return, the predictor can capture expected risk premium, and thus help forecast a future stock return. Inspired by the argument of Bakshi et al., we suggest the third hypothesis:

Hypothesis 3: Return predictability is driven by time-varying risk premia

Finally, we consider learning theory that may affect predictive power. McLean and Pontiff (2014) study post-publication predictability and show that market participants may not rapidly respond to publication about market anomalies, and thus, it may take a long time after publication date to incorporate the publication's information into stock prices. Shleifer and Vishny (1997) show that investors may be aware of anomalies in a financial market, but in reality, arbitrages still exist due to a range of market fictions and realistic conditions for professional arbitrage. As a result, professional investors who seriously learn about this mispricing may take advantages of these anomalies.

Why should investors not learn about anomalies? Bakshi et al. (2014) argue that, as time goes by, investors start paying more attention to new predictors and gradually become familiar with return predictability. Stock return predictability, as a result, tends to diminish over time. A growing amount of literature shows the increasing importance of time variation in return predictability, including Henkel, Martin, and Nardari (2011), Dangl and

Halling (2012), and Bakshi et al. (2014). We, therefore, examine the possible learning theory in the following hypothesis:

Hypothesis 4: Stock return predictability diminishes over time due to investor's learning effect

3. Data and methodology

3.1. Data

We choose five information indices from La Porta et al.'s (2006) survey as a benchmark to assess country information processing environment. As they note, the country indices are based on the answers of attorneys from a sample of 49 countries with the largest stock market capitalisation in 1993 (La Porta et al., 1998). We compute these five indices using the arithmetic mean of the corresponding sub-indexes taken from the Appendix of La Porta et al.'s (2006) study[11]. Specifically, the Disclosure requirements index is the mean of six sub-indexes (Prospect, Compensation, Shareholders, Inside ownership, Contracts Irregular, and Transactions); the Liability standard index is the mean of three sub-indexes (Liability standard for the issuer and its directors, Liability standard for the distributor, and Liability standard for the accountant); the Public enforcement index is the mean of five sub-indexes (Supervisor characteristics index, Rule-making power index, Investigative powers index, Orders index, and Criminal index); plus the Anti-director rights index and Efficiency of the judiciary index. Table 1.1 reports the selected country indices and Appendix A provides a summary for the corresponding sub-indexes from the survey of La Porta et al.

The selected indices from the survey of La Porta et al. (2006) provide a comprehensive assessment for information processing environments across countries. First, academic studies often show that "disclosure is central to information environment" (Haw, Hu, Lee, & Wu, 2012, p.391) and that the quality of disclosure influences, to a great extent, the quality of investment decisions (Singhvi & Desai, 1971; Healy & Palepy, 2001). Expert analysis, however,

[11] The description for country indices from the survey of La Porta et al. (2006) is available in Rafael La Porta's Home Page (Link: http://faculty.tuck.dartmouth.edu/rafael-laporta/research-publications) or can be found in the Internet Appendix accompanied with the article: La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2006). What works in securities laws? The Journal of Finance, 61(1), 1-32.

often casts doubt on the quality of disclosure[12]. As suggested by La Porta et al. (2006), the Disclosure requirements index quantifies affirmative disclosure requirements across markets while the Liability standard index specifies the liability standards to recover damages when information disclosure is inaccurate or omitted. Second, academic studies suggest that public enforcement plays a crucial role in information processing. Grossman and Hart (1980), for instance, show that corporate issuers have an incentive to reveal all relevant information under the efficient law enforcement. La Porta et al. (2006) also suggest that public enforcement benefits the information environment because "it can secure information from issuers and market participants…and because it can impose sanctions." (p. 3). We, therefore, use the Public enforcement index as an additional indicator for the country information environment. Third, we employ Anti-directors right index, which was introduced by La Porta et al. (1998) and has been widely used as a measure of shareholder protection in academic studies (Spamann, 2010, p. 467), as an additional indicator for the information environment. Regarding the decision-making process when choosing which country to invest in, La Porta et al. (1998) raise the question "Does being a shareholder in France give an investor the same privileges as being as shareholder in the United States, India..?" (p.1114) The differences in legal protection of investors across countries, which are measured by Anti-directors right index, contributes to explaining how investors behave so differently in different countries (La Porta et al., 1998). Last but not least, Efficiency of the judiciary index, which is produced by a country risk rating agency, assesses the "efficiency and integrity of legal environments as it affects business" (La Porta et al., 2006, p.10). Previous studies suggest that the selected indices provide a consistent measurement for a country's information environment. For example, some literature documents how countries with strong investor protection have better disclosure and corporate transparency (Bushman, Piotroski, & Smith, 2004; Durnev & Kim, 2005; Haw et al., 2012). In brief, the five indices which jointly create a comprehensive assessment for the information environment across countries are employed as a benchmark for country classification in further steps.

[12] Gilbert (2013) notes that according to a recent survey of investors and analysis by London-based Association of Chartered Certified Accountants and Paris-based European Sustainable Investment Forum, "*93 percent believed that disclosure doesn't shed enough light on how important these…factors are to investment decisions*". Retrieved from: http://www.institutionalinvestor.com/article/3282531/investors-endowments-and-foundations/companies-face-pressure-to-improve-nonfinancial-reporting.html#.VF_shjSsVic

From Global Financial Data (GFD), we obtain stock return indices from "Total Return Indices-Stocks" series, three-month Treasury bill rates from "Treasury Bill Yields" series[13], dividend yields from "Stocks- Dividend Yields and P/E Ratios" series, and exchange rate from "Exchange rates- Market" series. All of the return indices are value weighted according to market capitalisation. More information on the GFD's return indices is provided in Appendix B. For a robustness check, we obtain stock return indices from "Total market index- TOTMK" series in Thomson Reuters Datastream to provide a robust test for the return series from GFD[14]. We also obtain market capitalisation from "Total market index- TOTMK" series in Datastream[15].

We select countries and the sample period based on data availability, data consistency, and our desire to analyse return predictability for as many of the countries in La Porta et al.'s (2006) sample as possible. Particularly, we start with the full set of 49 countries from La Porta et al.'s survey, and then consider the following conditions for the sample selection: unavailable data; amount of missing values, and data inconsistency. We select the largest sample of countries in the survey of La Porta et al. that overcomes these limitations[16]. The

[13] GFD's Treasury Bill Yield series are not available for five countries (Brazil, Chile, Colombia, Peru, and Thailand) for the entire period, so we use the "Interbank Interest rates" series from the GFD for the same period for these five countries.

[14] We focus on excess return based on GFD country indices, since monthly data for country indices from Datastream exhibits a considerable amount of missing values in the period before 1996, while monthly indices from GFD begin in 1994 for all 38 countries in our sample. Furthermore, we choose return indices and risk-free rate indices from the same source (GFD) for computing excess returns.

[15] We choose market capitalization series from Datastream rather than from GFD since these series from GFD suffer from a considerable amount of missing values, compared to that from Datastream. Besides, the market capitalization series from the "TOTMK series" in Datastream are better proxies for total market capitalisation in each country.

[16] Our sample includes 38 countries after considering the following reasons: [1] no data availability from GFD and Datastream for 4 countries (Ecuador, Kenya, Uruguay, and Zimbabwe); [2] considerable amount of missing values for 5 countries, including Jordan (series start in 2006), Nigeria (series start in 2009), Egypt (series start in 1996:10), Argentina (series range from 1987:12 to 2005:01), and Norway (series end in 2001:09); and [3] data inconsistency: two countries, Turkey and Venezuela, witness economic crises and local currency conversion, and hence, exchange rate and risk free rate of these countries are not consistent for further analysis.

final sample includes 38 countries (24 developed countries and 14 emerging countries)[17], with monthly data from 1994:02 to 2013:12.

3.2. Methodology

3.2.1. Country Classification

We define the *More-Com* and *Less-Com* countries in three steps. In the first step, based on the five information indices from La Porta et al.'s (2006) survey, we rank each index in ascending order, in which the highest score is given to the country with the best information processing environment in each index and then sum these ranks. Using a percentile function, we classify the 38 countries in our sample into three groups by these sum ranks. We define the group with the highest sum of ranks as the *Highest-Rank* group and the group with the lowest sum of rank as the *Lowest-Rank* group. The rationale behind this step is that, since the selected indices in La Porta et al.'s sample indicates the level of market transparency, information disclosure, and stock market development in investigated countries, the higher the sum of ranks, the more transparent the stock market is, and as a result, the less complicated the country is. After sorting all countries into three groups, we only focus on the two extreme groups and leave out the middle group to observe the possible relation between the two extreme groups. This step defines a set of 13 countries in the *Highest-Rank* group and another set of 13 different countries in the *Lowest-Rank* group.

In the second step, after ranking each index in ascending order, we take the standard deviation and the mean of the ranks, and then calculate the coefficient of variation (CV)[18] of these ranks. In this approach, we classify all countries in the sample into three groups by their CV and define the group with the lowest CV as the *Least-Variation* group and the group with the highest CV as the *Most-Variation* group. The argument in favour of the second step

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[17] The lists of emerging countries and developed countries are from International Monetary Fund's World Economic Outlook Report, September 2011, p. 160-161. http://www.imf.org/external/pubs/ft/weo/2011/02/pdf/text.pdf.

[18] Coefficient variation (CV) = mean of ranks/ standard deviation of ranks.

is that the less variation in country indices, the more consistent the institutional and informational environment is, and hence, the less complicated the country is. The second step defines a set of 13 countries in the *Most-Variation* group and another set of 13 countries in the *Least-Variation* group.

Finally, we combine the first two steps into the union step to classify all countries in the sample into the *More-Com* and the *Less-Com* group. Particularly, we define an intersection between the *Highest-Rank* group and the *Least-Variation* group to create the *Less-Com* group; and define an intersection between the *Lowest-Rank* group and the *Most-Variation* group to create the *More-Com* group. Through this union step, the *More-Com* group includes ten countries while the *Less-Com* group includes nine countries.

Figure 1 illustrates the sample selection and classification process. The strict requirements of the union step provide a comprehensive assessment to classify countries into the *More-Com* (MC) and *Less-Com* (LC) group. We, therefore, use the results of the union step for all analyses in this paper.

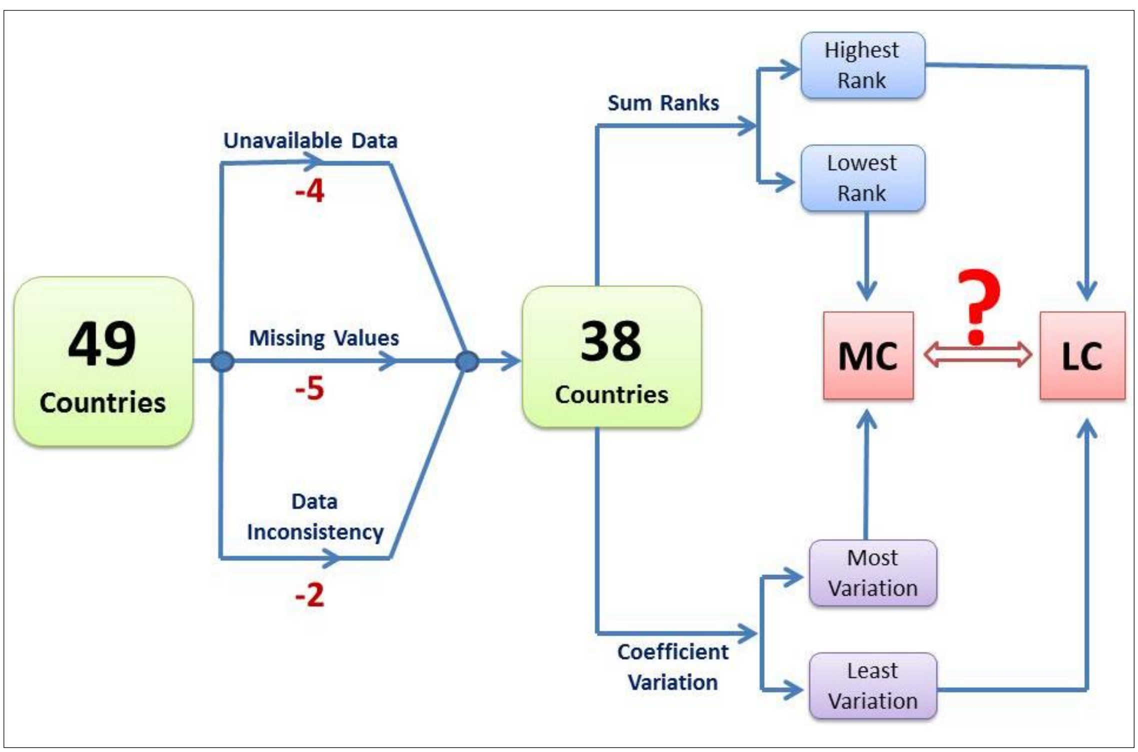

Figure 1: Sample Selection and Classification Process

3.2.2. Return predictability

For every country in the sample, we compute the US$ dominated excess return relative to each country's three-month Treasury bill rate. We use the US$ dominated return rather than domestic currency return[19] to take advantage of the same unit measurement for a big sample of countries. The calculation process is as follows. We first calculate local raw return[20] for each country, and then compute the local excess return relative to the local risk free rate (measured by the three-month Treasury bill rate[21]). We convert the local excess return into the US$ dominated excess return[22] and report the country average excess stock returns in Appendix C. We compute the *Sharpe ratio* which is the mean of the excess return divided by its standard deviation. We also report *Autocorrelation*, which displays the correlation between the excess return and lagged excess return. We use the excess log return for any further analysis in this paper. For the group return, we calculate both the equally weighted return and value weighted return (according to US$ dominated market capitalisation).

A growing body of literature that documents the roles of the US market in predicting international stock return, for example, Rapach, Strauss, and Zhou (2013), indicate the roles of lagged US returns in predicting returns for its trading partners; Bollerslev, Marrone, Xu, and Zhou (2012) show the roles of the US market in predicting non-US countries' variance risk premium. According to the union step's results, the US market stands out from all other countries in the sample, for all information indices. We, on one hand, are inspired by emerging literature favouring the predictability of the US return; and conversely, want to have a closer look at the roles of the US in international return predictability. We, therefore,

[19] Rapach et al. (2013) use domestic currency for international return predictability since they argue that national currency return is close to currency-hedged return for investors due to interest rate parity. In this paper, our focus is on returns for the *More-Com* group and the *Less-Com* group, and therefore, we choose to use the same unit measurement to compute the group's return.

[20] We compute local raw return as follows: for Local Log return = Log (RI/ lagged RI), where RI is the monthly return index and lagged RI is the lagged return index.

[21] T-bill yield (denoted by rf), that is originally in annual percentage, is converted into effective monthly percentage following the formula: monthly rf = $(1 + \frac{\mathrm{rf}}{100})^{1/12}$ - 1.

[22] US$ dominated excess return = (1 + local excess return)*(1+fx)-1; with fx = (lagged exchange rate – exchange rate)/exchange rate; exchange rate is local currency units relative to the US dollar.

investigate two other predictors from the *Less-Com* group: the US returns and the returns for the non-US, less complicated group (hereafter the *Non-US* group). Appendix D reports the summary statistics for the *Less-Com* group and the *More-Com* group, in a sample from 1994:02 to 2013:12.

We investigate the roles of the *Less-Com* group in predicting the return for the *More-Com* group by estimating the predictive regression model:

$$rMC_{t+1} = \beta_0 + \beta_1\, rLC_t + \beta_b\, billMC_t + \beta_d\, dyMC_t + \varepsilon_{t+1} \tag{1}$$

where rMC_{t+1} is the monthly US$ dominated excess return for the *More-Com* group; rLC_t is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_t$ ($dyMC_t$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for the *More-Com* group.

To understand the predictive ability of the *Less-Com* group, we examine the predictive power of two other predictors from the *Less-Com* group: the US returns, and returns for the *Non-US* group. In addition the inclusion of $billMC_t$ and $dyMC_t$ as additional explanatory variables in model (1) controls for the predictive ability of national variables[23]. We also compute the χ^2 statistic for testing the null hypothesis of no return predictability for $billMC_t$ and $dyMC_t$ in model (1):

$$H_o\colon \beta_b = \beta_d = 0. \tag{2}$$

Table 2.1 reports results from predictive regression models (1).

To further assess the role of the *Less-Com* group in predicting future returns for the *More-Com* group, we estimate the predictive regression model (1) for every individual country in the *More-Com* group. The new predictive regression model is as follows:

[23] A growing amount of research indicates the return predictability of a country's own indicators, for instance, nominal interest rate (Campbell & Yogo, 2006; Ang & Bekaert, 2007; Hjalmarsson, 2010; Rapach at al., 2009, 2013); dividend yield (Fama & French, 1988; Campbell, 1991; Cochrane, 1992; Goyal & Welch, 2003).

$$rMC_{i,t+1} = \beta_0 + \beta_{1,i}\, rLC_t + \beta_{i,b}\, billMC_{i,t} + \beta_{i,d}\, dyMC_{i,t} + \varepsilon_{t+1} \qquad (3)$$

where $rMC_{i,t+1}$ is the monthly US$ dominated excess return for country *i* in the *More-Com* group; rLC_t is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_{i,t}$ ($dyMC_{i,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for country *i* in the *More-Com* group. Following Rapach et al. (2013), we include $billMC_{i,t}$ and $dyMC_{i,t}$ as additional explanatory variables in model (3) to control for the predictive ability of country economic variables. Table 2.2 reports results of predictive regression model (3).

Can the *Less-Com* group in each region outperform the *Less-Com* group for the whole sample in predicting returns for the *More-Com* in that region? We answer this question by investigating the predictive ability of the *Less-Com* group in the regional context. Specifically, we group every country in the *More-Com* group and the *Less-Com* group into regions[24], and then calculate the regional group returns for the corresponding groups. Appendix D reports the summary statistics for excess returns for the *More-Com group* and the *Less-Com* group in each region for the sample from 1994:02 to 2013:12.

We then investigate and compare the predictive results for the *More-Com* group for each region and for the whole sample. We revise the predictive regression model (1) in the regional context to examine the predictive ability of the *Less-Com* group in each region. The new model is as follows:

$$rMC_{j,t+1} = \beta_0 + \beta_{1,j}\, rLC_{j,t} + \beta_{b,j}\, billMC_{j,t} + \beta_{d,j}\, dyMC_{j,t} + \varepsilon_{j.t+1} \qquad (4)$$

where $rMC_{\,j,t+1}$ is the monthly US$ dominated excess return for the *More-Com* group in region *j*; $rLC_{j,t}$ is the monthly US$ dominated excess return for the *Less-Com* group in

[24] We classify every country in the more (less) complicated group into 3 different regions: [1] the American region includes three *More-Com* countries (Brazil, Colombia, and Mexico) and two *Less-Com* countries (United States and Canada); [2] European region includes five *More-Com* countries (Austria, Belgium, Germany, Greece, and Italy) and one *Less-Com* countries (United Kingdom); [3] Asian region includes two *More-Com* countries (Indonesia and Korea) and five *Less-Com* countries (Hong Kong, India, Israel, Malaysia, and Singapore).

region *j*; and $billMC_{j,t}$ ($dyMC_{j,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for the *More-Com* group in region *j*. We report results of the predictive regression models (4) in each region in Table 2.3 with Panel A presenting results for American countries, Panel B reporting results for European countries, and Panel C reporting results for Asian countries.

To further assess the role of the *Less-Com* group in predicting returns for individual countries in the *More-Com* group in each region, we revise the predictive regression model (3) in the regional context. The new predictive regression model is as follows:

$$rMC_{ij,t+1} = \beta_0 + \beta_{1,ij}\, rLC_{j,t} + \beta_b\, billMC_{ij,t} + \beta_d\, dyMC_{ij,t} + \varepsilon_{ij,t+1} \qquad (5)$$

where $rMC_{ij,t+1}$ is the monthly US$ dominated excess return for country *i* in the *More-Com* group in region *j*; $rLC_{j,t}$ is the monthly US$ dominated excess return for the *Less-Com* group in region *j*; and $billMC_{ij,t}$ ($dyMC_{ij,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for country *i* in the *More-Com* group in region *j*. Table 2.4 reports results of predictive regression models (5).

Finally, we examine the predictive ability of national economic variables that are documented in previous intensive literature (e.g., Goyal & Welch, 2003; Campbell & Yogo, 2006; Hjalmarsson, 2010; Rapach, Strauss, & Zhou, 2010). Following Ang and Bekaert (2007) and Rapach et al. (2013), we use the nominal interest rate and dividend yield as two predictors for future stock returns in the benchmark predictive regression model. The predictability of dividend yield and nominal interest rate for future stock return, as proposed by Ang and Bekaert, can be attributed to their capacity to capture the variation of expected cash flow growth, future risk free rate or future risk premium. The benchmark predictive regression model is as follows:

$$rMC_{t+1} = \beta_0 + \beta_b\, billMC_t + \beta_d\, dyMC_t + \varepsilon_{t+1} \qquad (6)$$

where rMC_{t+1} is the monthly US$ dominated excess return of *More-Com* group and $billMC_t$ ($dyMC_t$) is the US$ dominated three-month Treasury bill rate (log dividend yield) of *More-Com* group. Following Rapach et al. (2013), we test the null hypothesis of no return predictability of Treasury-bill rate and dividend yield for *More-Com* group's future stock returns:

$$Ho\colon\ \beta_b = \beta_d = 0 \tag{7}$$

The results for this analysis are presented in Appendix E.

3.2.3. Out of sample performance

Theoretical literature points out the importance of out-of-sample tests for return predictability studies. Goyal and Welch (2008), for instance, document that a range of established predictors display a poor out-of-sample prediction for equity premium. Rapach et al. (2009) and Dou, Gallagher, Schneider, and Walter (2012) also suggest that a long list of well-known predictors fails to generate the superior out-of-sample performance that outperforms the simple forecasts based on historical averages.

To examine the statistical significance of return predictability, we compute the out-of-sample R^2 (R^2_{OS}) proposed by Campbell and Thompson (2008). This method compares the fitted value generated from the predictive regression model with the forecasts based on the historical average return (Campbell & Thompson, 2008; Dou et al., 2012; Jacobsen et al., 2014). The R^2_{OS} statistic is calculated as follows:

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T} (r_t - \hat{r}_t)^2}{\sum_{t=1}^{T} (r_t - \bar{r}_t)^2} \tag{8}$$

where $\hat{r}_t$ and $\bar{r}_t$ are the fitted values from the predictive regression and the average historical return, respectively. The historical average forecast of excess returns in month *t* is the average excess return from the beginning of the sample through month to *t-1.* It is denoted that both these fitted values are estimated through period *t-1.* The R^2_{OS} statistic shows the reduction in forecasting error of the predictive regression model relative to the historical average forecast (Rapach et al., 2013; Jacobsen et al., 2014). That is, the forecast from the predictive regression model outperforms the historical average forecast when R_{OS}^2 > 0 (Campbell & Thompson, 2008; Dou *et al.*, 2012). To make a deeper analysis of the out-of-sample performance, we compute the R_{OS}^2 statistic for model (1), with and without restriction (2): $\text{Ho: } \beta_b = \beta_d = 0$

To determine the statistical significance of the out-of-sample R^2, we compute the bootstrapping critical values of R_{OS}^2 following the approach proposed by Goyal and Welch (2008). As they note, this approach follows the work of Mark (1995) and Kilian (1999). According to Goyal and Welch, this bootstrapping procedure not only controls for Stambaugh (1999) bias, but it also maintains the cross-correlation structure of estimated residuals.

Regarding the procedures to compute the bootstrapping critical values of R_{OS}^2, we present the data generating process for the unrestricted predictive model (1) and restricted model under (2) in the following steps.

For the restricted model, we first compute residuals from the following models:

$$Y_{t+1} = \alpha + u_{1,t+1} \tag{9}$$

$$X_{t+1} = \mu + \rho \times X_t + u_{2,t+1} \tag{10}$$

where Y_{t+1} is US$ dominated excess return for the *More-Com* group; X_{t+1} is US$ dominated excess return for the *Less-Com* group; α is a constant (simply the mean of excess returns for the *More-Com* group in the sample); ρ and μ are estimated by OLS using the full sample of observations; x_t is the lagged excess return for the *Less-Com* group; and $u_{1,t+1}$ and $u_{2,t+1}$ are the estimated residuals from equation (9) and model (10), respectively. We store the estimated residuals ($u_{1,t+1}$ and $u_{1,t+1}$), α, μ, and ρ in equation (9) and (10) for sampling in the next steps.

Second, we generate 1000 bootstrapped time series by drawing with replacements from the stored residuals. Specifically, we randomly select $u^{*}_{1,t+1}$from the stored residuals $u_{1,t+1}$ in 1000 times, and then compute Y^{*}_{t+1} as follows:

$$Y^{*}_{t+1} = \alpha + u^{*}_{1,t+1} \tag{11}$$

where α is stored from equation (9).

Third, we jointly select a pair[25] of $u^{*}_{2,t+1}$ (from stored residuals $u_{2,t+1}$) and X_t (from actual data) 1000 times, and use the initial observation X_t to compute X^{*}_{t+1} as follows:

$$X^{*}_{t+1} = \mu + \rho \times X_t + u^{*}_{2,t+1} \tag{12}$$

where μ and ρ are stored from equation (10).

The process repeats 1000 times. We then regress $\mathrm{Y}^{*}_{\mathrm{t+1}}$ on $\mathrm{X}^{*}_{\mathrm{t+1}}$ and estimate R^{*2} for 1000 bootstrapped regressions. We rank the estimated R^{*2} in ascending order, and calculate percentiles of the bootstrap distributions.

Finally, we compute bootstrapping (90%, 95% and 99%) critical values of R^2_{OS}.

For the unrestricted model, the bootstrapping procedures remain unchanged, but we add some adjustments due to the appearance of the three-month Treasury-bill and log dividend yields as two additional predictors in the unrestricted model. Specifically, we keep equations (9) and (10) unchanged and add two additional models to compute residuals from two new predictors:

$$bill_{t+1} = \mu_1 + \rho_1 \times bill_t + u_{3,t+1} \tag{13}$$

$$dy_{t+1} = \mu_2 + \rho_2 \times dy_t + u_{4,t+1} \tag{14}$$

where $bill_{t+1}(dy_{t+1})$ is US$ dominated three-month Treasury bill (log dividend yield) for the *More-Com* group; $\rho_1,\ \rho_2,\ and\ \mu_1,\ \mu_2$ are estimated by OLS using the full sample of observations; $bill_t(dy_t)$ is the lagged Treasury bill (dividend yield) for the *More-Com*

[25] We randomly jointly select a pair of $\mathrm{u}^{*}_{1,t+1}$and $\mathrm{X_t}$ to make sure that $\mathrm{u}^{*}_{1,t+1}$and $\mathrm{X_t}$ have the same order.

group; and $u_{3,t+1}$ and $u_{4,t+1}$are the estimated residuals from equation (13) and model (14), respectively. We also store new estimated residuals ($u_{3,t+1}$ and $u_{4,t+1}$), and new estimated coefficients ($\mu_1,\ \mu_2,\ \rho_1, \rho_2$) in equation (13) and (14) for sampling.

In the next step, we draw residuals (${u^*}_{1,t+1}, {u^*}_{2,t+1},\ {u^*}_{3,t+1}$, and ${u^*}_{4,t+1}$) jointly from stored residuals ($\mathrm{u}_{1,\mathrm{t}+1}, \mathrm{u}_{2,\mathrm{t}+1}, \mathrm{u}_{3,\mathrm{t}+1}$, and $\mathrm{u}_{4,\mathrm{t}+1}$) 1000 times, and jointly draw the initial value of $X_t, bill_t$, and dy_t to compute ${Y^*}_{t+1}$, ${X^*}_{t+1}$, ${bill^*}_t$, and ${dy^*}_t$. Finally, we estimate R^{*2} for 1000 bootstrapped regressions and compute bootstrapping critical values of R^2_{OS} for the unrestricted model. We report out-of-sample performance for group return and individual country return predictability in Table 3.1 and Table 3.2, respectively.

3.2.4. Sources of return predictability

To test Hypothesis 2, which supports the arguments of cash flows and discount rates as sources of return predictability, we follow two approaches.

In the first approach, to test if return predictability is due to the capacity to predict news related to cash flows (or discount rates) in returns, we compute news related to future cash flows and news related to discount rates (denoted by NCF_t and NDR_t, respectively) following the approach proposed by Bakshi et al. (2014). As they note, this is based on the work of Campbell (1991), Campbell and Vuolteenaho (2004), and Campbell et al. (2010). The calculation process is as follows.

First, we use a first order VAR model to obtain estimated residuals and coefficients from the following models:

$$rMC_{,t+1} = \beta_0 + \beta_1\, rLC_t + \beta_2\, dyMC_t + \varepsilon_{1,t+1} \tag{15}$$

$$dyMC_{t+1} = \gamma_0 + \gamma_1\, rMC_t + \gamma_2 dyMC_t + \varepsilon_{2,t+1} \tag{16}$$

where rMC_{t+1} is the monthly US$ dominated excess return for the *More-Com* group; $dyMC_t$ is the US$ dominated log dividend yield for the *More-Com* group; β_1, β_2, γ_1, and

$\gamma_2$are estimated coefficients from VAR model; $\varepsilon_{1,t+1}$ and $\varepsilon_{2,t+1}$ are estimated residuals from model (15) and (16), respectively. We store estimated coefficients and residuals for the next steps.

Second, we construct a matrix of constant parameters and a vector of shocks (denoted by Γ and $\boldsymbol{u}_{t+1}$, respectively) as follows:

$$\Gamma_{2\times 2} = \begin{bmatrix} \beta_1 & \beta_2 \\ \gamma_1 & \gamma_2 \end{bmatrix} \quad \text{and} \quad \boldsymbol{u}_{t+1\ (2\times T)} = \begin{bmatrix} \varepsilon_{1,t+1} \\ \varepsilon_{2,t+1} \end{bmatrix} \tag{17}$$

where β_1, β_2, γ_1, and $\gamma_2$are estimated coefficients from the VAR model; and $\varepsilon_{1,t+1}$ and $\varepsilon_{2,t+1}$ are stored residuals from models (15) and (16).

Finally, we estimate NCF_t and NDR_t as follows:

$$NCF_{t+1} = (\mathbf{e1}' + \mathbf{e1}' \times \boldsymbol{\lambda}) \times \boldsymbol{u}_{t+1} \quad \text{and} \quad NDR_{t+1} = \mathbf{e1}' \times \boldsymbol{\lambda} \times \boldsymbol{u}_{t+1} \tag{18}$$

where $\mathbf{e1} = [1 \quad 0]'$; $\mathbf{I} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$; ρ is a constant number (ρ = 0.95);

and $\boldsymbol{\lambda}_{2\times 2} = \rho \times \Gamma \times (\mathbf{I} - \rho \times \Gamma)^{-1}$

Hypothesis 2 would be valid if the excess returns for the *Less-Com* group can predict NCF_{t+1} (NDR_{t+1}) in excess returns for the *More-Com* group. We test the validity of Hypothesis 2 using the simple OLS model:

$$NCF_{t+1} = \alpha + \beta_{CF}\, rLC_t + \epsilon_{t+1} \tag{19}$$

$$NDR_{t+1} = \gamma + \beta_{DR}\, rLC_t + \varepsilon_{t+1} \tag{20}$$

If β_{CF} and β_{DR} from model (19) and (20) are positive and statistically significant, Hypothesis 2, which supports the return predictability by predicting the cash flow (or discount rate) components in returns, would be valid.

Table 4.1 and Table 4.2 report the results for testing Hypothesis 2 for group return predictability and individual country return predictability, respectively.

In the second approach to test Hypothesis 2, we examine the relation between predictability of stock return and economic fundamentals by adopting the approach pioneered by Bakshi et al. (2014). As they note, this approach adapts the theory in Hong et al. (2007). We consider the following procedure to test the validity of Hypothesis 2.

We first report β_i in model (3) that presents the predictive slope coefficient on returns for the *Less-Com* group for country *i*. We then estimate the coefficient θ_i for fundamentals for country *i* from the following predictive regression model:

$$\text{Log}\left(D_{i,t+1}/D_{i,t}\right) = \theta_{i,0} + \theta_i \times rLC_t + \varepsilon_{i,t+1} \tag{21}$$

where dividend growth, $\text{Log}\ (D_{i.t+1}/D_{i.t})$, is the proxy for fundamentals (proposed by Cochrane, 2011) for stock return for country *i* in the *More-Com* group; and rLC_t is the US$ dominated excess return for the *Less-Com* group.

Finally, we use θ_i in model (21) to estimate φ in the following model:

$$\beta_i = \varphi_0 + \varphi\ \theta_i + e_i \tag{22}$$

where β_i is the predictive slope coefficient in equation (3).

The object of interest in equation (22) is the slope coefficient φ, whereby φ > 0 would indicate that the ability to forecast stock returns of country *i* in the *More-Com* group is positively related to the ability to forecast its economic fundamentals, as proxied by dividend growth (Hong et al., 2007; Bakshi et al., 2014).

We report in Table 5.1 the two estimated coefficients (β_i and θ_i) for every country in the *More-Com* group in the full sample from 1994:02 to 2013:12. Figure 2, which accompanies Table 5.1, plots these estimates in the full sample.

Furthermore, we suggest two additional tests to examine the validity of Hypothesis 2. In the first additional test, we consider the estimated coefficients (β_i and θ_i) for every country in the *More-Com* group for every five years in the full sample. If stock returns for the *Less-Com* group can predict stock returns for countries in the *More-Com* group by forecasting its economic fundamentals in the full sample, does this process still work for every 5 years in the sample? Our first test provides an answer to this claim.

For the second additional test, we use a pooled sample that integrates the estimated coefficients for every 5 years into one sample, and thus, each country in the *More-Com* group has four estimated β_i and θ_i in the full sample. This test overcomes the limitation of the previous two tests since the number of observations in model (22) is above 30, and as result, the test's results have statistical meaning[26]. In addition, this test provides an additional out of sample test to investigate the validity of Hypothesis 2. We report the results of those additional tests in Appendix H. Along with Appendix H, Appendix H1 and H2 also plot the predictive slope coefficients β_i against θ_i for all investigated countries, for every 5 years and for the pooled sample, respectively.

Hypothesis 3 supports the argument that returns for the *Less-Com* group can predict returns for the *More-Com* group by capturing variation in risk premiums, as measured by volatility. We adopt the approach suggested by Bakshi et al. (2014) to estimate an E-GARCH (1,1) model that includes lagged excess return for the *More-Com* group in the volatility equation as an exogenous predictor. The specification is as follows:

$$rMC_{t+1} = \alpha + \beta\, rLC_t + \varepsilon_{t+1}, \text{ where } \varepsilon_{t+1} = \delta_t z_{t+1}, z_{t+1} \sim \text{i.i.d.}(0,1) \quad (23)$$

$$\log(\delta_t^2) = \gamma_0 + \gamma_1 \frac{|\varepsilon_{t-1}|}{\delta_{t-1}} + \gamma_2 \frac{\varepsilon_{t-1}}{\delta_{t-1}} + \gamma_3 \log(\delta_{t-1}^2) + \boldsymbol{\gamma_{less}} rLC_t \quad (24)$$

Our focus is on $\boldsymbol{\gamma_{less}}$, which captures the relation between returns for the *Less-Com* group and the estimated variance. A significantly positive γ_{less} would indicate a positive relation between returns for the *Less-Com* group and the expected volatility, and thus, support Hypothesis 3. We report the results for testing Hypothesis 3 for group returns and individual country returns in Table 6.1 and Table 6.2, respectively.

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[26] When the number of observations in the regression is larger than 30, the regression's results have statistical meaning.

Hypothesis 4 considers the learning affect, which claims that once the new predictor gains more attention, its predictability tends to diminish over time. We assess this hypothesis by adopting two approaches proposed by Bakshi et al. (2014). The first approach considers the time evolution of the slope coefficients that are obtained in the predictive regression model. According to Bakshi et al., if these coefficients tend to decline over time, the learning hypothesis would be validated. Inspired by this rationale, we run predictive regressions on rolling five subsamples, each with a length of 10 years (120 monthly observations), whereby the first subsample starts in November 1994 and the remaining ones start at 24-month intervals. In each sub-sample, we estimate the slope coefficients $\boldsymbol{\beta}$ from the following predictive regression model:

$$rMC_{t+1} = \alpha + \boldsymbol{\beta}\, rLC_t + \varepsilon_{t+1} \tag{25}$$

where rMC_{t+1} is the monthly US$ dominated excess return for the *More-Com* group; and rLC_t is the monthly US$ dominated excess return for the *Less-Com* group. For predicting stock returns for each country in the *More-Com* group, the predictive regression model is as follows:

$$rMC_{i,t+1} = \gamma + \boldsymbol{\beta}\, rLC_t + \varepsilon_{t+1} \tag{26}$$

where $rMC_{i,t+1}$ is the monthly US$ dominated excess return for country *i* in the *More-Com* group. We report the estimated slope coefficients $\boldsymbol{\beta}$ in Section (1) in Table 7.

For the second approach to testing the learning hypothesis, we assess the time variation in the predictive slope coefficient from the following model:

$$rMC_{t+1} = \alpha + (\beta + \boldsymbol{\beta^{trend}})\, rLC_t + \varepsilon_{t+1} \tag{27}$$

Furthermore, following Bakshi et al. (2014), we conduct a robust test for model (27) by including the dividend yield for the *More-Com* group as an additional predictor. The new version of the predictive model is as follows:

$$rMC_{t+1} = \alpha + \left(\beta + \boldsymbol{\beta^{trend}}\right) rLC_t + \delta(dyMC_t) + \varepsilon_{t+1} \tag{28}$$

Table 7 reports the estimated results from models (26), (27), and (28). Specifically, Section (2) reports the estimated results when the time trend is on a monthly basis, while Section (3) reports results when the time trend is on an annual basis. We consider time trends on a monthly basis and on an annual basis to fully assess the learning theory, since learning on an annual time basis may allow investors to have more time to learn, compared to learning on a monthly basis. Furthermore, Section (2) and (3) also report the estimated coefficients $\boldsymbol{\beta}^{trend}$ with and without including dividend yield as an additional predictor. Generally, the learning hypothesis is validated when $\boldsymbol{\beta}^{trend}$ is negative.

3.3. Summary Statistics

Table 1.2 reports the summary statistics for the average monthly raw stock returns for the 38 countries in the sample from 1994:02 to 2013:12. We use US$ dominated returns, rather than the domestic currency return, to take advantage of the same currency unit for the return measurement for a large sample of countries. This common unit in return measurement also allows us to compute the group return for further steps. In addition, we use log return for all analyses in this paper.

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For the whole sample, the average monthly raw returns range from 0.07% (Japan) to 1.23% (Colombia). Among the developed countries, while Denmark and Sweden stand out from the rest (both have average raw returns of 1.00%), Japan has the lowest average raw return of 0.07%. Among the emerging markets, Colombia (1.23%) and Peru (1.17%) have the highest average returns; whereas, the lowest average returns belong to Thailand (0.17%).

The standard deviations, as well as the minimum and maximum values, indicate the volatility of raw returns for each country. Specifically, for the whole set of 38 countries, Indonesia witnesses the highest volatility over the sample; whereas, the lowest volatility belongs to the US. In addition, Korea and Greece display the greatest volatility among developed countries, while Chile and South Africa witness the lowest volatility among developing markets.

In the whole sample, there are three countries that have monthly Sharpe ratios above 0.16: Switzerland, Denmark, and the US. Colombia (0.14) has the highest Sharpe ratio among emerging markets, while the lowest ratio belongs to Thailand (0.02).

Some countries exhibit relatively higher autocorrelation over the sample. For instance, among advanced economies, Austria and Ireland display the highest autocorrelations of 0.20; and among emerging countries, Malaysia (0.22) and Colombia (0.19) stand out from the rest. On the other hand, several markets display relatively small autocorrelations, including Italy (0.02), South Africa (0.003), and Peru (0.00).

Table 1.3 reports the summary statistics for the average monthly excess stock returns for every country in the *More-Com* group (Panel A) and in the *Less-Com* group (Panel B) in the sample, from 1994:02 to 2013:12. Specifically, among the *More-Com* countries, the average monthly excess log returns range from -0.57% (Brazil) to 0.53% (Belgium); whereas, these figures in the *Less-Com* group range from-0.16% (Israel) to 0.56% (Canada). Regarding the volatility of excess return, Indonesia displays the highest volatility among the *More-Com* group, while the lowest volatility among the *More-Com* group belongs to the Belgium. Among the *Less-Com* group, Malaysia and the US display the highest and lowest volatility, respectively.

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Regarding the Sharpe ratios, among the *More-Com* group, Belgium (0.09) has the highest Sharpe ratio while the lowest figure belongs to Brazil (-0.05). Among the *Less-Com* group, the US (0.11) and Israel (-0.02) have the highest and lowest Sharpe ratios, respectively. Some countries exhibit relatively higher autocorrelation over the sample, for instance: Colombia (0.21) and Austria (0.20) in the *More-Com* group; and Malaysia (0.22) and the United Kingdom (0.15) in the *Less-Com* group. On the other hand, several markets display very small autocorrelations, such as: Italy (0.02), Germany (0.06) and

Korea (0.06) in the *More-Com* group; and Hong Kong (0.04), Austria (0.05), and Israel (0.05) in the *Less-Com* group.

We also report the summary statistics for the average monthly excess return for every country in the sample in Appendix C. In brief, among the developed countries, regarding the average monthly excess return, while Denmark stands out from the rest, Greece has the lowest average excess return of -0.26%. Among the emerging markets, Peru (0.52%) and Colombia (0.30%) have the highest average returns; whereas, the lowest average returns belong to Brazil (-0.57%) and Sri Lanka (-0.60%). For the whole sample, Indonesia witnesses the highest volatility over the sample; whereas, the lowest volatility belongs to the US. There are four countries that have a monthly Sharpe ratio above 0.10: Switzerland, Denmark, the US, and Sweden. In addition, some countries exhibit relatively higher autocorrelation over the sample, for instance, Austria (0.20) and Ireland (0.20) among the advanced economies; and Malaysia (0.22) and Colombia (0.21) among the emerging countries. On the other hand, several markets display relatively small autocorrelations, including Italy (0.02), South Africa (0.01), and Peru (0.002).

Furthermore, Appendix D reports summary statistics for the excess return for the *More-Com* and the *Less-Com* group in the whole sample and in each region. Generally, compared to the *More-Com* group, the *Less-Com* group has a relatively higher average return and Sharpe ratio, while exhibiting lower volatility and autocorrelation. In addition, equally-weighted returns exhibit a lower return and Sharpe ratio while displaying smaller volatility and autocorrelation compared to value-weighted returns.

4. Stock return predictability: Group results

This section investigates the lead-lag relationship among monthly country stock returns and identifies the leading roles of the *Less-Com* group.

4.1. Group return predictability

Table 2.1 reports OLS estimates of β_1, robust t-statistic, and adjusted R-square for predictive regression model (1).

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Dependent variables are excess returns for the *More-Com* group, while main explanatory variables are excess returns for the *Less-Com* group. We consider results from both the equally-weighted and value-weighted methods. Specifically, Panel A reports the predictive results with predictor as returns for the whole *Less-Com* group; whereas, Panel B presents the predictive results by the US return and Panel C reports the results with the return for the *Non-US Less-Com* group[27] as a predictor. The inclusion of $bill_t$ and dy_t as additional explanatory variables in model (1) controls for the predictive ability of a country's economic variables. We report the Newey and West's (1987) robust t-statistic in parentheses in the first, second, third, fifth, sixth, and seventh columns. The $\hat{\beta}_1$ estimates are statistically positive and significant at 10% level of significance or better, indicating that returns for the *Less-Com* group can predict future stock returns for the *More-Com* group. These results are consistent for both the equally-weighted method and value-weighted methods. The only exceptions are the predictive results from the US returns, which can predict equally-weighted returns for the *More-Com* group but display no predictability for the value-weighted returns for the same group. These results suggest that returns for countries with a less complicated information processing capacity can predict returns for countries with more complicated information processing. In other words, the complications in information processing across countries do help forecast stock return[28].

[27] We do not use the US returns and returns for the *Non-US* group as joint predictors in model (3) due to their high correlation. We report these correlations in Appendix I.

[28] We also estimate the predictive regression model (1) for excess returns computed from Thompson Reuters Datastream and report results in Appendix G1. These results are relatively similar to those from GFD's return indices.

We also consider the predictive ability of a group's economic variables, proxied by the three-month Treasury bill rate and log dividend yield for the *More-Com* group. Parentheses below the $\overline{\mathrm{R}}^2$ statistic in the fourth and eighth columns report the heteroskedasticity-robust χ^2 statistic for testing the null hypothesis of no return predictability for Treasury bill rate ($bill_t$) and log dividend yield (dy_t) in model (2): Ho: β_b = β_d = 0. We reject this null hypothesis for results from the equally-weighted method in Panel A and Panel B, and do not reject the null hypothesis for the rest.

We examine the reversed relationship to test if returns for the *More-Com* group can predict stock returns for the *Less-Com* group. This relationship, if it exists, will cast doubt on the return predictability generated from country information processing capacities. We report the predictive results in Appendix F.1. Overall, there is no significant evidence to support the reversed relation since returns for the *More-Com* group have very limited predictive ability for the *Less-Com* group's future returns.

We also report, in Appendix E, the benchmark predictive regression that examines the return predictability for the three month Treasury-bill rate and log dividend yield for the *More-Com* group. The estimated results in Appendix E are consistent with previous findings. In brief, the Treasury-bill rate and log dividend yield for the *More-Com* group present some predictive power for future stock returns for the *More-Com* group.

For further analysis, we examine the predictive ability of the *Less-Com* group for the *More-Com* group's return for each region by estimating the predictive regression (4). Table 2.3 reports OLS estimates of β_1, robust t-statistic, and adjusted R-square ($\overline{\mathrm{R}}^2$) for regression model (4). Dependent variables are returns for the *More-Com* group in each region, while the main explanatory variables are returns for the *Less-Com* group in that region. Specifically, we estimate the predictive ability for four predictors from the *Less-Com* group: (1) returns for the Regional *Less-Com* group; (2) returns for the *Less-Com* group; (3) the US returns; and (4) returns for the *Non-US* group. The inclusion of $billMC_t$ and $dyMC_t$ as additional explanatory variables in model (4) controls for the predictive ability of the regional group's economic variables. Panel A reports the predictive results for the *More-Com* group in the American region; whereas, Panel B presents the predictive results for the European region and Panel C reports the results for Asian countries. The estimated results suggest that not only does the *Less-Com* group in the whole sample, but also the *Less-Com* group in each region, and the *Non-US* group predict future returns for the *More-Com* group in that region. Consistent with previous findings, the equally-weighted method in each region provides more significant evidence for return predictability than that from the value-weighted method.

Furthermore, for the American and European regions, the adjusted R-square is relatively higher for the *Less-Com* group compared to the Regional *Less-Com* group. However, a reversed trend is captured in the Asian region, with the Regional *Less-Com* exhibiting higher $\bar{R}^2$ than the *Less-Com* group. For the value-weighted method, only the Asian region displays a substantial difference between estimated $\overline{\mathrm{R}}^2$ from the Regional *Less-Com* and the *Less-Com* group. This evidence suggests that under the equally-weighted method, returns from the *Less-Com* group seem to do better than returns from the Regional *Less-Com* group in predicting returns for the Regional *More-Com* group in the American and European regions; whereas; a reversed trend is captured when the Regional *Less-Com* group's returns seem to be the better predictors for the Asian *More-Com* group's return. In addition, regarding the value-weighted method, returns from the Regional *Less-Com* group seem to be the best predictor for future returns for the *More-Com* group in each region.

Surprisingly, the US, the largest economy in the American region can, on one hand, predict future stock returns for the *More-Com* group in Asian and European countries; but on other hand, displays no predictive power for returns for the American *More-Com* group. The combination of the US and Canadian returns, which are illustrated by the Regional *Less-Com* group in the American region, however, can predict the *More-Com* group in every region. These results may suggest the role of the Canadian market, along with the US market, in international country return predictability.

4.2. Out-of-Sample Performance: Group results

Table 3.1 reports the out-of-sample performance for group return predictability. Panel A reports the out-of-sample predictive results for model (1); whereas, Panel B reports results for predictive model (1) under the restriction β_b = β_d = 0. This table reports the out of sample performance for three predictors from the *Less-Com* group, including returns for *Less-Com* group; the US returns; and returns for the *Non-US* group. We compute the out-of-sample R-square (R^2_{OS}) in accordance with Campbell and Thompson (2008). We determine the statistical significance based on the bootstrap critical value of R^2_{OS} by Goyal and Welch (2008) that is originally based on the works of Mark (1995) and Kilian (1999).

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Table 3.1 results indicate the strong out-of-sample predictive power for group return. Specifically, the R^2_{OS} are all positive and statistically significant at 10% level or better. These positive R^2_{OS} indicate that the forecast from predictive regression model (1) outperforms the historical average forecast. The R^2_{OS} are generally higher than in-sample R-square (R^2_{IS}), reported in Table 2.1, for all predictors from the *Less-Com* group. The R^2_{OS} under the equally-weighted method are highly statistically significant at the 1% level. Compared to the results from the restricted model in Panel B, the R^2_{OS} in Panel A are relatively higher. These results suggest that the Treasury-bill rate and dividend yield have some predictive power for future returns for the *More-Com* group, and thus, when restricting these two variables in model (1), the R^2_{OS} in the restricted model are relatively smaller than that in the unrestricted model. These results are also consistent with previous findings that indicate some return predictability for the group's Treasury-bill rate and dividend yield.

4.3. Cash flows and Discount rates are the sources for group return predictability

This section aims to report on the search for the underlying economic rationale for the *Less-Com* group's predictive ability by investigating the sources of return predictability.

We test Hypothesis 2, which supports the argument of cash flows and discount rates as sources of return predictability, by following two approaches. In the first approach, to test if return predictability is due to capacity to predict news related to cash flows (or discount rates) in returns, we compute news related to future cash flows, and news related to discount rates (denoted by NCF_t and NDR_t, respectively) following the approach proposed by Bakshi et al. (2014). As they note, this is based on the work of Campbell (1991), Campbell and Vuolteenaho (2004), and Campbell et al. (2010).

Table 4.1 presents results for the predictive regression with news related to cash flows and discount rates (denoted by NCF_{t+1} and NDR_{t+1}, respectively).

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Regarding the cash flow and discount rates channel, the predictive slope coefficient estimates for NCF_{t+1} and NDR_{t+1} under Equally-Weighted (EW) methods are significant at 10% level or better for all predictors. In contrast, the estimated coefficients for NCF_{t+1} and NDR_{t+1} under Value-Weighted (VW) methods are all insignificant in all cases. In addition, when significant, the estimated coefficients for NCF_t (denoted by β_{CF}) are much larger in absolute value than that for $NDR_t (\text{denoted by } \beta_{DR})$. Overall, the results in Table 4.1 suggest that the return predictability of the *Less-Com* group can be attributed to its ability to predict both cash flow related components, and discount rate related components, in returns. Our results, therefore, confirm the important role of cash flows and discount rates as two main predictive channels of return, which have been highlighted in previous literature, for instance, Campbell (1991), Campbell and Vuolteenaho (2004), Campbell et al. (2010), and Bakshi et al. (2014).

In search for the sources of return predictability, Hypothesis 3 suggests another source of predictability, which argues that the return predictability of the *Less-Com* group is due to its ability to capture variation in risk premiums, as measured by volatility. We adopt the approach suggested by Bakshi et al. (2014) to estimate an E-GARCH (1,1) model that includes the lagged excess return of the *More-Com* group in the volatility equation as an exogenous predictor. Our focus is on $\boldsymbol{\gamma_{\mathbf{less}}}$, which captures the relation between returns for the *Less-Com* group and estimated variance. A significantly positive γ_{less} would indicate a positive relation between returns for the *Less-Com* group and expected volatility, and thus, support Hypothesis 3. We report the estimated results from model (12) in Table 6.1.

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Table 6.1 reports the estimated results for an E-GARCH (1,1) model for three predictors from the *Less-Com* group: returns for *Less-Com* group (EW and VW); the US returns; and returns for the *Non-US* group (EW and VW). Obviously, the estimated γ_{less} are negative and insignificant in all cases. Thus, these results provide no supporting evidence for the volatility-based channel of return predictability. We, therefore, reject Hypothesis 3, that the return predictability of the *Less-Com* group is driven by time-varying risk premiums.

4.4. Learning effects: Group results

We use two approaches, proposed by Bakshi et al. (2014), to test the learning hypothesis, which claims that once the new predictor gains more attention, its predictability tends to diminish over time. In the first approach, we consider the time evolution of the slope coefficients that are obtained in the predictive regression model (13.1). According to Bakshi et al., if these coefficients tend to decline over time, the learning hypothesis would be validated. We run predictive regressions on rolling five subsamples, each with a length of 10 years (120 observations), whereby the first subsample starts in November 1994 and the remaining ones start at 24-month intervals. We report the estimated slope coefficients $\boldsymbol{\beta}$ in Section (1) in Table 7. For the second approach to test the learning hypothesis, we assess the time variation of the predictive slope coefficient and report the estimated coefficients $\boldsymbol{\beta}^{trend}$ in Section (2) and (3) in Table 7. Particularly, Section (2) reports results when the time trend is on a monthly basis, while Section (3) reports results when the time trend is on an annual basis. Furthermore, Sections (2) and (3) also report the estimated coefficients $\boldsymbol{\beta}^{\boldsymbol{trend}}$ from model (14.1) with and without including dividend yield as an additional predictor. Generally, the learning hypothesis is validated when $\boldsymbol{\beta}^{\boldsymbol{trend}}$ is negative.

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Insert Table 7 here
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Table 7 includes five Panels which, in turn, report estimated results for five predictors from the *Less-Com* group. According to Table 7 results, for the first test, the estimated slope coefficients $\boldsymbol{\beta}$ in Section (1) generally do not tend to decrease over time in all Panels, which casts doubt on the validity of the learning hypothesis. For the second test, the majority of the estimated coefficients $\boldsymbol{\beta}^{\boldsymbol{trend}}$ for the group return results in Panel A and Panel D are negative, regardless of whether dividend yield is included as an additional predictor or not. The coefficients $\boldsymbol{\beta}^{\boldsymbol{trend}}$ in Panel B, C, and E, however, provide mixed results, with half positive estimated coefficients (for the American and Asian *More-Com* groups) and another half negative coefficients (for the European *More-Com* group and the whole *More-Com* group). In addition, there are no significant differences in estimated results when the time trend is on a monthly or annual basis. The results for group return predictability suggest that there is some evidence that investors do learn group return predictability.

5. Stock return predictability: Individual country results

This section provides evidence of stock return predictability for each country in the *More-Com* group based on returns from the *Less-Com* group.

5.1. Country return predictability

Table 2.2 reports OLS estimates of β_1, robust t-statistic, and adjusted R-square for regression model (3). Dependent variables are returns for individual countries in the *More-Com* group while the main explanatory variables are lagged returns for the *Less-Com* group. We consider results from both the equally-weighted and value-weighted methods. The inclusion of $bill_{i,t}$

and $dy_{i,t}$ as additional explanatory variables in (2), controls for the predictive ability of national economic variables for each country in the *More-Com* group.

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From Panel A, of the ten $\hat{\beta}_1$ estimates under the equally-weighted (EW) method, eight are statistically positive and significant at 10% level of significance or better. This indicates that returns for the *Less-Com* group can predict future stock returns for eight individual countries in the *More-Com* group. The results for the other two countries, Germany and Italy, display no evidence for return predictability by the *Less-Com* group. Under the value-weighted (VW) method, stock excess returns for six out of ten countries are predictable, for instance: Australia, Belgium, Colombia, Greece, Indonesia, and Korea. The US return, reported in Panel B, displays a predictive power for future stock returns for five out of ten countries in the *More-Com* group, including Austria, Belgium, Greece, Indonesia, and Korea. According to results from Panel C, which examines the predictability by returns for the *Non-US* group, the EW method can help forecast future stock returns for eight of ten individual countries in the *More-Com* group; whereas, the VW method displays predictive evidence for nine out of ten countries in the same group. In brief, there is significant evidence that returns from the *Less-Com* group can predict future stock returns for individual countries in the *More-Com* group, with returns for the *Non-US* group exhibiting the strongest predictive power among predictors from the *Less-Com* group, followed by returns for the *Less-Com* group and the US returns[29].

In Table 2.2, we also examine the return predictability of national economic variables for individual countries in the *More-Com* group. Parentheses below $\overline{\mathrm{R}}^2$ statistic report the heteroskedasticity-robust χ^2 statistic for testing the null hypothesis of no return predictability for each country's Treasury bill rate ($bill_t$) and log dividend yield (dy_t) in model (3):

[29] We also estimate the predictive regression model (3) for excess returns computed from Thompson Reuters Datastream and report results in Appendix G2. These results are relatively similar to that from GFD's return indices.

$$\text{Ho: } \beta_{i,b} = \beta_{i,d} = 0. \tag{3.1}$$

The country's dividend yield is a significant return predictor for Indonesia while nominal interest rate, proxied by the three-month Treasury-bill rate, shows some return predictability for Colombia. Since estimated results in model (5) suggest no significant evidence for return predictability for the rest of the countries in the *More-Com* group, we do not reject this null from both the equally-weighted and value-weighted methods. To summarise, the Treasury-bill rate and log dividend yield from each country in the *More-Com* group cannot predict future stock returns for its own country.

Furthermore, we also examine the reverse relationship, to test if returns for the *More-Com* group can predict future stock returns for individual countries in the *Less-Com* group. This relationship, if it exists, will cast doubt on the return predictability generated from country information processing capacities. We report the predictive results in Appendix F2. Overall, the *More-Com* group has very limited predictive ability for future returns for countries in the *Less-Com* group. These results are consistent with previous findings of the no return predictability of the *More-Com* group.

Finally, we examine the return predictability of the *Less-Com* group for individual countries in the *More-Com* group in each region by estimating the predictive regression model (5). Table 2.4 reports predictive results for model (5), with dependent variables as excess returns for individual countries in the *More-Com* group in each region, and the main predictors as lagged excess returns for the *Less-Com* group in the same region. Specifically, regarding the European region, returns for the European *Less-Com* group can predict four out of five countries in the *More-Com* group: Austria, Belgium, Germany, and Greece. The Asian *Less-Com* group also displays a strong predictability for all countries in the Asian *More-Com* group (Indonesia and Korea). The American *Less-Com* group can predict future returns for only one country (Colombia) out of a total of three countries in the American *More-Com* group. Overall, the predictive results from the regional context points out the leading role of the *Less-Com* group in predicting returns for the *More-Com* group.

5.2. Out-of-Sample Performance: Individual country results

Table 3.2 reports the out-of-sample return predictability for each country in the *More-Com* group. Particularly, Panel A reports out-of-sample predictive results for model (3); whereas, Panel B reports results for predictive model (3) under the restriction β_b = β_d = 0. This table reports the out of sample performance for three predictors from the *Less-Com* group, including returns for the *Less-Com* group; the US returns; and returns for *Non-US* group. The out-of-sample R-square (R^2_{OS}) is calculated in accordance with Campbell and Thompson (2008). We determine the statistical significance based on the bootstrap critical value of R^2_{OS} by Goyal and Welch (2008), which is originally based on the works of Mark (1995) and Kilian (1999).

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Table 3.2 results indicate strong out-of-sample return predictability for individual countries in the *More-Com* group. Specifically, from Panel A, of the 10 R^2_{OS} under the EW method, eight are statistically positive and significant at 5% level of significance or better. This indicates a strong out-of-sample predictive power for both the *Less-Com* group and the *Non-US* group under the EW method. The R^2_{OS} for the other two countries, Germany and Italy, however, are statistically insignificant, suggesting no evidence for return predictability by the *Less-Com* group and the *Non-US* group. On the other hand, regarding R^2_{OS} under the VW method, six R^2_{OS} (predicted by the *Less-Com* group) and eight R^2_{OS} (predicted by the *Non-US* group) are statistically positive and significant at 5% level of significance or better. Again, these out-of-sample results suggest no evidence for Italy and Germany using the VW method. According to the out-of-sample results with the US return as a main predictor, six countries exhibit significant R^2_{OS} including: Austria, Belgium, Colombia, Greece, Indonesia, and Mexico. Overall, compared to the in-sample performance reported in Table 2.2, the out-of-sample performances are strongly consistent.

Compared to the results obtained from the unrestricted model in Panel A, the R_{OS}^2 obtained from the restricted model in Panel B are very similar. These results suggest that the Treasury-bill rate and dividend yield are not significant predictors for future return for individual countries in the *More-Com* group, and thus, when restricting these two variables in model (3), there are no substantial differences between the R_{OS}^2 in the restricted model and these figures in the unrestricted model. These results support previous findings, which suggest that a country's Treasury-bill rate and dividend yield are not strong predictors for future stock returns in its own country.

5.3. In Search of Economic Interpretation for Country Return Predictability

This section reports on investigation of the underlying economic rationale for country return predictability by investigating the sources of return predictability for each country in the *More-Com* group.

We test Hypothesis 2, which supports the arguments of cash flows and discount rates as sources of country return predictability by following two approaches. In the first approach, we test whether return predictability is due to a capacity to predict news related to cash flows (or news related to discount rates) in returns, by following the approach proposed by Bakshi et al. (2014).

Table 4.2 presents results for the predictive regression, with news related to cash flows and news related to discount rates (denoted by NCF_{t+1} and NDR_{t+1}, respectively) for individual countries in the *More-Com* group. Panel A and Panel B report results with predictors as returns for the *Less-Com* group; Panel C reports results with the US return as a predictor; whereas, Panel D and E report results for predictive regression with predictors as returns for the *Non-US* group.

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Regarding EW methods, among the eight countries for which returns can be predicted by the *Less-Com* group, six have statistically positive estimated coefficients for NCF_{t+1} and NDR_{t+1}. These countries, in which the estimated coefficients (either β_{DR} or β_{CF}) are significant at 10% level or better under the EW method, include Austria, Belgium, Greece, Indonesia, Korea, and Mexico. On the other hand, there are five countries in the *More-Com* group that have statistically significant estimated coefficients for NCF_{t+1} and NDR_{t+1} under the VW method. Compared to the EW method, predictors under the VW method display insignificant results in the Korean market. In addition, regardless of using either the EW or VW method, when significant, the estimated coefficients for NCF_t (denoted by β_{CF}) are much larger in absolute value than that for $NDR_t(\text{denoted by } \beta_{DR})$. These results, for country return predictability, are consistent with previous findings in group return predictability. Colombia is the only country that exhibits significantly negative coefficients (β_{CF}= -0.47) under the predictive regression model with the US return as a main predictor. Overall, the results in Table 4.2 suggest that cash flows and discount rates channels are the sources of return predictability for the majority of countries in the *More-Com* group. These findings not only support Hypothesis 1, but also affirm the essential roles of cash flows and discount rates as two main predictive channels of return.

In the second approach to test Hypothesis 2, we examine the relation between the predictability of country stock return and economic fundamentals, based on the approach proposed by Bakshi et al. (2014). Table 5.1 presents the relationship between the capacity to predict future stock returns for individual countries in the *More-Com* group (denoted by β_i) and capacity to predict economic fundamentals for stock returns for these countries (denoted by θ_i). Specifically, Panel A and Panel B reports results with predictors as returns for the *Less-Com* group; Panel C reports results with the US returns as predictors; and Panel D and Panel E present results with predictors as returns for the *Non-US* group.

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We report in Figure 2, which accompanies Table 5.1, the predictive slope coefficients β_i against θ_i for all ten countries in the *More-Com* group for the full sample from 1994-2013. The slope coefficients φ for all predictors are statistically positive and significant at 1% level. These results suggest that a higher ability to predict economic fundamentals leads to a higher ability to predict stock returns. For instance, in Panel A, Indonesia has the highest θ_i (0.75) and also has the highest β_i (0.77). At the other extreme, among countries that exhibit significant slope coefficients in Panel A, Belgium has the lowest θ_i (0.32) and at the same time the lowest β_i (0.19). Our results, therefore, provide cross-country evidence to support the growing literature that documents the gradual diffusion of information as an explanation for return predictability (Hong & Stein, 1999; Rapach et al., 2013; Bakshi et al., 2014).

Furthermore, we suggest two additional tests to examine the validity of Hypothesis 2. In the first additional test, we compute estimated coefficients (β_i and θ_i) for every country in the *More-Com* group for every five years in the full sample. If returns for the *Less-Com* group can predict returns for countries in the *More-Com* group by forecasting its economic fundamentals in the full sample, do these processes work for every five years in the sample? Our first test provides an answer to this claim. For the second additional test, we use a pooled sample that integrates the estimated coefficients for every five years into one sample, and thus, each country in the *More-Com* group has four estimated β_i and θ_i in the full sample[30]. This test overcomes the limitation of the previous two tests, since the number of observations in regression model (22) is above 30, and hence, the test's results have statistical meaning. In addition, this test provides additional out of sample test to examine the validity of Hypothesis 2.

We report the estimated results for two additional tests in Appendix H. Along with Appendix H, Appendix H1 and Appendix H2 plot the predictive slope coefficients β_i against

[30] We estimate two coefficients (β_i and θ_i) for 10 countries in the *More-Com* group for each five year period in the full sample of 20 years (1994-2013). Each country has four estimated coefficients in the full sample of 20 years, and hence, 10 countries have a total of 40 observations.

θ_i for all investigated countries, for every five years, and for the pooled sample, respectively. Overall, according to Appendix H1, the results from the Pooled sample are highly consistent with the previous findings, in the sense that the ability to predict stock return is positively related to the ability to predict economic fundamentals. These results are highly significant at the 1% level. However, Appendix H2, which reports the coefficients obtained from every five years model, provides mixed results. Specifically, the slope coefficients φ estimated from the first two five-year periods (1994-1998 and 1999-2003), which are positive and statistically significant, suggests that a higher ability to predict economic fundamentals leads to a higher ability to predict stock return. The estimated slopes φ obtained from the last two 5-year period (2004-2008 and 2009-2013) are all positive, but insignificant. These results may suggest that the 5-year period may be not long enough to exhibit a significantly positive relationship between ability to predict stock return and ability to predict its economic fundamentals.

In brief, empirical tests provide strong evidence to support the validity of Hypothesis 2, which documents the cash flows and discount rates as the sources of return predictability.

In search for the sources of return predictability for individual countries in the *More-Com* group, Hypothesis 3 suggests that the return predictability of the *Less-Com* group is due to its ability to capture variation in risk premiums, as measured by volatility. We adopt the approach suggested by Bakshi et al. (2014) to estimate an E-GARCH (1,1) model, that includes the lagged excess return of the *More-Com* group in the volatility equation as an exogenous predictor. Our focus is on $\boldsymbol{\gamma_{\mathrm{less}}}$, which captures the relation between returns of the *Less-Com* group and estimated variance. A significantly positive γ_{less} would indicate a positive relation between return of the *Less-Com* group and expected volatility, and thus, support Hypothesis 3. We report the estimated results for individual countries in the *More-Com* group in Table 6.2.

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Insert Table 6.2 here
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Table 6.2 reports estimated results for an E-GARCH (1,1) model for all 10 countries in the *More-Com* group. Obviously, the estimated γ_{less} are either negative or insignificant in all investigated markets. Thus, these results suggest that there is no evidence for the volatility-based channel of return predictability. We, therefore, do not accept Hypothesis 3, that the return predictability of the *Less-Com* group for individual countries in the *More-Com* group is driven by time-varying risk premiums.

5.4. Learning effects: Individual country results

We test the Learning Hypothesis by applying two approaches proposed by Bakshi et al. (2014). In the first approach, we consider the time evolution of slope coefficients that are obtained in the predictive regression model (28). We report the estimated slope coefficients $\boldsymbol{\beta}$ for individual countries in the *More-Com* group in Section (1) in Table 7. In the second approach, we assess the time variation in the predictive slope coefficient and report the estimated coefficients $\boldsymbol{\beta^{trend}}$ for all countries in the *More-Com* group in Section (2) and (3) in Table 7.

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Insert Table 7 here
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Regarding the results for the first test, the estimated slope coefficients $\boldsymbol{\beta}$ in Section (1) generally do not tend to decrease over time in each country in the *More-Com* group across all Panels, which casts doubt on the validity of the learning hypothesis. For the second test, the coefficients $\boldsymbol{\beta^{trend}}$ for each country in the *More-Com* group provide mixed results across all Panels. Specifically, five countries exhibit the negative coefficient $\boldsymbol{\beta^{trend}}$, regardless of whether the time trend is on a monthly or annual basis: Brazil, Colombia, Indonesia, Korea, and Mexico. On the other hand, the other five markets in the *More-Com* group exhibit positive coefficients $\boldsymbol{\beta^{trend}}$. Compared to results when the time trend is on a monthly basis, the estimated results, when the time trend is on an annual basis, seem to favour the learning theory, with six of the ten countries exhibiting negative coefficients $\boldsymbol{\beta^{trend}}$. Overall, the results for the individual country return predictability do not strongly support the hypothesis that investors do learn country return predictability.

6. Further Discussion

The complexity in information processing across countries is closely related to the disagreement about an asset's value in financial markets. A growing strand of literature, pioneered by Miller (1997), tries to cast light on the impact of heterogeneous beliefs in cross-sectional asset prediction. Specifically, Miller suggests that great disagreement about a stock's value is often accompanied by its lowest subsequent return, according to the price-optimism model. A recent study by Yu (2011) extends Miller's finding by investigating portfolio disagreement and comes to a similar conclusion. Diether, Malloy, and Scherbina (2002) provide cross-sectional evidence for Miller's prediction. They also suggest that differences of opinion, which can be induced by asymmetric information, significantly affect asset prices. Academic studies report a range of various measurements for differences of opinion. Lee and Swaminathan (2000), for example, use trading volume as a proxy for the differences of opinion. Chen, Hong, and Stein (2002) use breadth of mutual fund ownership to measure the degree of disagreement among investors, while Diether et al. (2002) employ dispersion in analyst's earning forecasts as proxy for the divergence of opinion. Regardless of measure approaches, these studies' results are consistent with Miller's prediction, and all suggest the asset pricing implications of differences of opinion. At the country level, the variations in information processing environment, which are induced by asymmetric information, resemble the differences of opinion across countries, and hence, provide a setting for cross-country asset prediction. Furthermore, Yu (2011) finds a strong correlation between variations in disagreements and discount rate news and cash flow news, which are two return decompositions in Campbell and Shiller (1989). Since cash flow news and discount rate news have vital implications for asset pricing (Campbell & Shiller, 1989; Yu, 2011), the correlation between disagreement and these two return decompositions adds to the understanding of the roles of disagreement in the asset price discovery process.

Furthermore, Fama and French (1988) raise an interesting economic question about "whether the predictability of returns…is driven by rational economic behaviour…or by animal spirits" (p. 5). In efficient markets, future returns cannot be forecast on the basis of existing information under the efficient market hypothesis (Fama, 1970). Thaler (1999), however, suggests that "market behaviour often diverges from what we expect in a rational efficient market" and that "stock prices are at least partly predictable" (p. 14). Behavioural finance, which is described as "the application of psychology to financial decisions" (Shefrin, 2010), provides a framework to understand market anomalies and return predictability. Daniel Kahneman, the winner of the Nobel Prize in Economics in 2002, in his book "Thinking, Fast and Slow" (2011) introduces two thinking systems that generate a person's decisions and actions. According to Kahneman (2011), our brain processes information in two ways: the fast-thinking system and the slow-thinking system. An example of the fast thinking system (or System 1) is the survival instinct: when we face dangerous situations, we act quickly and instinctively to save ourselves. The slow thinking system (or System 2) facilitates our analytical functions with limited information in a complex world, such as deciding which markets to invest in, or which stocks to buy. In the world of uncertainty, given information barriers across countries, the investor's irrational actions (either to over-react or under-react) to relevant macroeconomic information can create the sources for cross-country return predictability.

7. Conclusion

We examine the roles of information processing complexity in price discovery process across countries. We show that returns from less complicated countries predict future returns for more complicated countries with the out-of-sample R^2's ranging from 3% to 14%. The results suggest that the predictability induced by the complications in information processing is consistent at both group and country level. Our results prevail after we control for regional effects. Our findings are consistent with previous literature that documents the roles of information asymmetry in return predictability. The predictability induced by the complexity in information processing is also closely related to the disagreement about an asset's value and investors' irrationality.

We provide evidence for the economic linkage between the complications in country information processing and stock return predictability. Information barriers among countries seem to be natural candidates for gradual diffusion of information. We show that the return predictability is closely related to its ability to predict stock return components, both cash flow and discount rate. We also find a positive relation between ability to predict future stock return and ability to predict economics fundamentals for returns. Our findings support the learning theory for the group level prediction, but remain controversial for the country level prediction. We also find no evidence to support the hypothesis that return predictability is driven by the time-varying risk premium. Our results suggest that the return predictability induced by information processing complexity is a true phenomenon at both group level and country level.

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Table 1.1: Country Classification Description

The table describes the three steps to define the *More-Com* and *Less-Com* countries, including (1) Sum of ranks; (2) Coefficient of Variation (CV), and (3) Union approach. In the first step, based on the five information indices from La Porta et al.'s (2006) survey (Information Disclosure, Liability Standard, Public Enforcement, Anti-director, and Judiciary Efficiency) we rank each index in ascending order, in which the highest score is given to country with the best information processing environment in each index and then sum these ranks. After sorting countries in the sample using their sum of ranks, we define the group with the highest sum of ranks as the *Highest-Rank* (HR) group and the group with the lowest sum of rank as the *Lowest-Rank* (LR) group. In the second step, we classify all countries in the sample into three groups by the coefficient of variations and define the group with lowest coefficient of variation as the *Least-Variation* (LV) group and the group with highest variation as the *Most-Variation* (MV) group. Finally, in the union step, we define an intersection between the highest sum of rank group (HR) and the lowest coefficient variation group (LV) as the *Less-Com* (LC) group; and define an intersection between the lowest sum of rank group (LR) and the most variation group (MV) as the *More-Com* (MC) group. For every step, the blank denotes the middle group.

	Rankings					Sum Ranks	Rank variation	Mean of Rank	CV	Group by 3 steps		
Country	Information Disclosure	Liability Standard	Public Enforcement	Anti-director	Judiciary Efficiency					Group by Sum rank	Group by CV	Group by Union
Australia	23	19	37	24	26	129	6.05	25.8	0.23	HR	LV	LC
Austria	1	2	3	5	24	35	8.60	7	1.23	LR	MV	MC
Belgium	5	13	2	1	24	45	8.60	9	0.96	LR	MV	MC
Brazil	1	9	20	13	6	49	6.43	9.8	0.66	LR	MV	MC
Canada	32	36	33	31	23	155	4.34	31	0.14	HR	LV	LC
Chile	13	9	24	31	16	93	7.91	18.6	0.43	HR		
Colombia	5	2	20	13	16	56	6.73	11.2	0.60	LR	MV	MC
Denmark	13	18	13	5	26	75	6.90	15	0.46			
Finland	9	19	7	13	26	74	6.94	14.8	0.47			
France	23	5	30	13	18	89	8.52	17.8	0.48			
Germany	5	1	4	2	21	33	7.34	6.6	1.11	LR	MV	MC
Greece	3	17	7	5	14	46	5.38	9.2	0.58	LR	MV	MC
Hong Kong, China	32	19	35	31	26	143	5.61	28.6	0.20	HR	LV	LC
Indonesia	9	19	25	5	1	59	8.91	11.8	0.75	LR	MV	MC
India	32	19	27	31	18	127	5.89	25.4	0.23	HR	LV	LC
Ireland	18	13	13	24	20	88	4.22	17.6	0.24		LV	
Israel	18	19	26	13	26	102	5.00	20.4	0.25	HR	LV	LC
Italy	18	5	17	2	11	53	6.34	10.6	0.60	LR	MV	MC
Japan	23	19	1	24	26	93	9.09	18.6	0.49	HR		
Korea, Rep.	23	19	5	5	7	59	7.65	11.8	0.65	LR	MV	MC
Malaysia	32	19	30	24	21	126	5.04	25.2	0.20	HR	LV	LC
Mexico	13	2	12	2	7	36	4.71	7.2	0.65	LR	MV	MC

Table 1.1 *(Continue)*

Country	Rankings					Sum Ranks	Rank variation	Mean of Rank	CV	Group by 3 steps		
	Information Disclosure	Liability Standard	Public Enforcement	Anti-director	Judiciary Efficiency					Group by Sum rank	Group by CV	Group by Union
Netherlands	9	35	16	5	26	91	11.02	18.2	0.61		MV	
Pakistan	13	11	22	31	4	81	9.37	16.2	0.58			
Peru	3	19	32	13	11	78	9.67	15.6	0.62		MV	
Philippines	29	36	34	13	3	115	12.85	23	0.56	HR		
Portugal	5	19	22	13	5	64	7.00	12.8	0.55	LR		
Singapore	37	19	35	24	26	141	6.79	28.2	0.24	HR	LV	LC
Spain	9	19	11	24	10	73	5.89	14.6	0.40	LR		
Sri Lanka	23	11	15	13	14	76	4.12	15.2	0.27		LV	
Sweden	13	8	18	13	26	78	6.09	15.6	0.39			
Switzerland	18	13	9	5	26	71	7.30	14.2	0.51	LR		
Taiwan	23	19	19	13	11	85	4.38	17	0.26		LV	
Thailand	32	7	29	5	2	75	12.79	15	0.85		MV	
United Kingdom	29	19	28	31	26	133	4.13	26.6	0.16	HR	LV	LC
United States	37	36	37	31	26	167	4.32	33.4	0.13	HR	LV	LC
South Africa	29	19	6	31	7	92	10.54	18.4	0.57	HR		

Table 1.2: Summary statistics, Country Stock Raw Returns, 1994:02 to 2013:12

The table reports summary statistics for average monthly US$ dominated raw return (in percentage) for 38 countries in the whole sample. Sharpe ratio is the mean of the raw return divided by its standard deviation; and Autocorrelation displays the correlation between raw return and lagged raw return. Country return indices are from Global Financial Data; the sample is from 1994:02 to 2013:12.

		(1)	(2)	(3)	(4)	(5)	(6)
No.	Country	Mean	Standard Deviation	Minimum	Maximum	Autocorrelation	Sharpe Ratio
1	Australia	0.91	6.22	-28.53	16.55	0.05	0.15
2	Austria	0.51	7.00	-39.22	22.83	0.20	0.07
3	Belgium	0.75	5.79	-28.64	18.14	0.18	0.13
4	Canada	0.82	5.99	-28.22	21.34	0.13	0.14
5	Denmark	1.00	5.70	-28.08	17.00	0.14	0.18
6	Finland	0.88	8.52	-32.27	29.77	0.18	0.10
7	France	0.69	6.09	-23.82	15.15	0.09	0.11
8	Germany	0.71	6.71	-26.90	21.06	0.06	0.11
9	Greece	0.49	10.06	-39.24	38.05	0.13	0.05
10	Hong Kong, China	0.57	7.43	-34.59	25.61	0.04	0.08
11	Ireland	0.66	6.30	-26.08	17.71	0.20	0.10
12	Israel	0.40	6.92	-26.73	15.24	0.05	0.06
13	Italy	0.57	6.87	-24.84	19.56	0.02	0.08
14	Japan	0.07	5.40	-16.22	16.63	0.19	0.01
15	Korea, Rep.	0.75	10.97	-35.44	59.22	0.06	0.07
16	Netherlands	0.73	6.14	-26.68	14.12	0.03	0.12
17	New Zealand	0.84	5.95	-20.31	16.61	0.03	0.14
18	Portugal	0.58	6.34	-30.97	15.77	0.18	0.09
19	Singapore	0.51	7.57	-32.79	23.90	0.10	0.07
20	Spain	0.91	6.96	-22.12	20.10	0.08	0.13
21	Sweden	1.00	7.16	-28.61	21.38	0.06	0.14
22	Switzerland	0.80	4.90	-16.77	13.76	0.10	0.16
23	Taiwan	0.42	8.31	-24.67	27.56	0.09	0.05
24	United Kingdom	0.65	4.72	-21.29	13.98	0.15	0.14
25	United States	0.72	4.45	-18.39	10.37	0.09	0.16
26	Brazil	0.90	12.09	-50.92	39.98	0.09	0.07
27	Colombia	1.23	8.95	-30.41	27.26	0.19	0.14
28	Chile	0.67	6.87	-33.90	19.71	0.10	0.10
29	Indonesia	0.57	13.00	-45.91	55.46	0.17	0.04
30	India	0.58	8.42	-34.12	31.61	0.07	0.07
31	Mexico	0.83	8.85	-38.55	18.37	0.08	0.09
32	Malaysia	0.45	8.55	-37.12	44.90	0.22	0.05
33	Peru	1.17	9.34	-44.90	31.11	0.00	0.12
34	Philippines	0.27	8.32	-29.63	34.12	0.12	0.03
35	Pakistan	0.47	11.19	-69.21	33.52	0.02	0.04
36	South Africa	0.80	7.83	-35.99	20.37	0.00	0.10
37	Sri Lanka	0.34	9.99	-28.55	49.07	0.10	0.03
38	Thailand	0.17	10.91	-38.71	36.83	0.07	0.02

Table 1.3: Summary Statistics, Excess Return for Countries in Groups

The table reports summary statistics for monthly US$ dominated excess return (in percentage) for individual countries in the more complicated group (Panel A) and in the less complicated group (Panel B). Countries are classified in to the more (less) complicated group based on the results of the union approach. The excess return is computed relative to each country's three-month Treasury bill rate; Sharpe ratio is the mean of the excess return divided by its standard deviation; and Autocorrelation displays the correlation between excess return and lagged excess return. Country return indices are from Global Financial Data; the sample is from 1994:02 to 2013:12.

No.	Country	(1) Mean	(2) Standard Deviation	(3) Minimum	(4) Maximum	(5) Autocorrelation	(6) Sharpe Ratio
Panel A: Countries in The More Complicated Group							
1	Austria	0.28	7.02	-39.57	22.72	0.20	0.04
2	Belgium	0.53	5.80	-28.85	17.98	0.18	0.09
3	Brazil	-0.57	12.02	-52.60	36.78	0.10	-0.05
4	Colombia	0.30	9.07	-31.14	24.80	0.21	0.03
5	Germany	0.50	6.72	-27.11	20.88	0.06	0.07
6	Greece	-0.26	10.20	-39.62	37.06	0.16	-0.03
7	Indonesia	-0.46	12.98	-48.68	50.15	0.17	-0.04
8	Italy	0.28	6.88	-24.99	19.10	0.02	0.04
9	Korea	0.22	11.00	-36.40	57.93	0.06	0.02
10	Mexico	-0.18	8.91	-40.45	17.81	0.09	-0.02
Panel B: Countries in The Less Complicated Group							
1	Australia	0.49	6.22	-28.88	16.28	0.05	0.08
2	Canada	0.56	5.99	-28.35	21.32	0.13	0.09
3	Hong Kong, China	0.34	7.45	-35.38	25.10	0.04	0.05
4	Israel	-0.16	6.93	-27.25	14.38	0.05	-0.02
5	India	-0.07	8.44	-34.68	31.18	0.07	-0.01
6	Malaysia	0.16	8.58	-37.86	44.36	0.22	0.02
7	Singapore	0.40	7.57	-32.86	23.84	0.10	0.05
8	United Kingdom	0.32	4.73	-21.52	13.93	0.15	0.07
9	United States	0.49	4.44	-18.42	10.37	0.09	0.11

Table 2.1: Predictive Regression Model Results: Group Return Predictability

The table reports OLS estimates of β_1, β_b, and β_d (denoted by $\hat{\beta}_1$, $\hat{\beta}_b$, and $\hat{\beta}_d$, respectively) and the Adjusted R-square (denoted by $\overline{R}^2$) for the predictive regression model:

$$rMC_{t+1} = \beta_0 + \beta_1\, rLC_t + \beta_b\, billMC_t + \beta_d\, dyMC_t + \varepsilon_{t+1} \quad (1)$$

where rMC_{t+1} is the monthly US$ dominated excess return for the *More-Com* group; rLC_t is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_t$ ($dyMC_t$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for the *More-Com* group. This table reports predictive results from equally weighted and value weighted variables. Panel A reports the predictive results with predictor as return for the *Less-Com* group; whereas, Panel B presents the predictive results by the US return, and Panel C reports the results with return for the *Non-US* group as predictors. We report Newey and West (1987) robust t-statistic in parentheses in the first, second, third, fifth, sixth, and seventh columns. The fifth and tenth columns report heteroskedasticity-robust χ^2 statistic for testing Ho: β_b = β_d= 0. Brackets report p-values. The sample period is from 1994:02 to 2013:12. The signals ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Equally Weighted					**Value Weighted**				
$\hat{\beta}_1$	$\hat{\beta}_b$ bill	$\hat{\beta}_d$ dy	$\overline{R}^2$	χ^2	$\hat{\beta}_1$	$\hat{\beta}_b$ bill	$\hat{\beta}_d$ dy	$\overline{R}^2$	χ^2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Predictors are Returns for the *Less-Com* Group									
0.40***	-0.20	0.06**	9.19%	4.42	0.20*	0.03	0.03	1.14%	0.84
(3.13)	(-0.68)	(2.38)		[0.10]	(1.74)	(0.13)	(0.82)		[0.66]
[0.00]	[0.49]	[0.02]			[0.08]	[0.90]	[0.41]		
Panel B: Predictor are the US return									
0.25**	0.12	0.06**	5.38%	6.25	0.15	0.10	0.03	0.60%	1.03
(2.01)	(0.41)	(2.34)		[0.04]	(1.42)	(0.37)	(0.75)		[0.60]
[0.05]	[0.68]	[0.02]			[0.16]	[0.71]	[0.46]		
Panel C: Predictors are Returns for the *Non-US* Group									
0.39***	-0.21	0.06**	9.33%	4.27	0.24**	-0.08	0.02	2.00%	0.71
(3.17)	(-0.72)	(2.33)		[0.11]	(2.06)	(-0.33)	(0.83)		[0.70]
[0.00]	[0.47]	[0.02]			[0.04]	[0.74]	[0.41]		

Table 2.2: Predictive Regression Model Results: Individual Country Return Predictability

The table reports OLS estimates of β_1, β_b and β_d (denoted by $\hat{\beta}_1$, $\hat{\beta}_b$ and $\hat{\beta}_d$, respectively) and the Adjusted R-square (denoted by $\bar{R}^2$) for the predictive regression model:

$$rMC_{i,t+1} = \beta_0 + \beta_{1,i}\, rLC_t + \beta_b\, billMC_{i,t} + \beta_d\, dyMC_{i,t} + \varepsilon_{t+1} \quad (3)$$

where $rMC_{i,t+1}$ is the monthly US$ dominated excess return for country *i* in the *More-Com* group; $rLC_{,t}$ is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_{i,t}$ ($dyMC_{i,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for country *i* in the *More-Com* group. This table reports predictive results from equally weighted (EW) and value weighted (VW) variables. Panel A reports the predictive results with predictors as returns for the *Less-Com* group; whereas, Panel B presents the predictive results by the US return, and Panel C reports the results with returns for the *Non-US* group as predictors. We report the Newey and West (1987) robust t-statistic in parentheses (under coefficients). Parentheses below $\bar{R}^2$ report heteroskedasticity-robust χ^2 statistic for testing null hypothesis Ho: $\beta_{i,b}$ = $\beta_{i,d}$ = 0. The sample period is from 1994:02 to 2013:12. The signal * indicates significance at the 10% level or better.

	Panel A: Predictors are Returns for the *Less-Com* group								Panel B: Predictors are the US returns				Panel C: Predictors are Returns for the *Non-US* group							
	EW				VW								EW				VW			
(i)	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$
Austria	0.35*	-0.04	0.00	5.13%	0.33*	0.02	0.00	3.53%	0.29*	0.08	0.00	2.38%	0.34*	-0.04	0.00	5.18%	0.35*	-0.08	0.00	4.69%
	(2.90)	(-0.22)	(0.02)	(0.04)	(2.57)	(0.14)	(0.11)	(0.04)	(2.40)	(0.45)	(0.10)	(0.24)	(2.87)	(-0.25)	(0.01)	(0.06)	(2.57)	(-0.46)	(0.09)	(0.17)
Belgium	0.18*	0.05	-0.01	1.78%	0.23*	0.06	0.00	2.24%	0.20*	0.10	0.00	1.65%	0.17*	0.05	-0.01	1.67%	0.22*	0.01	0.00	2.39%
	(1.77)	(0.33)	(-0.03)	(0.09)	(2.10)	(0.39)	(0.06)	(0.14)	(2.03)	(0.61)	(0.05)	(0.38)	(1.71)	(0.30)	(-0.05)	(0.10)	(1.87)	(0.05)	(0.01)	(0.01)
Brazil	0.45*	-0.18	0.03	2.76%	0.26	-0.10	0.02	0.52%	0.14	-0.06	0.03	-0.04%	0.45*	-0.19	0.03	3.06%	0.42*	-0.18	0.03	2.25%
	(2.55)	(-1.19)	(1.29)	(2.72)	(1.37)	(-0.71)	(1.19)	(1.97)	(0.76)	(-0.43)	(1.12)	(1.74)	(2.65)	(-1.23)	(1.29)	(2.79)	(2.37)	(-1.19)	(1.31)	(2.73)
Colombia	0.31*	0.33	0.01	6.13%	0.29*	0.37*	0.01	5.37%	0.25	0.42*	0.01	4.96%	0.29*	0.33	0.01	6.13%	0.33*	0.29	0.01	6.26%
	(1.92)	(1.48)	(0.89)	(2.86)	(1.65)	(1.68)	(0.96)	(3.70)	(1.47)	(1.99)	(1.03)	(4.95)	(1.94)	(1.50)	(0.90)	(2.90)	(1.96)	(1.28)	(0.89)	(2.22)
Germany	0.15	-0.03	0.00	-0.10%	0.14	-0.01	0.00	-0.36%	0.12	0.02	0.00	-0.61%	0.14	-0.03	0.00	-0.10%	0.16*	-0.05	0.00	-0.06%
	(1.61)	(-0.18)	(0.12)	(0.03)	(1.41)	(-0.03)	(0.98)	(0.01)	(1.18)	(0.14)	(0.10)	(0.02)	(1.62)	(-0.19)	(0.11)	(0.03)	(1.64)	(-0.31)	(0.16)	(0.08)
Greece	0.40*	-0.27	0.00	2.42%	0.36*	-0.20	0.00	1.01%	0.29*	-0.14	0.00	0.27%	0.39*	-0.27	0.00	2.51%	0.39*	-0.30	0.00	2.02%
	(2.61)	(-1.02)	(0.23)	(1.32)	(2.03)	(-0.76)	(0.12)	(0.77)	(1.70)	(-0.53)	(0.07)	(0.38)	(2.66)	(-1.04)	(0.23)	(1.35)	(2.44)	(-1.15)	(0.17)	(1.65)
Indonesia	0.73*	-0.04	0.06*	10.86%	0.64*	0.06	0.06*	8.12%	0.59*	0.08	0.07*	7.30%	0.71*	-0.04	0.06*	10.95%	0.62*	0.04	0.06*	8.80%
	(3.40)	(-0.17)	(3.02)	(7.54)	(2.48)	(0.33)	(3.28)	(8.94)	(2.10)	(0.42)	(3.38)	(9.86)	(3.49)	(-0.20)	(2.98)	(7.38)	(3.10)	(0.21)	(3.06)	(7.58)
Italy	0.14	-0.07	-0.01	-0.23%	0.15	-0.05	-0.01	-0.27%	0.13	-0.02	-0.01	-0.56%	0.13	-0.07	-0.01	-0.24%	0.16	-0.10	-0.01	-0.01%
	(1.25)	(-0.40)	(-0.27)	(0.22)	(1.24)	(-0.32)	(-0.15)	(0.12)	(1.05)	(-0.14)	(-0.14)	(0.04)	(1.25)	(-0.41)	(-0.28)	(0.23)	(1.38)	(-0.61)	(-0.23)	(0.34)
Korea	0.59*	-0.64*	0.01	7.85%	0.56*	-0.63*	0.01	5.52%	0.48*	-0.58*	0.01	4.33%	0.57*	-0.64*	0.01	7.9%	0.56*	-0.65*	0.01	6.76%
	(3.98)	(-3.20)	(0.48)	(2.73)	(3.18)	(-2.83)	(0.34)	(2.21)	(2.62)	(-2.51)	(0.34)	(1.84)	(3.87)	(-3.15)	(0.47)	(2.71)	(3.58)	(-3.06)	(0.27)	(2.61)
Mexico	0.28*	0.10	0.02	2.24%	0.10	0.22	0.02	0.31%	0.01	0.27	0.02	0.09%	0.29*	0.09	0.02	2.56%	0.24*	0.13	0.02	1.48%
	(1.91)	(0.34)	(0.76)	(0.60)	(0.69)	(0.79)	(0.68)	(1.09)	(0.05)	(1.03)	(0.60)	(1.49)	(2.00)	(0.31)	(0.76)	(0.56)	(1.64)	(0.44)	(0.79)	(0.72)

Table 2.3: Predictive Regression Model Results: Regional Group Return Predictability

The table reports OLS estimates of β_1, (denoted by $\hat{\beta}_1$) and the Adjusted R-square (denoted by $\bar{R}^2$) for the predictive regression model:

$$rMC_{j,t+1} = \beta_0 + \beta_{1,j}\, rLC_{j,t} + \beta_{b,j}\, billMC_{j,t} + \beta_{d,j}\, dyMC_{j,t} + \varepsilon_{j.t+1} \qquad (4)$$

where $rMC_{\ j,t+1}$ is the monthly US$ dominated excess return for the *More-Com* group in region *j*; $rLC_{j,t}$ is the monthly US$ dominated excess return for the *Less-Com* group in region *j*; and $billMC_{j,t}$ ($dyMC_{j,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for the *More-Com* group in region *j*. This table reports predictive results from equally weighted (EW) and value weighted (VW) variables. Panel A reports the predictive results for the American region; whereas, Panel B presents the predictive results for the Asian region and Panel C reports the results with return for the European region. We report the Newey and West (1987) robust t-statistic in parentheses under coefficients. We do not report estimates $billMC_t$ ($dyMC_t$) to save space. Parentheses below $\bar{R}^2$ report heteroskedasticity-robust χ^2 statistic for testing null hypothesis H_0: $\beta_{b,j}$ = $\beta_{d,j}$ = 0. The sample period is from 1994:02 to 2013:12. The signals ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

(1) Regional Less-Com				(2) All Less-Com				(3) US return				(4) Non-US			
EW		VW		EW		VW		EW		VW		EW		VW	
$\hat{\beta}_1$	$\bar{R}^2$	$\hat{\beta}_1$	$\bar{R}^2$	$\hat{\beta}_1$	$\bar{R}^2$	$\hat{\beta}_1$	$\bar{R}^2$	$\hat{\beta}_1$	$\bar{R}^2$	$\hat{\beta}_1$	$\bar{R}^2$	$\hat{\beta}_1$	$\bar{R}^2$	$\hat{\beta}_1$	$\bar{R}^2$
Panel A: For the American region															
0.37**	1.78%	0.56**	1.68%	0.60***	7.03%	1.09**	1.52%	0.22	0.25%	0.66	0.03%	0.60***	7.59%	1.75***	5.76%
(2.18)	(9.61)	(2.13)	(11.91)	(3.50)	(35.81)	(2.04)	(9.50)	(1.48)	(3.60)	(1.41)	(3.35)	(3.57)	(39.12)	(3.16)	(33.81)
Panel B: For the European region															
0.24*	2.28%	1.20*	2.28%	0.23**	2.91%	1.13**	2.21%	0.19*	1.63%	0.97*	1.63%	0.22**	2.92%	1.17**	2.72%
(1.75)	(6.24)	(1.75)	(6.24)	(2.37)	(9.89)	(1.96)	(9.67)	(1.75)	(12.28)	(1.75)	(12.28)	(2.39)	(9.88)	(2.10)	(7.61)
Panel C: For the Asian region															
0.67***	8.96%	0.26***	11.07%	0.76***	8.62%	1.12***	6.88%	0.45**	3.90%	0.94**	5.78%	0.75***	8.93%	1.20***	8.28%
(4.62)	(16.27)	(4.38)	(45.88)	(4.31)	(15.61)	(2.58)	(41.56)	(2.03)	(1.32)	(2.12)	(41.71)	(4.41)	(16.92)	(3.23)	(43.69)

Table 2.4: Predictive Regression Model Results: Regional Country Return Predictability

The table reports OLS estimates of β_1 (denoted by $\hat{\beta}_1$) for the predictive regression model:

$$rMC_{ij,t+1} = \beta_0 + \beta_{1,ij}\, rLC_{j,t} + \beta_b\, billMC_{ij,t} + \beta_d\, dyMC_{ij,t} + \varepsilon_{ij,t+1} \qquad (5)$$

where $rMC_{ij,t+1}$ is the monthly US$ dominated excess return for country *i* in the *More-Com* group in region *j*; $rLC_{j,t}$ is the monthly US$ dominated excess return for the *Less-Com* group in region *j*; and $billMC_{ij,t}$ ($dyMC_{ij,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for country *i* in the *More-Com* group in region *j*. This table reports predictive results from equally weighted (EW) and value weighted (VW) variables. We report the Newey and West (1987) robust t-statistic in parentheses (under coefficient). We do not report estimates $billMC_t$ ($dyMC_t$) to save space. The sample period is from 1994:02 to 2013:12. The signals ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

		(1) Brazil	(2) Colombia	(3) Mexico	(4) Austria	(5) Belgium	(6) Germany	(7) Greece	(8) Italy	(9) Indonesia	(10) Korea
American *More-Com* Group	EW	0.20	0.31**	0.05							
		(1.15)	(2.39)	(0.42)							
	VW	0.10	0.15**	0.03							
		(1.15)	(2.39)	(0.42)							
European *More-Com* Group	EW				0.34***	0.25***	0.17*	0.40***	0.17		
					(3.25)	(2.83)	(1.65)	(2.56)	(1.64)		
	VW				0.34***	0.25***	0.17*	0.40***	0.17		
					(3.25)	(2.83)	(1.65)	(2.56)	(1.64)		
Asian *More-Com* Group	EW									0.65***	0.49***
										(4.42)	(4.06)
	VW									0.13***	0.10***
										(4.42)	(4.06)

Table 3.1: Out-of-Sample Performance for Group Return Predictability

The table reports out-of-sample for performance for group return predictability. Panel A reports out-of-sample predictive results for unrestricted model (1) and Panel B report results under the restriction $\beta_b = \beta_d = 0$ (2) as follows:

$$rMC_{t+1} = \beta_0 + \beta_1 \, rLC_t + \beta_b \, billMC_t + \beta_d \, dyMC_t + \varepsilon_{t+1} \tag{1}$$

where rMC_{t+1} is the monthly US$ dominated excess return for the *More-Com* group; rLC_t is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_t$ ($dyMC_t$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for the *More-Com* group. This table reports the out of sample performance for three predictors from the *Less-Com* group, including returns for *Less-Com* group; the US returns; and returns for the *Non-US* group. The out-of-sample (00S) R-square is calculated in accordance with Campbell and Thompson (2008). Bootstrap critical value of the OOS R-square follows the approach adopted Goyal and Welch (2008), that is based on the work of Mark (1995) and Kilian (1999). Coefficients that are statistically significant at the 10% level are in **bold.**

	Returns for the *Less-Com* Group		The US Returns		Returns for the *Non-US* Group	
	EW (1)	VW (2)	EW (3)	VW (4)	EW (5)	VW (6)
Panel A: Unrestricted Model						
OOS R-square	**14.072%**	**3.648%**	**9.646%**	**3.172%**	**14.181%**	**4.273%**
Bootstrap OOS R-square P-value	0.000	0.065	0.000	0.076	0.000	0.054
Bootstrap 90% Critical OOS R-square	2.160%	2.235%	2.145%	2.360%	2.160%	2.145%
Bootstrap 95% Critical OOS R-square	3.435%	4.405%	3.480%	4.370%	3.460%	4.390%
Bootstrap 99% Critical OOS R-square	5.880%	6.680%	5.660%	6.555%	5.855%	7.285%
Panel B: Restricted Model						
OOS R-square	**8.983%**	**2.039%**	**3.748%**	**1.414%**	**9.192%**	**2.901%**
Bootstrap OOS R-square P-value	0.000	0.042	0.011	0.063	0.000	0.043
Bootstrap 90% Critical OOS R-square	1.810%	1.120%	1.170%	0.950%	1.810%	1.750%
Bootstrap 95% Critical OOS R-square	2.755%	1.850%	1.945%	1.640%	2.755%	2.690%
Bootstrap 99% Critical OOS R-square	4.860%	3.615%	3.840%	3.355%	4.860%	4.740%

Table 3.2: Out-of-Sample Performance for predicting Individual Country

The table reports out-of-sample performance for return predictability for country *i* in the more complicated group from the following predictive regression model:

$$rMC_{i,t+1} = \beta_0 + \beta_{1,i}\, rLC_t + \beta_{i,b}\, billMC_{i,t} + \beta_{i,d}\, dyMC_{i,t} + \varepsilon_{t+1} \quad (3)$$

where $rMC_{i,t+1}$ is the monthly US$ dominated excess return for country *i* in the *More-Com* group; $rLC_{,t}$ is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_{i,t}$ ($dyMC_{i,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for country *i* in the *More-Com* group. Panel A reports the out of sample performances from model (3) and Panel B report the out-of sample performance from model (3) under the restriction ($\beta_{i,b}$ = $\beta_{i,d}$ = 0). This table reports results for three predictors from the *Less-Com* group, including returns for All *Less-Com* group; the US returns; and returns for the *Non-US* group. The out-of-sample (00S) R-square is calculated in accordance with Campbell and Thompson (2008). Bootstrap critical value of the OOS R-square follows the approach adopted Goyal and Welch (2008), that is based on the work of Mark (1995) and Kilian (1999). Coefficients that are statistically significant at the 10% level or better are in **bold.**

Panel A: Out-of-Sample Performance for Unrestricted model

		Returns for the *Less- Com* Group		The US returns	Returns for the *Non-US* Group	
		EW	VW		EW	VW
i		(1)	(2)	(3)	(4)	(5)
Austria	OOS R-square	**7.370%**	**6.05%**	**5.11%**	**7.33%**	**6.71%**
	Bootstrap OOS R-square P-value	0.004	0.007	0.013	0.004	0.007
	Bootstrap 90% Critical OOS R-square	2.645%	2.160%	2.110%	2.730%	3.105%
	Bootstrap 95% Critical OOS R-square	3.760%	3.350%	2.955%	3.860%	4.120%
	Bootstrap 99% Critical OOS R-square	5.895%	5.330%	5.245%	6.005%	5.930%
Belgium	OOS R-square	**4.595%**	**5.531%**	**5.133%**	**4.455%**	**5.278%**
	Bootstrap OOS R-square P-value	0.011	0.001	0.005	0.011	0.003
	Bootstrap 90% Critical OOS R-square	2.270%	2.165%	2.185%	2.300%	2.215%
	Bootstrap 95% Critical OOS R-square	3.060%	2.930%	2.950%	3.060%	3.125%
	Bootstrap 99% Critical OOS R-square	4.750%	4.420%	4.310%	4.675%	4.750%
Brazil	OOS R-square	**4.981%**	**2.597%**	**2.090%**	5.305%	4.403%
	Bootstrap OOS R-square P-value	0.012	0.073	0.114	0.008	0.020
	Bootstrap 90% Critical OOS R-square	2.195%	2.185%	2.185%	2.205%	2.065%
	Bootstrap 95% Critical OOS R-square	3.280%	3.185%	3.190%	3.260%	3.090%
	Bootstrap 99% Critical OOS R-square	5.040%	5.575%	5.635%	5.115%	5.575%
Colombia	OOS R-square	**10.560%**	**9.206%**	**8.317%**	**10.529%**	**11.163%**
	Bootstrap OOS R-square P-value	0.000	0.000	0.001	0.000	0.000
	Bootstrap 90% Critical OOS R-square	2.825%	2.825%	2.975%	2.825%	2.610%
	Bootstrap 95% Critical OOS R-square	3.395%	3.500%	3.660%	3.355%	3.300%
	Bootstrap 99% Critical OOS R-square	4.625%	4.880%	5.150%	4.745%	4.575%
Germany	OOS R-square	1.195%	1.096%	0.935%	1.189%	1.259%
	Bootstrap OOS R-square P-value	0.190	0.214	0.203	0.196	0.211
	Bootstrap 90% Critical OOS R-square	2.100%	2.650%	2.220%	2.130%	2.700%
	Bootstrap 95% Critical OOS R-square	3.390%	3.070%	2.490%	3.451%	3.195%
	Bootstrap 99% Critical OOS R-square	4.860%	4.845%	3.445%	4.200%	4.945%

Table 3.2- Panel A *(Continue)*

i		Returns for the *Less- Com* Group EW (1)	Returns for the *Less- Com* Group VW (2)	The US returns (3)	Returns for the *Non-US* Group EW (4)	Returns for the *Non-US* Group VW (5)
Greece	OOS R-square	**5.034%**	**3.393%**	**2.789%**	**5.109%**	**4.113%**
	Bootstrap OOS R-square P-value	0.000	0.001	0.052	0.000	0.001
	Bootstrap 90% Critical OOS R-square	0.510%	0.440%	0.460%	0.525%	0.430%
	Bootstrap 95% Critical OOS R-square	0.935%	0.985%	0.940%	0.885%	0.835%
	Bootstrap 99% Critical OOS R-square	2.330%	2.240%	2.025%	2.430%	2.240%
Indonesia	OOS R-square	**15.831%**	**11.928%**	**10.703%**	**15.908%**	**13.215%**
	Bootstrap OOS R-square P-value	0.000	0.000	0.001	0.000	0.000
	Bootstrap 90% Critical OOS R-square	1.905%	1.980%	2.010%	1.920%	1.815%
	Bootstrap 95% Critical OOS R-square	2.745%	2.785%	2.910%	2.740%	2.745%
	Bootstrap 99% Critical OOS R-square	4.840%	4.600%	4.660%	4.830%	4.835%
Italy	OOS R-square	1.340%	1.53%	1.34%	1.31%	1.60%
	Bootstrap OOS R-square P-value	0.164	0.134	0.156	0.174	0.148
	Bootstrap 90% Critical OOS R-square	2.045%	2.115%	2.065%	1.975%	2.170%
	Bootstrap 95% Critical OOS R-square	3.205%	3.110%	2.960%	3.205%	3.500%
	Bootstrap 99% Critical OOS R-square	5.380%	5.710%	5.405%	5.360%	5.995%
Korea	OOS R-square	**9.780%**	**7.317%**	**6.252%**	**9.861%**	**8.579%**
	Bootstrap OOS R-square P-value	0.000	0.000	0.000	0.006	0.000
	Bootstrap 90% Critical OOS R-square	1.040%	1.050%	1.110%	1.055%	0.895%
	Bootstrap 95% Critical OOS R-square	1.550%	1.440%	1.605%	1.540%	1.350%
	Bootstrap 99% Critical OOS R-square	2.810%	2.690%	2.760%	2.875%	2.395%
Mexico	OOS R-square	**5.675%**	**3.482%**	**3.310%**	**6.073%**	**4.811%**
	Bootstrap OOS R-square P-value	0.000	0.007	0.012	0.000	0.001
	Bootstrap 90% Critical OOS R-square	1.070%	1.170%	1.245%	1.040%	1.070%
	Bootstrap 95% Critical OOS R-square	1.735%	1.840%	1.835%	1.725%	1.785%
	Bootstrap 99% Critical OOS R-square	2.815%	3.255%	3.355%	2.760%	2.875%

Panel B: Out-of-Sample Performance for Restricted model

		Returns for the *Less- Com* Group		The US returns	Returns for the *Non-US* Group	
		EW	VW		EW	VW
i		(1)	(2)	(3)	(4)	(5)
Austria	OOS R-square	**7.077%**	**5.669%**	**4.525%**	**7.032%**	**6.423%**
	Bootstrap OOS R-square P-value	0.002	0.003	0.005	0.002	0.005
	Bootstrap 90% Critical OOS R-square	2.060%	1.350%	1.060%	2.180%	2.190%
	Bootstrap 95% Critical OOS R-square	2.960%	2.170%	1.760%	3.110%	3.220%
	Bootstrap 99% Critical OOS R-square	5.155%	4.100%	3.595%	5.275%	5.320%
Belgium	OOS R-square	**2.901%**	**3.811%**	**3.216%**	**2.760%**	**3.757%**
	Bootstrap OOS R-square P-value	0.039	0.022	0.021	0.043	0.032
	Bootstrap 90% Critical OOS R-square	1.660%	1.710%	1.410%	1.630%	2.045%
	Bootstrap 95% Critical OOS R-square	2.560%	2.635%	2.230%	2.510%	3.090%
	Bootstrap 99% Critical OOS R-square	4.680%	4.835%	4.265%	4.760%	5.660%
Brazil	OOS R-square	**3.225%**	**1.193%**	0.843%	**3.541%**	**2.607%**
	Bootstrap OOS R-square P-value	0.006	0.047	0.113	0.005	0.004
	Bootstrap 90% Critical OOS R-square	0.780%	0.590%	0.955%	0.880%	0.465%
	Bootstrap 95% Critical OOS R-square	1.365%	1.145%	1.690%	1.500%	0.955%
	Bootstrap 99% Critical OOS R-square	2.865%	2.540%	3.305%	3.045%	2.035%
Colombia	OOS R-square	**9.096%**	**7.803%**	**6.380%**	**8.977%**	**10.262%**
	Bootstrap OOS R-square P-value	0.000	0.000	0.008	0.000	0.000
	Bootstrap 90% Critical OOS R-square	0.750%	1.600%	2.600%	0.905%	0.500%
	Bootstrap 95% Critical OOS R-square	1.375%	2.455%	3.650%	1.595%	0.980%
	Bootstrap 99% Critical OOS R-square	2.805%	4.385%	5.865%	3.120%	2.195%
Germany	OOS R-square	1.043%	0.921%	0.713%	1.039%	1.133%
	Bootstrap OOS R-square P-value	0.122	0.109	0.118	0.121	0.125
	Bootstrap 90% Critical OOS R-square	1.585%	1.120%	1.560%	1.670%	1.910%
	Bootstrap 95% Critical OOS R-square	2.790%	2.105%	2.495%	2.810%	2.220%
	Bootstrap 99% Critical OOS R-square	3.095%	3.480%	3.445%	3.120%	3.725%

Table 3.2- Panel B *(Continue)*

		Returns for the *Less- Com* Group		The US returns	Returns for the *Non-US* Group	
		Equally weighted	Value weighted		Equally weighted	Value weighted
i		(1)	(2)	(3)	(4)	(5)
Greece	OOS R-square	**4.085%**	**2.709%**	**2.175%**	**4.129%**	**3.213%**
	Bootstrap OOS R-square P-value	0.022	0.034	0.030	0.024	0.047
	Bootstrap 90% Critical OOS R-square	2.230%	1.560%	1.040%	2.350%	2.315%
	Bootstrap 95% Critical OOS R-square	3.130%	2.280%	1.695%	3.260%	3.155%
	Bootstrap 99% Critical OOS R-square	4.995%	3.980%	3.385%	5.175%	4.850%
Indonesia	OOS R-square	**13.360%**	**8.871%**	**7.258%**	**13.436%**	**10.607%**
	Bootstrap OOS R-square P-value	0.000	0.000	0.005	0.000	0.000
	Bootstrap 90% Critical OOS R-square	1.290%	1.715%	3.020%	1.600%	0.670%
	Bootstrap 95% Critical OOS R-square	2.110%	2.580%	4.095%	2.565%	1.290%
	Bootstrap 99% Critical OOS R-square	3.940%	4.540%	6.220%	4.560%	2.615%
Italy	OOS R-square	0.952%	1.192%	0.980%	0.912%	1.235%
	Bootstrap OOS R-square P-value	0.085	0.076	0.092	0.090	0.073
	Bootstrap 90% Critical OOS R-square	0.810%	0.940%	0.880%	0.800%	0.940%
	Bootstrap 95% Critical OOS R-square	1.440%	1.630%	1.535%	1.455%	1.630%
	Bootstrap 99% Critical OOS R-square	2.835%	3.260%	3.275%	2.915%	3.170%
Korea	OOS R-square	**4.256%**	2.009%	1.388%	**4.427%**	**3.045%**
	Bootstrap OOS R-square P-value	0.010	0.118	0.225	0.010	0.028
	Bootstrap 90% Critical OOS R-square	1.310%	2.250%	2.800%	1.330%	1.420%
	Bootstrap 95% Critical OOS R-square	2.075%	3.270%	3.820%	2.195%	2.290%
	Bootstrap 99% Critical OOS R-square	4.240%	5.735%	6.465%	4.445%	4.405%
Mexico	OOS R-square	**4.981%**	**2.158%**	**1.631%**	**5.424%**	**3.984%**
	Bootstrap OOS R-square P-value	0.004	0.015	0.030	0.003	0.004
	Bootstrap 90% Critical OOS R-square	1.525%	0.670%	0.690%	1.680%	1.020%
	Bootstrap 95% Critical OOS R-square	2.335%	1.250%	1.255%	2.560%	1.630%
	Bootstrap 99% Critical OOS R-square	4.045%	2.455%	2.490%	4.335%	3.150%

Table 4.1. Predict news related to Cash flows and Discount rates for Group Return

This table presents results for predictive regression with news related to cash flows and news on discount rates (denoted by NCF_{t+1} and NDR_{t+1}, respectively). We compute NCF_t and NDR_t follow the approach proposed by Bakshi, Panayotov, and Skoulakis (2014) and Campbell and Vuolteenaho (2004). We report results from the following predictive regression:

$$Y_{t+1} = \alpha + \beta\, rLC_t + \varepsilon_{t+1} \qquad \text{(19) and (20)}$$

where Y_{t+1} is either NCF_{t+1} or NDR_{t+1} of excess return for the *More-Com* group; and rLC_t is excess return for the *Less-Com* group. We report results for three predictors from the *Less-Com* group: returns for the *Less-Com* group; the US return; and returns for the *Non-US* group. The sample period is from 1994:02 to 2013:12. Coefficients that are statistically significant at the 10% level or better are **in bold**.

		Predicted is NCF (t+1) (news about cash flows)		**Predicted is NDR (t+1)** (news about discount rates)	
Predictors		β_{CF}	p-value	β_{DR}	p-value
Returns for the *Less-Com* Group	EW	**0.24**	0.04	**0.14**	0.03
	VW	0.13	0.31	0.05	0.51
The US returns	EW	**0.23**	0.09	**0.13**	0.10
	VW	0.09	0.51	0.02	0.81
Returns for the *Non-US* group	EW	**0.23**	0.04	**0.14**	0.03
	VW	0.18	0.12	0.08	0.20

Table 4.2: Predict news related to Cash flows and Discount rates for Country Return

This table presents results for predictive regression with news related to cash flows and news on discount rates (denoted by NCF_{t+1} and NDR_{t+1}, respectively). I compute NCF_t and NDR_t follow the approach proposed by Bakshi et al. (2010) and Campbell and Vuolteenaho (2004). I report results from the following predictive regression

$$Y_{i,t+1} = \alpha + \beta\, rLC_t + \varepsilon_{t+1}$$

where $Y_{i,t+1}$ is either NCF_t or NDR_t of excess return for country *i* in the *More-Com* group; and rLC_t is excess return for the *Less-Com* group. The sample period is from 1994:02 to 2013:12. Coefficients that are statistically significant at the 10% level or better are **in bold**.

		(1) Austria	(2) Belgium	(3) Brazil	(4) Colombia	(5) Germany	(6) Greece	(7) Indonesia	(8) Italy	(9) Korea	(10) Mexico
Panel A: Predictors are Returns for The *Less-Com* Group (EW)											
Predicted is NCF	coef.	**0.33**	0.15	0.33	-0.17	0.17	**0.60**	0.39	0.03	0.25	**0.28**
	p-val	0.10	0.28	0.14	0.46	0.25	0.00	0.17	0.83	0.22	0.10
Predicted is NDR	coef.	**0.30**	**0.19**	0.23	-0.11	0.08	**0.48**	**0.41**	0.05	**0.24**	**0.20**
	p-val	0.08	0.07	0.17	0.59	0.45	0.00	0.08	0.58	0.07	0.08
Panel B: Predictors are Returns for The *Less-Com* Group (VW)											
Predicted is NCF	coef.	**0.41**	**0.28**	0.31	-0.40	0.18	**0.69**	0.27	0.07	-0.07	0.28
	p-val	0.07	0.07	0.23	0.40	0.26	0.00	0.41	0.66	0.77	0.15
Predicted is NDR	coef.	**0.43**	**0.31**	0.30	-0.15	0.12	**0.62**	**0.62**	0.08	0.16	**0.28**
	p-val	0.03	0.01	0.12	0.51	0.31	0.00	0.02	0.43	0.30	0.03
Panel C: Predictors are The US Returns											
Predicted is NCF	coef.	0.37	**0.30**	0.24	**-0.47**	0.16	**0.62**	0.16	0.09	0.16	0.26
	p-val	0.11	0.07	0.37	0.08	0.16	0.01	0.64	0.56	0.30	0.19
Predicted is NDR	coef.	**0.43**	**0.32**	0.28	-0.16	0.13	**0.60**	**0.61**	0.11	0.13	**0.29**
	p-val	0.03	0.01	0.15	0.51	0.29	0.00	0.02	0.29	0.41	0.03
Panel D: Predictors are Returns for The *Non-US* Group (EW)											
Predicted is NCF	coef.	0.31	0.13	0.32	-0.14	0.16	**0.57**	0.39	0.02	0.27	**0.27**
	p-val	0.11	0.33	0.13	0.53	0.25	0.00	0.15	0.86	0.16	0.10
Predicted is NDR	coef.	**0.28**	**0.17**	0.22	-0.10	0.07	**0.45**	**0.37**	0.04	**0.24**	**0.18**
	p-val	0.09	0.09	0.18	0.60	0.48	0.00	0.09	0.62	0.07	0.10
Panel E: Predictors are Returns for The *Non-US* Group (VW)											
Predicted is NCF	coef.	**0.41**	0.20	0.31	-0.26	0.20	**0.66**	0.38	0.02	0.09	0.26
	p-val	0.04	0.15	0.17	0.28	0.18	0.00	0.20	0.87	0.67	0.13
Predicted is NDR	coef.	**0.37**	**0.22**	0.24	-0.14	0.10	**0.53**	**0.49**	0.03	0.19	**0.22**
	p-val	0.04	0.04	0.17	0.48	0.35	0.00	0.04	0.73	0.16	0.05

Table 5.1: Relation between predictive ability of less complicated group for stock return and dividend growth

This table reports two estimated coefficients (β_i and θ_i) for every country in the *More-Com* group in full sample of 1994:02 to 2013:12. This table includes 5 Panels (Panel A- Panel E) that reports these two coefficients for five predictors from the *Less-Com* group. Estimated coefficient β_i present the predictive slope coefficients on return for the *Less-Com* group for country *i* for following model (3):

$$rMC_{i,t+1} = \beta_0 + \beta_1\, rLC_t + \beta_b\, billMC_{i,t} + \beta_d\, dyMC_{i,t} + \varepsilon_{t+1} \quad (3)$$

where $rMC_{i,t+1}$ is the monthly US$ dominated excess return for country *i* in the *More-Com* group; rLC_t is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_{i,t}$ ($dyMC_{i,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for country *i* in the *More-Com* group. Estimated coefficient θ_i for fundamentals for country *i* are estimated from the following predictive regression model (21):

$$\text{Log}\left(D_{i,t+1}/D_{i,t}\right) = \theta_{i,0} + \theta_i \times rLC_t + \varepsilon_{i,t+1} \quad (21)$$

where dividend growth, $\text{Log}\left(D_{i.t+1}/D_{i.t}\right)$, is the proxy for fundamentals for stock return for country *i* in *More-Com* group; and rLC_t is the US$ dominated excess return for the *Less-Com* group.

		(1) Austria	(2) Belgium	(3) Brazil	(4) Colombia	(5) Germany	(6) Greece	(7) Indonesia	(8) Italy	(9) Korea	(10) Mexico
Panel A: Predictors are Returns for The *Less-Com* Group (EW)											
Beta	coef.	0.34*	0.19*	0.35*	0.42*	0.14*	0.35*	0.77*	0.13	0.40*	0.34*
	p-val	0.00	0.01	0.02	0.00	0.10	0.01	0.00	0.14	0.00	0.01
Delta	coef.	0.45*	0.32*	0.34*	0.32	0.12	0.66*	0.75*	0.15	0.35*	0.30*
	p-val	0.01	0.01	0.07	0.14	0.33	0.00	0.00	0.19	0.02	0.02
Panel B: Predictors are Returns for The *Less-Com* Group (VW)											
Beta	coef.	0.34*	0.24*	0.19	0.44*	0.14	0.31*	0.70*	0.15	0.32*	0.17
	p-val	0.00	0.00	0.27	0.00	0.14	0.03	0.00	0.14	0.04	0.18
Delta	coef.	0.56*	0.45*	0.33	0.34	0.14	0.78*	0.95*	0.17	0.24	0.29*
	p-val	0.01	0.00	0.12	0.17	0.32	0.00	0.00	0.19	0.16	0.05
Panel C: Predictors are The US Returns											
Beta	coef.	0.30*	0.21*	0.09	0.40*	0.12	0.27*	0.64*	0.13	0.27*	0.09
	p-val	0.00	0.01	0.60	0.00	0.22	0.07	0.00	0.20	0.10	0.49
Delta	coef.	0.54*	0.44*	0.27*	0.31	0.14	0.74*	0.89*	0.18	0.18	0.24*
	p-val	0.01	0.00	0.20	0.22	0.34	0.00	0.00	0.18	0.31	0.10
Panel D: Predictors are Returns for The *Non-US* Group (EW)											
Beta	coef.	0.33*	0.18*	0.36*	0.41*	0.14*	0.34*	0.74*	0.12	0.39*	0.31*
	p-val	0.00	0.01	0.01	0.00	0.10	0.01	0.00	0.14	0.00	0.00
Delta	coef.	0.42*	0.29*	0.33*	0.30	0.11	0.63*	0.70*	0.14	0.35*	0.29*
	p-val	0.02	0.01	0.06	0.15	0.34	0.00	0.00	0.20	0.02	0.02
Panel E: Predictors are Returns for The *Non-US* Group (VW)											
Beta	coef.	0.33*	0.22*	0.32*	0.45*	0.14*	0.32*	0.68*	0.14	0.34*	0.30*
	p-val	0.00	0.00	0.04	0.00	0.10	0.01	0.00	0.11	0.01	0.02
Delta	coef.	0.49*	0.36*	0.33*	0.31	0.13	0.69*	0.82*	0.13	0.30*	0.27*
	p-val	0.01	0.00	0.08	0.16	0.29	0.00	0.00	0.26	0.05	0.02

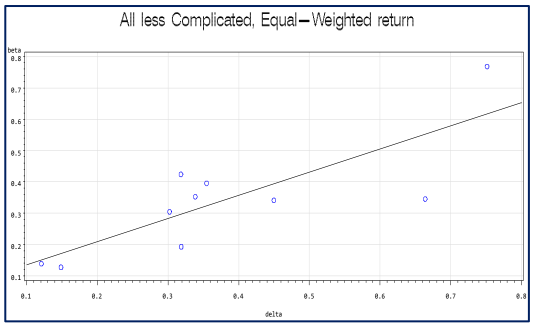
Figure 2: Relation between predictive ability of less complicated group for stock return and dividend growth (related Table 5.1)

Figure 2 plots the predictive slope coefficients β_i against θ_i for all 10 countries in the *More-Com* group for the full sample from 1994-2013.

(1) The *Less-Com* Group (EW)

β_i = 0.063 + **0.741** θ_i

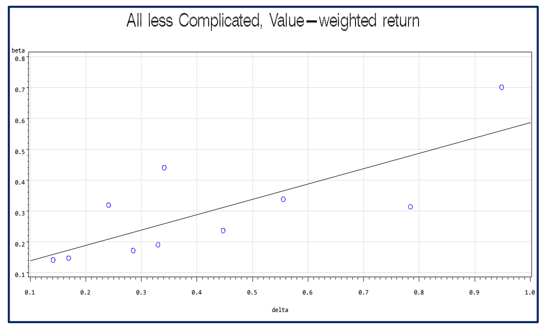
Slope = **0.741**; p-value = 0.005; R^2= 0.653; Adj R^2= 0.609



(2) The *Less-Com* Group (VW)

β_i = 0.089 + **0.496** θ_i

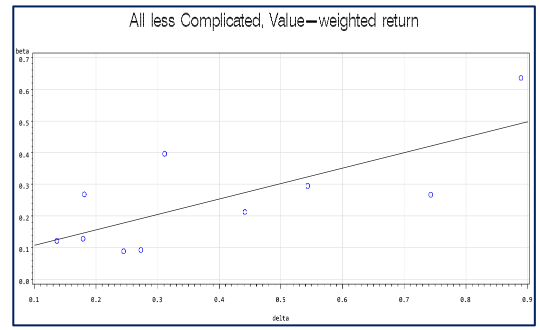
Slope = **0.496**; p-value = 0.009; R^2 = 0.594; Adj R^2= 0.543



(3) The US Return

β_i = 0.059 + **0.486** θ_i

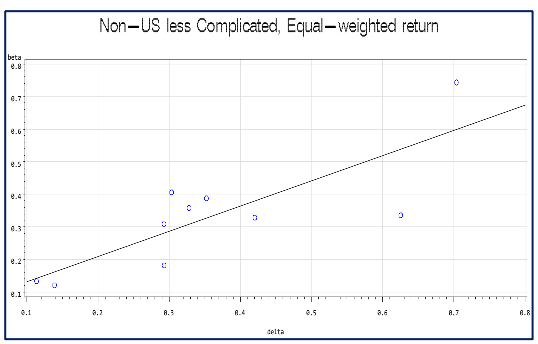
Slope = **0.486**; p-value = 0.015; R^2 = 0.547; Adj R^2 = 0.490



(4) The *Non-US* Group (EW)

β_i = 0.054 + **0.774** θ_i

Slope = **0.774**; p-value = 0.004; R^2 = 0.661; Adj R^2 = 0.619



(5) The *Non-US* Group (VW)

β_i = 0.109 + **0.549** θ_i

Slope = **0.549**; p-value = 0.009; R^2 = 0.599; R^2 = 0.549

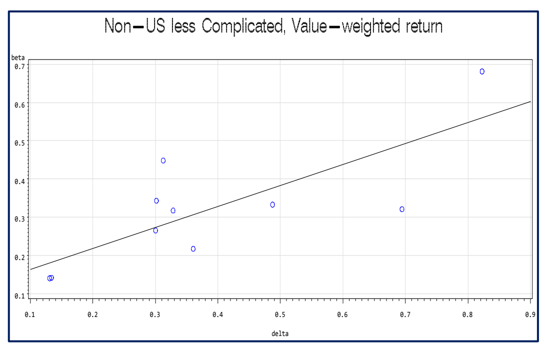


Table 6.1: Relationship between Returns for the less-complicated group and volatility-based measures of risk: Group results

This table shows estimated results for an E-GARCH (1,1) model, which includes lagged returns for the *Less-Com* group (denoted by rLC_t) both in the return and the variance equation as an exogenous regressor. (1) - (6) denotes three predictors generated from the *Less-Com* group: returns for the *Less-Com* group (EW and VW); the US return, and returns for the Non-US group (EW and VW). E-GARCH (1,1) is as follows:

$$rMC_{t+1} = \alpha + \beta\, rLC_t + \varepsilon_{t+1}, \text{ where } \varepsilon_{t+1} = \delta_t z_{t+1}, z_{t+1} \sim \text{i.i.d.}(0,1) \quad (23)$$

$$\log(\delta_t^2) = \gamma_0 + \gamma_1 \frac{|\varepsilon_{t-1}|}{\delta_{t-1}} + \gamma_2 \frac{\varepsilon_{t-1}}{\delta_{t-1}} + \gamma_3 \log(\delta_{t-1}^2) + \boldsymbol{\gamma_{less}} rLC_t \quad (24)$$

E-GARCH specification: Group results

	(1) The *Less-Com* Group (EW)		(2) The *Less-Com* Group (VW)		(3) The US Return (Predict EW)		(4) The US Return (Predict VW)		(5) The *Non-US* Group (EW)		(6) The *Non-US* Group (EW)	
	coef.	p-val	coef.	p-val	coef.	p-val	coef.	p-val	coef.	p-val	coef.	p-val
α	0.00	0.89	0.00	0.34	0.00	0.85	0.00	0.01	0.00	0.87	0.00	0.47
β	0.40	0.00	-0.22	0.06	-0.06	0.63	-0.22	0.03	0.40	0.00	0.19	0.24
γ0	0.11	0.34	-0.24	0.00	-0.21	0.02	-0.22	0.02	0.11	0.27	0.02	0.85
γ1	-1.12	0.07	-0.91	0.10	-0.90	0.01	-0.86	0.13	-1.12	0.06	-0.90	0.14
γ2	0.26	0.04	0.37	0.01	0.24	0.02	0.39	0.01	0.27	0.03	0.33	0.02
γ3	0.80	0.00	0.84	0.00	0.84	0.00	0.85	0.00	0.80	0.00	0.84	0.00
γless	-0.58	0.13	-0.39	0.15	-0.72	0.11	-0.35	0.11	-0.55	0.14	-0.34	0.31

Table 6.2: Relationship between returns for the Less Complicated Group and volatility-based measures of risk: Individual Country results

This table shows estimated results for an E-GARCH (1,1) model, which includes lagged return for the *Less-Com* group (denoted by rLC_t) both in return and the variance equation as an exogenous regressor. (1) - (5) denotes 5 predictors generated from the *Less-Com* group: returns for the *Less-Com* group (EW and VW), the US returns, and returns for the *Non-US* group (EW and VW). Coefficients that are statistically significant at the 10% level or better are in bold. The E-GARCH (1,1) is as follows:

$$\log(\delta_t^2) = \gamma_0 + \gamma_1 \frac{|\varepsilon_{t-1}|}{\delta_{t-1}} + \gamma_2 \frac{\varepsilon_{t-1}}{\delta_{t-1}} + \gamma_3 \log(\delta_{t-1}^2) + \gamma_{Less}\ rLC_t$$

E-GARCH specification: Individual Country Results

	(1)		(2)		(3)		(4)		(5)	
	Predictors are Returns for the *Less-Com* group				Predictors are US returns		Predictors are Returns for the Non-US group			
	EW		VW				EW		VW	
i	γless	p-val	γless	p-val	γless	p-val	γless	p-val	γless	p-val
Austria	**-0.52**	0.08	**-0.54**	0.06	**-0.54**	0.06	**-0.53**	0.10	**-0.56**	0.07
Belgium	**-0.54**	0.06	**-0.53**	0.08	**-0.53**	0.07	**-0.54**	0.08	**-0.53**	0.06
Brazil	**-0.54**	0.07	0.16	0.31	0.16	0.31	-0.50	0.22	-0.60	0.19
Colombia	-0.41	0.82	-0.39	0.78	-0.33	0.85	-0.61	0.81	-0.33	0.70
Germany	-0.59	0.19	-1.34	0.26	-1.29	0.27	-0.57	0.16	**-0.81**	0.00
Greece	**-0.41**	0.02	**-0.47**	0.01	-0.50	0.78	0.00	0.90	**-0.42**	0.05
Indonesia	-1.18	0.15	-0.90	0.13	-0.81	0.14	-1.22	0.18	-1.01	0.15
Italy	**-0.52**	0.04	**-0.57**	0.05	**-0.57**	0.02	**-0.51**	0.04	**-0.52**	0.04
Korea	**-0.75**	0.02	**-0.69**	0.02	**-0.69**	0.01	**-0.76**	0.02	**-0.69**	0.02
Mexico	**-1.25**	0.08	-1.48	0.17	-1.77	0.23	**-1.19**	0.10	**-1.36**	0.10

Table 7: Slow diffusion of information and the trend in the predictive slope coefficients

The table reports results for testing the learning hypothesis that may affect the return predictability. Table 7 includes 3 Sections (1)-(3) and 5 Panels. Specifically, Section (1) reports estimated results from 5 rolling sub-samples. Each sample has a length of 10 years (120 observations) whereby the first subsample starts in November 1994 and the remaining ones start at 24-month intervals. In each sub-samples, we estimate following the regression model:

$$rMC_{t+1} = \alpha + \beta\, rLC_t + \varepsilon_{t+1} \quad (25)$$

where rMC_{t+1} is the monthly US$ dominated excess return for the *More-Com* group; and rLC_t is the monthly US$ dominated excess return for the *Less-Com* group. We report in Section (1) the estimated slope coefficients β.

Section (2) and (3) report the time trend β^{trend} from running full sample following the regression model:

$$rMC_{t+1} = \alpha + (\beta + \beta^{trend})\, rLC_t + \delta(dyMC_t) + \varepsilon_{t+1} \quad (28)$$

where $(d/p)_t$ is the log dividend yield. We consider model (28) with and without the restriction δ = 0. We also consider time trend on the monthly basic (in Section 2), and on the annual basic (in Section 3).

Panel A: Predictors are Returns for the *Less-Com* Group (EW)

	Section (1) Rolling Sub-samples					**Section (2)** Coefficient of Beta Trend *(time on a monthly basic)*		**Section (3)** Coefficient of Beta Trend *(time on an annual basic)*	
	2004	2006	2008	2010	2012	Restrict	Unrestricted	Restrict	Unrestricted
Country									
Austria	0.23	0.25	0.44	0.51	0.47	0.0015	0.0015	0.0147	0.0148
Belgium	0.08	0.10	0.30	0.39	0.35	0.0019	0.0019	0.0169	0.0169
Brazil	0.35	0.23	0.40	0.41	0.31	-0.0022	-0.0019	-0.0145	-0.0160
Colombia	0.73	0.75	0.74	0.41	0.28	-0.0027	-0.0027	-0.0483	-0.0488
Germany	0.05	0.08	0.27	0.27	0.27	0.0019	0.0019	0.0142	0.0143
Greece	0.36	0.39	0.52	0.43	0.42	0.0001	0.0001	-0.0096	-0.0095
Indonesia	1.27	1.25	1.09	0.73	0.37	-0.0066	-0.0069	-0.0902	-0.0963
Italy	0.06	0.08	0.21	0.27	0.26	0.0016	0.0016	0.0065	0.0064
Korea	0.58	0.55	0.46	0.31	0.28	-0.0030	-0.0030	-0.0406	-0.0422
Mexico	0.03	0.00	0.04	0.07	0.04	-0.0022	-0.0022	-0.0084	-0.0081
Group									
All *More-Com* Group	0.41	0.38	0.48	0.41	0.33	-0.0010	-0.0008	-0.0159	-0.0165
American *More-Com* Group	0.47	0.37	0.49	0.39	0.28	-0.0024	-0.0024	-0.0237	-0.0238
Asian *More-Com* Group	0.93	0.90	0.77	0.52	0.33	-0.0048	-0.0048	-0.0654	-0.0662
European *More-Com* Group	0.16	0.18	0.35	0.37	0.35	0.0014	0.0015	0.0085	0.0097

Panel B: Predictors are Returns for Less Complicated Group (VW)

	Section (1) Rolling Sub-samples					**Section (2)** Coefficient of Beta Trend *(time on a monthly basic)*		**Section (3)** Coefficient of Beta Trend *(time on an annual basic)*	
	2004	2006	2008	2010	2012	Restrict	Unrestricted	Restrict	Unrestricted
Country									
Austria	0.22	0.25	0.42	0.50	0.48	0.0012	0.0012	0.0133	0.0138
Belgium	0.18	0.19	0.35	0.41	0.38	0.0013	0.0013	0.0074	0.0076
Brazil	-0.01	-0.05	0.26	0.43	0.35	0.0004	0.0004	0.0259	0.0165
Colombia	0.72	0.77	0.89	0.54	0.34	-0.0025	-0.0026	-0.0425	-0.0441
Germany	0.06	0.08	0.24	0.28	0.30	0.0019	0.0019	0.0137	0.0136
Greece	0.27	0.29	0.46	0.40	0.42	-0.0001	-0.0001	-0.0075	-0.0074
Indonesia	1.10	1.08	1.13	0.87	0.45	-0.0052	-0.0055	-0.0656	-0.0735
Italy	0.10	0.13	0.23	0.31	0.30	0.0012	0.0012	0.0002	0.0010
Korea	0.39	0.38	0.52	0.37	0.30	-0.0012	-0.0012	-0.0119	-0.0120
Mexico	0.05	-0.04	0.32	0.41	0.30	0.0006	0.0006	0.0331	0.0328
Group									
All *More-Com* Group	0.11	0.11	0.30	0.35	0.33	0.0011	0.0010	0.0103	0.0089
American *More-Com* Group	0.77	0.67	1.46	1.38	0.99	-0.0015	-0.0016	0.0166	0.0160
Asian *More-Com* Group	1.48	1.45	1.66	1.24	0.75	-0.0064	-0.0063	-0.0776	-0.0870
European *More-Com* Group	0.82	0.93	1.70	1.92	1.89	0.0055	0.0066	0.0272	0.0426

Panel C: Predictors are Returns for the US market

	Section (1) Rolling Sub-samples					Section (2) Coefficient of Beta Trend *(time in a monthly basic)*		Section (3) Coefficient of Beta Trend *(time in an annual basic)*	
	2004	2006	2008	2010	2012	Restrict	Unrestricted	Restrict	Unrestricted
Country									
Austria	0.20	0.23	0.35	0.45	0.45	0.0009	0.0009	0.0109	0.0116
Belgium	0.18	0.18	0.30	0.38	0.36	0.0010	0.0010	0.0060	0.0063
Brazil	-0.09	-0.10	0.16	0.41	0.35	0.0015	0.0013	0.0339	0.0241
Colombia	0.59	0.65	0.81	0.55	0.35	-0.0018	-0.0019	-0.0285	-0.0308
Germany	0.06	0.07	0.17	0.25	0.28	0.0016	0.0016	0.0117	0.0116
Greece	0.23	0.25	0.37	0.33	0.38	-0.0005	-0.0006	-0.0097	-0.0098
Indonesia	0.94	0.92	1.03	0.87	0.44	-0.0038	-0.0042	-0.0467	-0.0535
Italy	0.09	0.12	0.19	0.29	0.30	0.0010	0.0010	0.0011	0.0020
Korea	0.29	0.29	0.48	0.34	0.29	-0.0005	-0.0004	-0.0019	-0.0014
Mexico	-0.04	-0.06	0.24	0.38	0.29	0.0020	0.0020	0.0429	0.0427
Group (EW Method)									
All *More-Com* Group	0.25	0.26	0.41	0.43	0.35	0.0001	0.0001	0.0020	-0.0014
American *More-Com* Group	0.15	0.16	0.40	0.45	0.33	0.0006	0.0006	0.0161	0.0162
Asian *More-Com* Group	0.62	0.61	0.75	0.61	0.37	-0.0022	-0.0021	-0.0243	-0.0247
European *More-Com* Group	0.15	0.17	0.28	0.34	0.36	0.0008	0.0010	0.0040	0.0072
Group (VW Method)									
All *More-Com* Group	0.09	0.09	0.24	0.33	0.32	0.0011	0.0010	0.0113	0.0099
American *More-Com* Group	0.46	0.49	1.21	1.35	0.98	0.0017	0.0016	0.0483	0.0472
Asian *More-Com* Group	1.23	1.21	1.51	1.21	0.74	-0.0043	-0.0042	-0.0486	-0.0554
European *More-Com* Group	0.77	0.85	1.39	1.71	1.78	0.0040	0.0051	0.0199	0.0359

Panel D: Predictors are Returns for the *Non-US* Group (EW)

	Section (1) Rolling Sub-samples					**Section (2)** Coefficient of Beta Trend *(time on a monthly basic)*		**Section (3)** Coefficient of Beta Trend *(time on an annual basic)*	
	2004	2006	2008	2010	2012	Restrict	Unrestricted	Restrict	Unrestricted
Country									
Austria	0.22	0.24	0.43	0.50	0.46	0.0016	0.0016	0.0154	0.0154
Belgium	0.07	0.09	0.29	0.38	0.34	0.0020	0.0020	0.0177	0.0177
Brazil	0.37	0.25	0.40	0.40	0.29	-0.0023	-0.0020	-0.0172	-0.0176
Colombia	0.69	0.72	0.70	0.39	0.26	-0.0026	-0.0025	-0.0453	-0.0458
Germany	0.04	0.08	0.27	0.26	0.26	0.0019	0.0019	0.0142	0.0143
Greece	0.35	0.37	0.51	0.42	0.41	0.0002	0.0002	-0.0078	-0.0077
Indonesia	1.22	1.21	1.04	0.70	0.36	-0.0063	-0.0065	-0.0857	-0.0916
Italy	0.06	0.07	0.21	0.26	0.25	0.0016	0.0016	0.0072	0.0069
Korea	0.57	0.54	0.44	0.30	0.27	-0.0029	-0.0030	-0.0403	-0.0419
Mexico	0.36	0.14	0.32	0.34	0.25	-0.0024	-0.0024	-0.0119	-0.0115
Group									
All *More-Com* Group	0.39	0.37	0.46	0.39	0.31	-0.0009	-0.0008	-0.0154	-0.0156
American *More-Com* Group	0.47	0.37	0.47	0.38	0.27	-0.0024	-0.0024	-0.0249	-0.0250
Asian *More-Com* Group	0.90	0.87	0.74	0.50	0.31	-0.0046	-0.0046	-0.0630	-0.0637
European *More-Com* Group	0.15	0.17	0.34	0.36	0.34	0.0015	0.0015	0.0093	0.0102

Panel E: Predictors are Returns for the *Non-US* Group (VW)

	(1) Rolling Sub-samples					(2) Coefficient of Beta Trend *(time on a monthly basic)*		(3) Coefficient of Beta Trend *(time on an annual basic)*	
	2004	2006	2008	2010	2012	Restrict	Unrestricted	Restrict	Unrestricted
Country									
Austria	0.21	0.23	0.45	0.49	0.44	0.0014	0.0014	0.0133	0.0135
Belgium	0.12	0.14	0.34	0.39	0.34	0.0015	0.0015	0.0096	0.0097
Brazil	0.25	0.12	0.40	0.38	0.31	-0.0023	-0.0020	-0.0070	-0.0120
Colombia	0.93	0.92	0.88	0.45	0.28	-0.0036	-0.0036	-0.0655	-0.0662
Germany	0.03	0.08	0.29	0.29	0.27	0.0020	0.0020	0.0139	0.0139
Greece	0.29	0.32	0.50	0.44	0.40	0.0005	0.0005	-0.0058	-0.0058
Indonesia	1.24	1.21	1.11	0.73	0.37	-0.0064	-0.0066	-0.0885	-0.0957
Italy	0.09	0.11	0.24	0.29	0.26	0.0013	0.0013	-0.0013	-0.0010
Korea	0.52	0.50	0.51	0.36	0.28	-0.0023	-0.0023	-0.0296	-0.0305
Mexico	0.26	0.01	0.37	0.37	0.26	-0.0020	-0.0020	0.0016	0.0013
Group									
All *More-Com* Group	0.14	0.13	0.34	0.34	0.29	0.0007	0.0008	0.0044	0.0041
American *More-Com* Group	1.43	1.06	1.66	1.21	0.85	-0.0063	-0.0064	-0.0709	-0.0700
Asian *More-Com* Group	1.76	1.70	1.62	1.09	0.65	-0.0087	-0.0085	-0.1181	-0.1291
European *More-Com* Group	0.75	0.88	1.82	1.89	1.71	0.0067	0.0073	0.0298	0.0393

Appendices

Appendix A: Summary Description of Selected Country Indices in La Port et al. (2006)

The table provides summary for corresponding sub-indexes in survey of La Porta et al. (2006).

Country	prospect	compensa	sharehol	insideow	contract	transact	disclose	burden issuer	Burden Director	burden distributor	burden accountant	bdn_iss_dir	bdn_proof
Australia	1	1	1	0.5	0	1	0.75	0.66	0.66	0.66	0.66	0.66	0.66
Austria	0	0.5	0	0.5	0	0.5	0.25	0.33	0.33	0	0	0.33	0.11
Belgium	0	0.5	1	0.5	0	0.5	0.42	0.66	0.66	0	0.66	0.66	0.44
Brazil	0	0.5	1	0	0	0	0.25	0.33	0.33	0.33	0.33	0.33	0.33
Canada	1	1	1	0.5	1	1	0.92	1	1	1	1	1	1.00
Switzerland	0	0.5	1	0.5	1	1	0.67	0.66	0.66	0	0.66	0.66	0.44
Chile	1	0.5	1	0	1	0	0.58	0.33	0.33	0.33	0.33	0.33	0.33
Colombia	0	0	1	1	0	0.5	0.42	0	0	0	0.33	0	0.11
Germany	0	0.5	1	0.5	0	0.5	0.42	0	0	0	0	0	0.00
Denmark	1	0.5	1	0.5	0	0.5	0.58	0.33	0.33	0.33	1	0.33	0.55
Spain	0	0.5	1	1	0	0.5	0.50	0.66	0.66	0.66	0.66	0.66	0.66
Finland	0	0.5	1	0.5	0.5	0.5	0.50	0.66	0.66	0.66	0.66	0.66	0.66
France	1	1	1	0.5	0.5	0.5	0.75	0.33	0.33	0	0.33	0.33	0.22
United Kingdom	0	1	1	1	1	1	0.83	0.66	0.66	0.66	0.66	0.66	0.66
Greece	0	0.5	0	0.5	0.5	0.5	0.33	0.66	0.33	0.66	0.33	0.495	0.50
Hong Kong, China	1	0.5	1	1	1	1	0.92	0.66	0.66	0.66	0.66	0.66	0.66
Indonesia	1	0	0	0.5	0.5	1	0.50	0.66	0.66	0.66	0.66	0.66	0.66
India	1	1	1	1	1	0.5	0.92	0.66	0.66	0.66	0.66	0.66	0.66
Ireland	1	0.5	1	0.5	0.5	0.5	0.67	0	0.66	0.33	0.66	0.33	0.44
Israel	0	0.5	1	1	1	0.5	0.67	0.66	0.66	0.66	0.66	0.66	0.66
Italy	0	1	1	1	0.5	0.5	0.67	0.33	0.33	0	0.33	0.33	0.22
Japan	1	0	1	0.5	1	1	0.75	0.66	0.66	0.66	0.66	0.66	0.66
Korea, Rep.	0	0.5	1	1	1	1	0.75	0.66	0.66	0.66	0.66	0.66	0.66
Sri Lanka	1	0.5	1	0.5	1	0.5	0.75	0.33	0.66	0	0.66	0.495	0.39
Mexico	0	0.5	1	0.5	1	0.5	0.58	0	0	0	0.33	0	0.11
Malaysia	1	0.5	1	1	1	1	0.92	0.66	0.66	0.66	0.66	0.66	0.66
Netherlands	0	0.5	1	0.5	0.5	0.5	0.50	1	0.33	1	1	0.665	0.89
New Zealand	0	0.5	1	0.5	1	1	0.67	0.66	0.66	0	0.66	0.66	0.44
Pakistan	1	0.5	0	0.5	1	0.5	0.58	0.33	0.66	0	0.66	0.495	0.39
Peru	1	0	1	0	0	0	0.33	0.66	0.66	0.66	0.66	0.66	0.66
Philippines	0	1	1	1	1	1	0.83	1	1	1	1	1	1.00
Portugal	0	0.5	1	0.5	0	0.5	0.42	0.66	0.66	0.66	0.66	0.66	0.66
Singapore	1	1	1	1	1	1	1.00	0.66	0.66	0.66	0.66	0.66	0.66
Sweden	0	0.5	1	1	0.5	0.5	0.58	0	0.33	0.33	0.33	0.165	0.28
Thailand	1	0.5	1	1	1	1	0.92	1	0.33	0	0	0.665	0.22
Taiwan	1	0.5	0	1	1	1	0.75	0.66	0.66	0.66	0.66	0.66	0.66
United States	1	1	1	1	1	1	1.00	1	1	1	1	1	1.00
South Africa	1	1	1	0.5	1	0.5	0.83	0.66	0.66	0.66	0.66	0.66	0.66

Appendices

Appendix A *(continue)*

Country	agency	witness	investig	Orders	**publ_enf**	**antidir**	**eff_jud**
Australia	0.67	1	1	1	0.9	4	10
Austria	0.33	0	0	0	0.166667	2	9.5
Belgium	0.00	0	0.25	0	0.15	0	9.5
Brazil	0.33	0.5	0.5	0.75	0.583333	3	5.75
Canada	0.67	1	1	1	0.8	5	9.25
Switzerland	0.33	0	0	0	0.333333	2	10
Chile	0.33	1	0.75	0.41667	0.6	5	7.25
Colombia	0.33	1	0.75	0.33333	0.583333	3	7.25
Germany	0.33	0	0.25	0	0.216667	1	9
Denmark	0.00	0.5	0.5	0.33333	0.366667	2	10
Spain	0.67	0.5	0.5	0	0.333333	4	6.25
Finland	0.67	0	0.25	0.16667	0.316667	3	10
France	1.00	1	1	1	0.766667	3	8
United Kingdom	0.00	1	1	1	0.683333	5	10
Greece	0.67	0	0.25	0.16667	0.316667	2	7
Hong Kong, China	0.33	1	1	1	0.866667	5	10
Indonesia	0.33	1	1	0.25	0.616667	2	2.5
India	0.33	1	1	0.66667	0.666667	5	8
Ireland	0.00	0	0	0	0.366667	4	8.75
Israel	0.67	1	1	1	0.633333	3	10
Italy	0.67	0	0.25	0	0.483333	1	6.75
Japan	0.00	0	0	0	0	4	10
Korea, Rep.	0.33	0.5	0.5	0.08333	0.25	2	6
Sri Lanka	0.33	0	0.5	0	0.433333	3	7
Mexico	0.00	0	0.25	0	0.35	1	6
Malaysia	0.33	1	1	1	0.766667	4	9
Netherlands	0.33	0	0.5	0	0.466667	2	10
New Zealand	0.33	1	1	0	0.333333	4	10
Pakistan	0.67	1	1	0.16667	0.583333	5	5
Peru	0.67	1	0.75	1	0.783333	3	6.75
Philippines	0.67	1	1	1	0.833333	3	4.75
Portugal	0.67	1	1	0.25	0.583333	3	5.5
Singapore	0.33	1	1	1	0.866667	4	10
Sweden	0.00	0	0.25	0.66667	0.5	3	10
Thailand	0.67	1	1	0.33333	0.716667	2	3.25
Taiwan	0.33	0	0.25	0.16667	0.516667	3	6.75
United States	1.00	1	1	1	0.9	5	10
South Africa	0.33	0.5	0.5	0	0.25	5	6

Appendices

Appendix B: Information about Return Indices in Global Financial Data

The table provides information on Global Financial Data Total Stock Return's Indices that are used for analysis in the main part. The first column provides names of all countries in the sample; the second column gives the names of the Total Return Indices- Stocks in Global Financial Data; the third column provides information about the coverage of the total stock return indices. All of the total returns are value-weighted according to market capitalisation.

Country	Total Stock Return Series Name	Coverage of Return Indices
Australia	Australia ASX Accumulation Index-All Ordinaries	500 Largest companies listed on the Australian Stock Exchange
Austria	Vienna SE ATX Total Return Index	All most-traded stocks on Vienna Stock Exchange
Belgium	Brussels All-Share Return Index (GFD extension)	All companies listed on the Euronext Brussels
Brazil	Brazil Bolsa de Valores de Sao Paulo (Bovespa)	All companies listed on Sao Paulo Stock Exchange
Canada	Canada S&P/TSX-300 Total Return Index	300 Largest companies listed on Toronto Stock Exchange
Switzerland	Swiss Performance Index	400 Largest companies listed on Swiss Exchange
Chile	Santiago SE Return Index	All companies listed on Santiago Stock Exchange
Colombia	Colombia Stock Return Index	All companies listed on Colombian Securities Exchange
Germany	Germany CDAX Total Return Index (w/GFD extension)	All companies listed on the Frankfurt Stock Exchange
Denmark	OMX Copenhagen All-Share Gross Index	All companies listed on Copenhagen Stock Exchange
Spain	Barcelona SE-30 Return Index (w/GFD extension)	30 Largest stocks traded on the Barcelona Stock Exchange.
Finland	OMX Helsinki All-Share Gross Index	All stocks traded on Helsinki Stock Exchange
France	France CAC All-Tradable Total Return Index	250 Largest companies listed on Paris Stock Exchange
United Kingdom	UK FTSE All-Share Return Index (w/GFD extension)	1000 Largest companies listed on London Stock Exchange
Greece	ASE Total Return General Index	All companies listed on Athens Stock Exchange
Hong Kong, China	Hang Seng Composite Return Index	48 largest constituent companies listed on Hong Kong Stock Exchange
Indonesia	Indonesia Stock Return Index	Over 460 companies listed on Indonesia Stock Exchange
India	S&P CNX Nifty Total Return Index	50 Largest companies listed on National Stock Exchange of India
Ireland	ISEQ Overall Total Return Index	All companies listed on Irish Stock Exchange
Israel	Tel Aviv SE Return Index	All companies listed on Tel Aviv Stock Exchange
Italy	Italy BCI Global Return Index (w/GFD extension)	Over 325 companies listed on the Milan Stock Exchange
Japan	Japan Nikko Securities Composite Total Return	All countries listed on Tokyo Stock Exchange and Osaka Stock exchange
Korea, Rep.	Korea Stocks Total Return Index	Over 770 companies listed on Korea Exchange
Sri Lanka	Sri Lanka Stock Return Index	All companies listed on Sri Lanka Colombo Stock Exchange
Mexico	Mexico SE Return Index	All companies listed on Mexican Stock Exchange
Malaysia	Kuala Lumpur SE Return Index	30 Largest companies listed on Bursa Malaysia
Netherlands	Netherlands All-Share Return Index (w/GFD extension)	All companies listed on Amsterdam Stock Exchange
New Zealand	New Zealand SE Gross All-Share Index	All domestic equity securities listed on the New Zealand Stock Exchange
Pakistan	Pakistan Stock Return Index	100 Largest companies listed on Karachi Stock Exchange
Peru	Peru Stock Return Index	All largest and most actively traded stocks on Lima Exchange
Philippines	Philippines Return Stock Index	All companies listed on Philippine Stock Exchange
Portugal	Lisbon BVL General Return Index	All companies listed on Euronext Lisbon
Singapore	Singapore SE Return Index	30 Largest companies listed on Singapore Exchange
Sweden	OMX Stockholm Benchmark Gross Index (GFD extension	About 80 Largest companies listed on Stockholm Stock Exchange
Thailand	Bangkok SE Return Index	All companies listed on Stock Exchange of Thailand
Taiwan	Taiwan FTSE/TSE-50 Return Index	50 Largest companies listed on Taiwan Stock Exchange
United States	S&P 500 Total Return Index (w/GFD extension)	500 Largest companies on NYSE/NASDAQ
South Africa	Johannesburg SE Return Index	All companies listed on Johannesburg Stock Exchange

Appendices

Appendix C: Summary statistics, Country Excess Stock Returns, 1994:02 to 2013:12

This table reports summary statistics for average monthly US$ dominated excess return (in percentage) for 38 countries in the whole sample. The excess return is computed relative to each country's three-month Treasury bill rate; Sharpe ratio is the mean of the excess return divided by its standard deviation; and Autocorrelation displays the correlation between excess return and lagged excess return. Country return indices are from Global Financial Data; sample is from 1994:02 to 2013:12

		(1)	(2)	(3)	(4)	(5)	(6)
No.	Country	Mean	Standard Deviation	Minimum	Maximum	Autocorrelation	Sharpe Ratio
1	Australia	0.49	6.22	-28.88	16.28	0.05	0.08
2	Austria	0.28	7.02	-39.57	22.72	0.20	0.04
3	Belgium	0.53	5.80	-28.85	17.98	0.18	0.09
4	Canada	0.56	5.99	-28.35	21.32	0.13	0.09
5	Denmark	0.77	5.70	-28.14	16.93	0.14	0.14
6	Finland	0.63	8.53	-32.66	29.39	0.18	0.07
7	France	0.46	6.11	-24.03	14.94	0.09	0.07
8	Germany	0.50	6.72	-27.11	20.88	0.06	0.07
9	Greece	-0.26	10.20	-39.62	37.06	0.16	-0.03
10	Hong Kong, China	0.34	7.45	-35.38	25.10	0.04	0.05
11	Ireland	0.40	6.30	-26.25	17.66	0.20	0.06
12	Israel	-0.16	6.93	-27.25	14.38	0.05	-0.02
13	Italy	0.28	6.88	-24.99	19.10	0.02	0.04
14	Japan	0.04	5.41	-16.26	16.63	0.19	0.01
15	Korea, Rep.	0.22	11.00	-36.40	57.93	0.06	0.02
16	Netherlands	0.50	6.16	-27.03	14.05	0.03	0.08
17	New Zealand	0.38	5.96	-20.71	16.21	0.04	0.06
18	Portugal	0.30	6.34	-31.12	15.70	0.18	0.05
19	Singapore	0.40	7.57	-32.86	23.84	0.10	0.05
20	Spain	0.64	6.96	-22.47	20.04	0.07	0.09
21	Sweden	0.73	7.17	-28.86	21.35	0.06	0.10
22	Switzerland	0.69	4.91	-16.90	13.66	0.10	0.14
23	Taiwan	0.20	8.32	-24.89	27.17	0.09	0.02
24	United Kingdom	0.32	4.73	-21.52	13.93	0.15	0.07
25	United States	0.49	4.44	-18.42	10.37	0.09	0.11
26	Brazil	-0.57	12.02	-52.60	36.78	0.10	-0.05
27	Colombia	0.30	9.07	-31.14	24.80	0.21	0.03
28	Chile	0.12	6.96	-35.28	19.47	0.09	0.02
29	Indonesia	-0.46	12.98	-48.68	50.15	0.17	-0.04
30	India	-0.07	8.44	-34.68	31.18	0.07	-0.01
31	Mexico	-0.18	8.91	-40.45	17.81	0.09	-0.02
32	Malaysia	0.16	8.58	-37.86	44.36	0.22	0.02
33	Peru	0.52	9.23	-45.42	26.05	0.00	0.06
34	Philippines	-0.30	8.34	-30.70	32.97	0.13	-0.04
35	Pakistan	-0.33	11.24	-70.30	32.54	0.03	-0.03
36	South Africa	0.02	7.84	-37.55	18.85	0.01	0.00
37	Sri Lanka	-0.60	10.03	-29.57	48.07	0.10	-0.06
38	Thailand	-0.28	10.98	-39.02	36.01	0.09	-0.03

Appendices

Appendix D: Summary statistics, Group Excess Stock Returns for Complicated group, 1994:02 to 2013:12

This table reports summary statistic for monthly US$ dominated excess return (in percentage) for each more (less) complicated group. Panel A reports results for more (less) complicated group for the whole sample; while Panel B, C, and D report results for more (less) complicated group in each region including American region, Asian region and European region. The excess return is computed relative to each country's three-month Treasury bill rate; Sharpe ratio is the mean of the excess return divided by its standard deviation; and Autocorrelation displays the correlation between excess return and lagged excess return. Country return indices are from Global Financial Data; sample is from 1994:02 to 2013:12

	(1) Group return	(2) Mean	(3) Standard Deviation	(4) Minimum	(5) Maximum	(6) Autocorrelation	(7) Sharpe Ratio
Panel A: The whole sample							
Equally weighted	All *Less-Com*	0.28	5.17	-25.39	15.77	0.18	0.05
	More-Com Group	0.06	6.63	-33.26	17.19	0.20	0.01
	Non-US *Less-Com*	0.26	5.39	-26.26	17.06	0.19	0.05
Value weighted	All *Less-Com*	0.41	4.52	-21.21	10.81	0.12	0.09
	All *More-Com*	0.11	6.37	-30.35	17.28	0.13	0.02
	Non-US *Less-Com*	0.30	5.08	-25.95	17.38	0.16	0.06
US return		0.49	4.44	-18.42	10.37	0.09	0.11
Panel B: American region							
Equally weighted	American *Less-Com*	0.52	4.95	-23.39	13.38	0.13	0.11
	American *More-Com*	-0.15	8.20	-40.31	19.51	0.21	-0.02
Value weighted	American *Less-Com*	1.04	9.91	-46.78	26.76	0.13	0.11
	American *More-Com*	-0.46	24.41	-120.92	58.53	0.21	-0.02
Panel C: Asian region							
Equally weighted	Asian *Less-Com*	0.14	5.94	-26.26	19.47	0.02	0.19
	Asian *More-Com*	-0.12	10.31	-36.42	39.16	-0.01	0.19
Value weighted	Asian *Less-Com*	0.68	29.68	-131.30	97.36	0.02	0.19
	Asian *More-Com*	-0.24	20.61	-72.83	78.32	-0.01	0.19
Panel D: European region							
Equally weighted	European *Less-Com*	0.31	4.73	-21.52	13.93	0.16	0.07
	European *More-Com*	0.26	6.43	-31.72	15.90	0.17	0.04
Value weighted	European *Less-Com*	0.31	4.73	-21.52	13.93	0.16	0.07
	European *More-Com*	1.32	32.17	-158.61	79.48	0.17	0.04

Appendices

Appendix E: Benchmark Predictive Regression Model: Group results

The table reports OLS estimates of β_b and β_d (denoted by $\hat{\beta}_b$ and $\hat{\beta}_d$) and the Adjusted R-square (denoted by $\overline{R}^2$) for the benchmark predictive regression model:

$$rMC_{t+1} = \beta_0 + \beta_b\, billMC_t + \beta_d\, dyMC_t + \varepsilon_{t+1}$$

where rMC_{t+1} is the monthly US$ dominated excess returns for the *More-Com* group and $billMC_t$ ($dyMC_t$) is the US$ dominated three month Treasury bill rate (log dividend yield) for the *More-Com* group. Panel A reports the predictive results from the equally-weighted method, while Panel B reports the predictive results from the value-weighted method. We report the Newey and West (1987) robust t-statistic in parentheses in the first, second, forth, and fifth columns. The fourth and eighth columns report heteroskedasticity-robust χ^2 statistic for testing null hypothesis: H_0: β_b = β_d= 0. Brackets report p-values. The sample period is from 1994:02 to 2013:12. The signals ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Equally Weighted				Panel B: Value Weighted			
$\hat{\beta}_b$ bill (1)	$\hat{\beta}_d$ dy (2)	$\overline{R}^2$ (3)	χ^2 (4)	$\hat{\beta}_b$ bill (5)	$\hat{\beta}_d$ dy (6)	$\overline{R}^2$ (7)	χ^2 (8)
0.33	0.06**	3.50%	7.30	0.19	0.02	0.06%	1.22
(1.20)	(1.94)		[0.03]	(0.71)	(0.53)		[0.54]
[0.23]	[0.05]			[0.48]	[0.60]		

Appendices

Appendix F.1: Test whether returns for the *More-Com* Group can predict returns for the *Less-Com* Group

We examine whether returns for the *More-Com* group can predict future returns for the *Less-Com* group. Appendix F.1 reports OLS estimates of β_1, β_b, and β_d (denoted by $\hat{\beta}_1$, $\hat{\beta}_b$, and $\hat{\beta}_d$, respectively) and the Adjusted R-square (denoted by $\bar{R}^2$) for the predictive regression model:

$$rLC_{t+1} = \beta_0 + \beta_1\, rMC_t + \beta_b\, billLC_t + \beta_d\, dyLC_t + \varepsilon_{t+1}$$

where rLC_{t+1} is the monthly US$ dominated excess return for the *Less-Com* group; rMC_t is the monthly US$ dominated excess return for the *More-Com* group; and $billLC_t$ ($dyLC_t$) is the US$ dominated three month Treasury bill rate (log dividend yield) for the *Less-Com* group. This table reports predictive results from equally weighted and value weighted (according to market capitalisation) variables. We report the Newey and West (1987) robust t-statistic in parentheses in the first, second, third, fifth, sixth, and seventh columns. Brackets report p-values. The sample period is from 1994:02 to 2013:12. The signals ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Equally Weighted				Value Weighted			
$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0.10	0.12	0.04	2.94%	0.06	0.42	0.03*	1.66%
(1.08)	(0.25)	(1.52)		(0.86)	(0.53)	(1.67)	
[0.28]	[0.80]	[0.13]		[0.39]	[0.59]	[0.10]	

Appendices

Appendix F.2: Test whether returns for the *More-Com* Group can predict returns for the *Less-Com* countries

We examine whether returns for the *More-Com* group can predict future returns for each countries in the *Less-Com* group. Appendix F2 reports OLS estimates of β_1, β_b and β_d (denoted by $\hat{\beta}_{more}$, $\hat{\beta}_b$ and $\hat{\beta}_d$, respectively) and the Adjusted R-square (denoted by $\bar{R}^2$) for the predictive regression model:

$$rLC_{i,t+1} = \beta_0 + \beta_1\, rMC_t + \beta_{i,b}\, billLC_t + \beta_{i,d}\, dyLC_t + \varepsilon_{t+1}$$

where $rLC_{i,t+1}$ is the monthly US$ dominated excess return for country *i* in the *Less-Com* group; $rMC_{,t}$ is the monthly US$ dominated excess return for the *More-Com* group; and $billLC_{i,t}$ ($dyLC_{i,t}$) is the US$ dominated three month Treasury bill rate (log dividend yield) for country *i* in the *Less-Com* group. This table reports predictive results from equally weighted and value weighted (according to market capitalisation) variables. We report the Newey and West (1987) robust t-statistic in parentheses (under coefficient). Brackets report p-values. The sample period is from 1994:02 to 2013:12. The signal * indicates significance at the 10% level or better.

	Predictor is Return for More Complicated Group							
	Equally Weighted				Value Weighted			
(i)	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$
Australia	0.02	0.10	0.05*	0.46%	-0.01	0.10	0.05*	0.42%
	(0.30)	(0.91)	(1.82)		(-0.05)	(0.92)	(1.77)	
	[0.76]	[0.36]	[0.07]		[0.96]	[0.36]	[0.08]	
Canada	0.03	0.09	0.01	-0.91%	0.01	0.10	0.01	-1.01%
	(0.49)	(0.57)	(0.58)		(0.03)	(0.60)	(0.54)	
	[0.62]	[0.57]	[0.56]		[0.98]	[0.55]	[0.59]	
Hong Kong, China	0.01	0.80	0.08***	3.85%	-0.01	0.76	0.08***	3.85%
	(0.06)	(0.40)	(3.51)		(-0.05)	(0.39)	(3.50)	
	[0.95]	[0.69]	[0.00]		[0.96]	[0.70]	[0.00]	
India	0.15*	0.37	0.05***	4.04%	0.10	0.39	0.05***	3.27%
	(1.82)	(1.36)	(2.86)		(1.18)	(1.43)	(2.84)	
	[0.07]	[0.17]	[0.00]		[0.24]	[0.15]	[0.00]	
Israel	0.11	0.07	0.01	0.17%	0.08	0.08	0.01	-0.40%
	(1.63)	(0.37)	(0.90)		(1.15)	(0.39)	(0.87)	
	[0.11]	[0.71]	[0.37]		[0.25]	[0.70]	[0.39]	
Malaysia	0.02	0.81	0.04***	5.68%	-0.01	0.81	0.04***	5.67%
	(0.19)	(3.25)	(2.81)		(-0.13)	(3.26)	(2.8)	
	[0.85]	[0.00]	[0.01]		[0.90]	[0.00]	[0.01]	
Singapore	0.03	-0.02	0.03**	0.42%	0.02	-0.02	0.03**	0.37%
	(0.44)	(-0.06)	(1.96)		(0.31)	(-0.06)	(1.96)	
	[0.66]	[0.95]	[0.05]		[0.76]	[0.96]	[0.05]	
United Kingdom	0.01	0.13	0.03*	0.50%	-0.01	0.13	0.03*	0.51%
	(0.09)	(0.98)	(1.81)		(-0.14)	(1.03)	(1.79)	
	[0.93]	[0.33]	[0.07]		[0.89]	[0.30]	[0.08]	
United States	-0.01	0.02	0.02*	0.02%	-0.02	0.01	0.02*	0.09%
	(-0.03)	(0.01)	(1.68)		(-0.41)	(0.01)	(1.64)	
	[0.98]	[0.99]	[0.09]		[0.68]	[0.99]	[0.10]	

Appendices

Appendix G.1: Predictive Regression Model: Group Return Predictability, Return Indices from Datastream

The table reports OLS estimates of β_1, β_b , and β_d (denoted by $\hat{\beta}_{less}$, $\hat{\beta}_b$, and $\hat{\beta}_d$, respectively) and the Adjusted R-square (denoted by $\overline{R}^2$) for the predictive regression model:

$$rMC_{t+1} = \beta_0 + \beta_1\, rLC_t + \beta_b\, billMC_t + \beta_d\, dyMC_t + \varepsilon_{t+1} \quad (1)$$

where rMC_{t+1} is the monthly US$ dominated excess return for the *More-Com* group; rLC_t is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_t$ ($dyMC_t$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for the *More-Com* group. This table reports predictive results from equally weighted and value weighted variables. Panel A reports the predictive results with predictor as return for the *Less-Com* group; whereas, Panel B presents the predictive results by the US return and Panel C reports the results with return for the *Non-US* group as predictors. We report the Newey and West (1987) robust t-statistic in parentheses in the first, second, third, fifth, sixth, and seventh columns. Brackets report p-values. The sample period is from 1994:02 to 2013:12. Return Indices are from Thompson Datastream. The signals ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Equally Weighted				**Value Weighted**			
$\hat{\beta}_{less}$ ret	$\hat{\beta}_b$ bill	$\hat{\beta}_d$ dy	$\bar{R}^2$	$\hat{\beta}_{less}$ ret	$\hat{\beta}_b$ bill	$\hat{\beta}_d$ dy	$\bar{R}^2$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Predictors are Returns for the *Less-Com* Group							
0.31	0.84***	0.01	24.57%	0.16*	0.55*	-0.03	8.35%
(4.38)	(5.09)	(0.56)		(1.83)	(1.79)	(-1.02)	
[0.00]	[0.00]	[0.58]		[0.07]	[0.01]	[0.31]	
Panel B: Predictors are the US returns							
0.21***	1.03***	0.01	21.01%	0.13	0.58**	-0.03	7.85%
(3.08)	(5.53)	(0.57)		(1.49)	(2.64)	(-1.03)	
[0.00]	[0.00]	[0.57]		[0.14]	[0.01]	[0.31]	
Panel C: Predictors are Returns for the *Non-US* Group							
0.31***	0.82***	0.01	24.76%	0.16**	0.48*	-0.03	8.57%
(4.39)	(4.98)	(0.54)		(1.99)	(2.44)	(-1.11)	
[0.00]	[0.00]	[0.59]		[0.05]	[0.02]	[0.27]	

Appendix G2: Predictive Regression Model Results: Individual Country Return Predictability, Return Indices from Datastream

The table reports OLS estimates of β_1, β_b and β_d (denoted by $\hat{\beta}_1$, $\hat{\beta}_b$ and $\hat{\beta}_d$, respectively) and the Adjusted R-square (denoted by $\bar{R}^2$) for the predictive regression model:

$$rMC_{i,t+1} = \beta_0 + \beta_{1,i}\, rLC_t + \beta_b\, billMC_{i,t} + \beta_d\, dyMC_{i,t} + \varepsilon_{t+1} \quad (3)$$

where $rMC_{i,t+1}$ is the monthly US$ dominated excess return for country *i* in the *More-Com* group; $rLC_{,t}$ is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_{i,t}$ ($dyMC_{i,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for country *i* in the *More-Com* group. This table reports predictive results from equally weighted (EW) and value weighted (VW) variables. Panel A reports the predictive results with predictors as returns for the Less-Com group; whereas, Panel B presents the predictive results by the US return, and Panel C reports the results with returns for the *Non-US* group as predictors. We report the Newey and West (1987) robust t-statistic in parentheses (under coefficients). The sample period is from 1994:02 to 2013:12. Return Indices are from Thompson Reuter Datastream. The signal * indicates significance at the 10% level or better.

	Panel A: Predictors are Returns for the *Less-Com* group								Panel B: Predictors are the U.S returns				Panel C: Predictors are Returns for the *Non-US* group							
	EW				VW								EW				VW			
(i)	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$	$\hat{\beta}_1$	$\hat{\beta}_b$	$\hat{\beta}_d$	$\bar{R}^2$
Austria	0.39*	0.31*	-0.01	11.66%	0.31*	0.41*	-0.01	7.86%	0.25*	0.45*	-0.01	6.30%	0.38*	0.28*	-0.01	12.00%	0.34*	0.27*	-0.01	9.57%
	(3.49)	(1.89)	(-0.94)		(2.81)	(2.08)	(-0.81)		(2.38)	(2.11)	(-0.81)		(3.50)	(1.81)	(-0.97)		(3.21)	(1.71)	(-0.88)	
Belgium	0.24*	0.11	-0.01	4.82%	0.24*	0.18	-0.01	4.43%	0.21*	0.22	-0.01	3.64%	0.24*	0.10	-0.01	4.76%	0.24*	0.08	-0.01	4.67%
	(2.04)	(0.75)	(-0.66)		(2.26)	(1.04)	(-0.59)		(2.08)	(1.16)	(-0.58)		(1.99)	(0.68)	(-0.67)		(2.15)	(0.57)	(-0.65)	
Brazil	0.51*	0.30	0.01	8.80%	0.32*	0.36	0.01	4.95%	0.19	0.37	0.01	3.60%	0.52*	0.29	0.01	9.38%	0.47*	0.31	0.01	8.09%
	(3.27)	(1.48)	(0.54)		(2.02)	(1.61)	(0.54)		(1.31)	(1.61)	(0.45)		(3.41)	(1.45)	(0.51)		(3.01)	(1.48)	(0.58)	
Colombia	0.44*	0.42*	-0.01	12.69%	0.35*	0.46*	-0.01	9.12%	0.27*	0.49*	-0.01	7.34%	0.44*	0.41*	-0.01	12.96%	0.41*	0.42*	-0.01	11.94%
	(4.93)	(2.60)	(-1.17)		(3.76)	(2.78)	(-0.94)		(2.91)	(2.90)	(-0.77)		(4.98)	(2.58)	(-1.18)		(5.16)	(2.61)	(-1.14)	
Germany	0.15*	0.03	-0.06	5.66%	0.09	0.06	-0.06	4.72%	0.07	0.08	-0.06	4.53%	0.16*	0.02	-0.06	5.77%	0.09	0.03	-0.06*	4.78%
	(1.87)	(0.20)	(-3.33)		(1.08)	(0.47)	(-3.40)		(0.83)	(0.55)	(-3.46)		(1.94)	(0.13)	(-3.34)		(1.15)	(0.19)	(-3.40)	
Greece	0.40*	0.34	-0.03	6.27%	0.32*	0.42*	-0.03*	4.79%	0.25*	0.46*	-0.03*	3.93%	0.39*	0.32	-0.03	6.40%	0.34*	0.31	-0.02*	5.40%
	(2.80)	(1.38)	(-1.64)		(2.27)	(1.66)	(-1.71)		(1.79)	(1.74)	(-1.73)		(2.83)	(1.31)	(-1.63)		(2.52)	(1.25)	(-1.73)	
Indonesia	0.79*	0.12	0.03	11.19%	0.40*	0.21	0.03*	3.84%	0.20	0.22	0.03	2.04%	0.81*	0.11	0.03	12.44%	0.69*	0.17	0.03	9.55%
	(4.18)	(0.56)	(1.48)		(2.79)	(0.90)	(1.65)		(1.33)	(0.94)	(1.63)		(4.22)	(0.50)	(1.42)		(4.62)	(0.79)	(1.52)	
Italy	0.21*	0.07	-0.02	2.89%	0.16	0.12	-0.02	1.74%	0.12	0.15	-0.02	1.33%	0.21*	0.06	-0.02	3.01%	0.16	0.06	-0.02	1.89%
	(1.95)	(0.43)	(-1.49)		(1.48)	(0.69)	(-1.28)		(1.18)	(0.78)	(-1.25)		(1.98)	(0.36)	(-1.53)		(1.53)	(0.35)	(-1.40)	
Korea	0.26*	0.45*	-0.02	6.05%	0.06	0.52*	-0.02	4.79%	-0.01	0.53*	-0.02	4.72%	0.28*	0.44	-0.02	6.34%	0.18	0.48*	-0.02	5.41%
	(2.08)	(1.68)	(-0.78)		(0.44)	(1.95)	(-0.98)		(-0.09)	(1.99)	(-1.04)		(2.30)	(1.61)	(-0.76)		(1.24)	(1.71)	(-0.92)	
Mexico	0.26*	0.65*	-0.02	14.16%	0.06	0.70*	-0.02	11.89%	-0.02	0.70*	-0.03	11.79%	0.28*	0.63*	-0.02	14.67%	0.05*	0.67*	-0.02	13.25%
	(2.61)	(3.18)	(-0.71)		(0.62)	(3.39)	(-0.86)		(-0.24)	(3.43)	(-0.95)		(2.78)	(3.14)	(-0.71)		(1.94)	(3.27)	(-0.73)	

APPENDIX

Appendix H: Relation between predictive ability of the less complicated group and dividend growth: Pooled Sample Results

This table reports two estimated coefficients (β_i and θ_i) for each country in the *More-Com* group in the pooled sample of every five years in the period from 1994 to 2013. This table includes 5 Panels (Panel A- Panel E) that reports these two coefficients for 5 predictors from the *Less-Com* group. Estimated coefficient β_i present the predictive slope coefficients on return of the *Less-Com* group for country *i* for each 5 years following model (2):

$$rMC_{i,t+1} = \beta_0 + \beta_i\, rLC_t + \beta_b\, billMC_{i,t} + \beta_d\, dyMC_{i,t} + \varepsilon_{t+1} \tag{2}$$

where $rMC_{i,t+1}$ is the monthly US$ dominated excess return for country *i* in the *More-Com* group; rLC_t is the monthly US$ dominated excess return for the *Less-Com* group; and $billMC_{i,t}$ ($dyMC_{i,t}$) is the US$ dominated three-month Treasury bill rate (log dividend yield) for country *i* in the *More-Com* group. Estimated coefficient θ_i for fundamentals for country *i* for each 5 years are estimated from the following predictive regression model (8):

$$\text{Log}\left(D_{i,t+1}/D_{i,t}\right) = \theta_{i,0} + \theta_i \times rLC_t + \varepsilon_{i,t+1} \tag{8}$$

where dividend growth, Log $(D_{i.t+1}/D_{i.t})$, is the proxy for fundamentals for stock return for country *i* in the *More-Com* group; and rLC_t is the US$ dominated excess return for the *Less-Com* group.

Appendix H1 plots the predictive slope coefficients for the pooled sample (1994-2013), while Appendix H2 plots the predictive slope coefficients for each five year-period in the full sample.

		(1) Austria	(2) Belgium	(3) Brazil	(4) Colombia	(5) Germany	(6) Greece	(7) Indonesia	(8) Italy	(9) Korea	(10) Mexico
Panel A: Predictors are Returns for The *Less-Com* Group (EW)											
1st 5 years	Beta	0.23	0.07	0.62	0.50	-0.02	0.49	0.89	0.39	0.32	0.51
	Delta	0.46	0.05	0.27	0.58	-0.05	0.46	1.38	0.11	0.79	0.52
2nd 5 years	Beta	0.16	0.04	0.20	0.71	0.04	0.41	0.69	0.04	0.24	0.17
	Delta	0.11	-0.03	-0.26	0.33	0.30	0.20	1.08	-0.11	0.27	0.12
3rd 5 years	Beta	0.66	0.50	0.51	0.33	0.41	0.49	0.13	-0.15	0.74	0.30
	Delta	1.08	0.71	0.60	0.26	0.27	0.60	0.67	0.39	0.52	0.47
last 5 years	Beta	0.22	0.11	0.07	0.15	0.06	1.13	1.35	0.30	0.05	0.22
	Delta	0.02	0.36	0.49	0.17	-0.04	0.21	0.01	0.07	-0.03	0.02
Panel B: Predictors are Returns for The *Less-Com* Group (VW)											
1st 5 years	Beta	0.36	0.13	0.35	0.56	-0.02	0.41	1.47	0.17	0.65	0.15
	Delta	0.59	0.16	0.10	0.52	-0.02	0.88	1.05	0.30	0.34	0.43
2nd 5 years	Beta	0.12	0.10	-0.05	0.79	-0.01	0.09	0.99	-0.08	0.28	0.09
	Delta	0.12	0.11	0.11	0.59	0.18	0.35	1.32	0.02	-0.18	0.13
3rd 5 years	Beta	0.82	0.58	0.67	0.43	0.48	0.71	0.79	0.49	0.63	0.58
	Delta	1.43	0.98	0.74	0.37	0.35	0.63	0.09	-0.09	0.88	0.39
last 5 years	Beta	0.15	0.09	-0.02	0.14	0.04	0.16	-0.03	0.03	-0.07	-0.02
	Delta	0.22	0.33	0.40	0.24	-0.05	1.12	1.39	0.33	-0.04	0.24

APPENDIX

Appendix H *(Continue)*

		(1) Austria	(2) Belgium	(3) Brazil	(4) Colombia	(5) Germany	(6) Greece	(7) Indonesia	(8) Italy	(9) Korea	(10) Mexico
Panel C: Predictors are the US Returns											
1st 5 years	Beta	0.37	0.13	0.15	0.54	0.02	0.37	1.32	0.16	0.55	-0.05
	Delta	0.51	0.14	0.04	0.42	0.03	0.89	0.85	0.18	0.32	0.29
2nd 5 years	Beta	0.12	0.11	-0.09	0.67	-0.02	0.08	0.88	-0.06	0.24	0.08
	Delta	0.09	0.12	0.17	0.60	0.13	0.34	1.35	0.03	-0.24	0.11
3rd 5 years	Beta	0.83	0.55	0.70	0.45	0.46	0.69	0.76	0.48	0.61	0.57
	Delta	1.64	1.14	0.76	0.50	0.36	0.64	0.07	-0.03	0.91	0.40
last 5 years	Beta	0.09	0.07	-0.07	0.11	0.04	0.12	-0.05	0.01	-0.08	-0.02
	Delta	0.31	0.32	0.34	0.13	-0.04	1.01	1.19	0.36	-0.08	0.23
Panel D: Predictors are Returns for the *Non-US* group (EW)											
1st 5 years	Beta	0.20	0.06	0.61	0.46	-0.02	0.43	1.30	0.10	0.76	0.53
	Delta	0.43	0.04	0.27	0.56	-0.05	0.42	0.84	0.38	0.30	0.50
2nd 5 years	Beta	0.16	0.03	0.22	0.68	0.05	0.21	1.06	-0.11	0.26	0.12
	Delta	0.11	-0.05	-0.30	0.28	0.31	0.40	0.57	0.04	0.29	0.17
3rd 5 years	Beta	0.63	0.49	0.48	0.32	0.39	0.57	0.65	0.37	0.50	0.45
	Delta	1.01	0.66	0.57	0.24	0.26	0.47	0.13	-0.15	0.71	0.28
last 5 years	Beta	0.23	0.11	0.07	0.15	0.06	0.21	0.02	0.07	-0.02	0.02
	Delta	0.00	0.35	0.49	0.17	-0.04	1.10	1.31	0.28	0.06	0.21
Panel E: Predictors are Returns for the *Non-US* group (VW)											
1st 5 years	Beta	0.24	0.09	0.67	0.49	-0.09	0.40	1.35	0.14	0.66	0.47
	Delta	0.57	0.12	0.14	0.60	-0.11	0.64	1.18	0.46	0.25	0.61
2nd 5 years	Beta	0.12	0.05	0.12	1.02	0.03	0.11	1.17	-0.12	0.35	0.13
	Delta	0.18	0.03	-0.14	0.43	0.35	0.29	0.89	-0.01	0.09	0.15
3rd 5 years	Beta	0.66	0.51	0.54	0.34	0.42	0.61	0.68	0.41	0.54	0.49
	Delta	1.02	0.68	0.61	0.18	0.28	0.53	0.10	-0.12	0.70	0.32
last 5 years	Beta	0.18	0.08	0.04	0.14	0.03	0.18	0.00	0.03	-0.05	0.00
	Delta	0.08	0.29	0.40	0.30	-0.05	1.06	1.35	0.24	0.01	0.20

APPENDIX

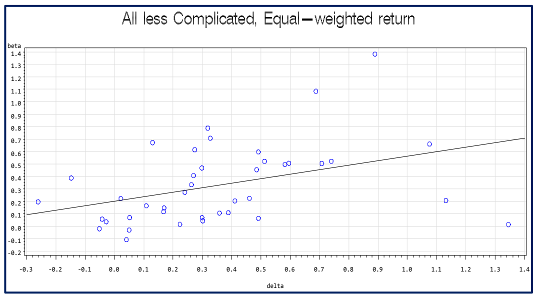
Appendix H1: Relation between predictive ability of less complicated group and dividend growth: Pooled Sample Results

Appendix H1 plots the predictive slope coefficients β_i against θ_i for all 10 countries in the *More-Com* group in the Pooled sample for each five year from 1994-2013.

(1) Returns for The *Less-Com* group (EW)

$\beta_i = 0.203 + \mathbf{0.362}\ \theta_i$

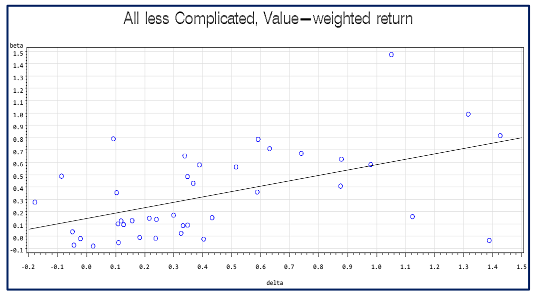
Slope = **0.362**; p-value = 0.012; R^2 = 0.155; Adj R^2 = 0.133



(2) Returns for The *Less-Com* group (VW)

$\beta_i = 0.144 + \mathbf{0.438}\ \theta_i$

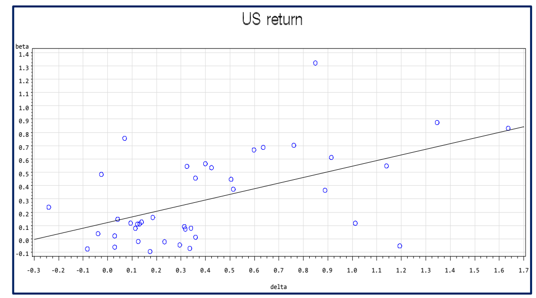
Slope = **0.438**; p-value = 0.001; R^2 = 0.272; Adj R^2 = 0.253



(3) The US Returns

$\beta_i = 0.121 + \mathbf{0.424}\ \theta_i$

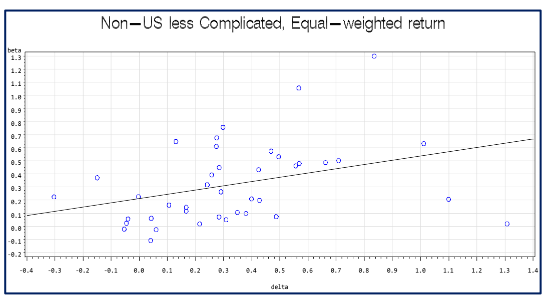
Slope = **0.424**; p-value = 0.000; R^2 = 0.2902; Adj R^2 = 0.272



(4) Returns for The *Non-US* Group (EW)

$\beta_i = 0.211 + \mathbf{0.326}\ \theta_i$

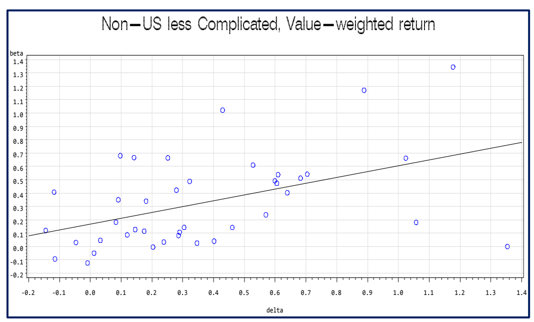
Slope = **0.326**; p-value = 0.023; R^2 = 0.128; Adj R-sq = 0.105



(5) Returns for The *Non-US* Group (VW)

$\beta_i = 0.168 + \mathbf{0.438}\ \theta_i$

Slope = **0.438**; p-value = 0.003; R^2 = 0.217; Adj R^2 = 0.196



APPENDIX

Appendix H2: Relation between predictive ability of less complicated group for stock return and dividend growth: Results for each five-year period

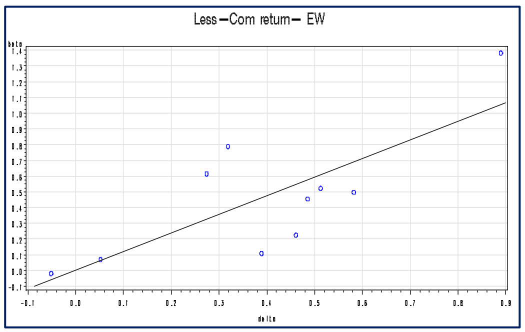
Appendix H2 plots the predictive slope coefficients β_i against θ_i for all 10 countries for each five year-period in the full sample (1994-2013). Panel A reports estimated results for the first five year period (1994-1998); Panel B reports estimated results in the second five-year period (1999-2003); Panel C reports results for the third five-year period (2004-2008); and Panel D reports results for the last five-year period (2009-2013).

Panel A: Estimated results for the first 5-year period (1994-1998)

(1) The *Less-Com* Group (EW)

β_i = 0.002 + **1.183** θ_i

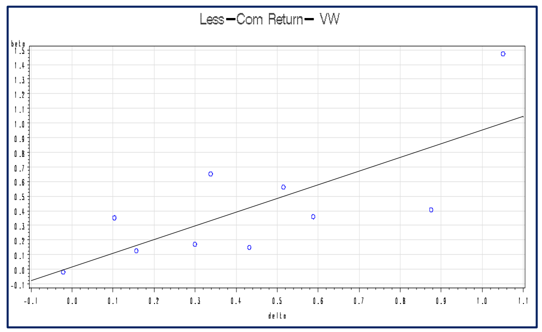
Slope = **1.183**; p-value = 0.010; R^2= 0.581; Adj R^2= 0.529



(2) The *Less-Com* Group (VW)

β_i = 0.018 + **0.937** θ_i

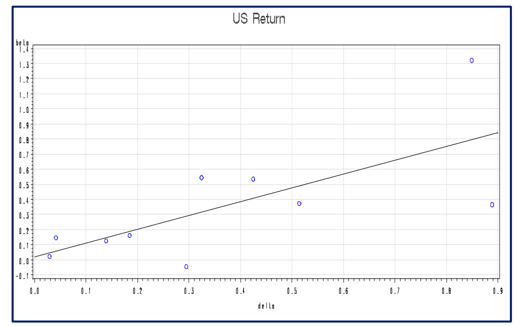
Slope = **0.937**; p-value = 0.013; R^2 = 0.561; Adj R^2= 0.506



(3) The US Return

β_i = 0.017 + **0.918** θ_i

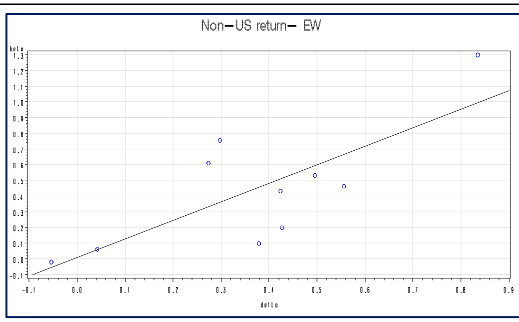
Slope = **0.918**; p-value = 0.021; R^2 = 0.504; Adj R^2 = 0.442



(4) The *Non-US* Group (EW)

β_i = 0.009 + **1.179** θ_i

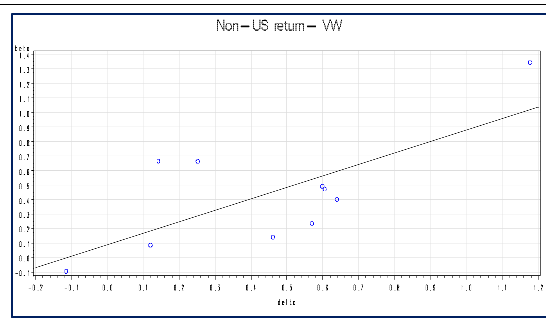
Slope = **1.179**; p-value = 0.012; R^2 = 0.569; Adj R^2 = 0.515



(5) The *Non-US* Group (VW)

β_i = 0.089 + **0.792** θ_i

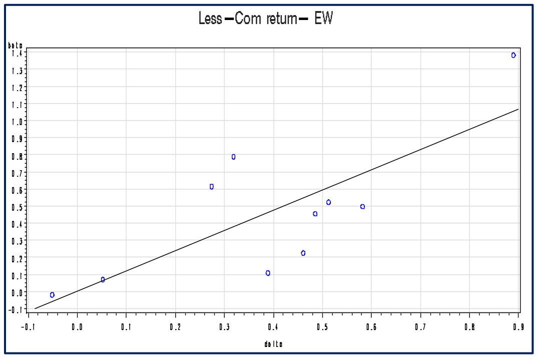
Slope = **0.792**; p-value = 0.021; R^2 = 0.508; R^2 = 0.447

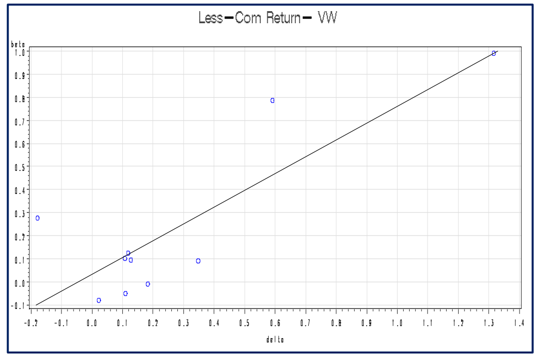


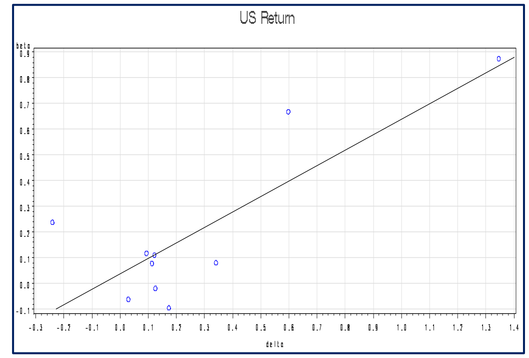
APPENDIX

Panel B: Estimated results for the second 5-year period (1999-2003)

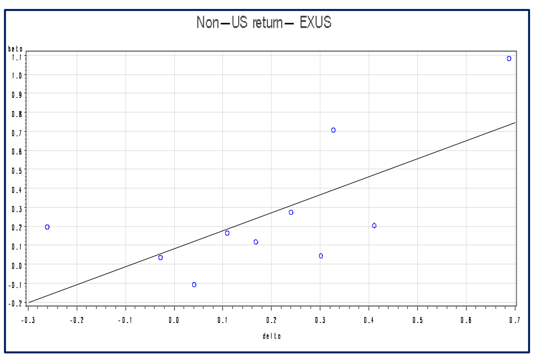
(1) The *Less-Com* Group (EW)	(2) The *Less-Com* Group (VW)	(3) The US Return
β_i = 0.083 + **0.948** θ_i Slope = **0.948**; p-value = 0.027; R^2= 0.478; Adj R^2= 0.412	β_i = 0.033 + **0.728** θ_i Slope = **0.728**; p-value = 0.003; R^2 = 0.699; Adj R^2= 0.661	β_i = 0.037 + **0.602** θ_i Slope = **0.602**; p-value = 0.004; R^2 = 0.666; Adj R^2 = 0.625

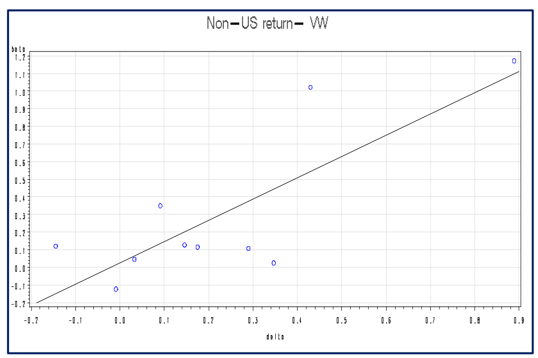






(4) The *Non-US* Group (EW)	(5) The *Non-US* Group (VW)
β_i = 0.122 + **0.808** θ_i Slope = **0.808**; p-value = 0.081; R^2 = 0.332; Adj R^2 = 0.248	β_i = 0.026 + **1.204** θ_i Slope = **1.204**; p-value = 0.006; R^2 = 0.632; R^2 = 0.586





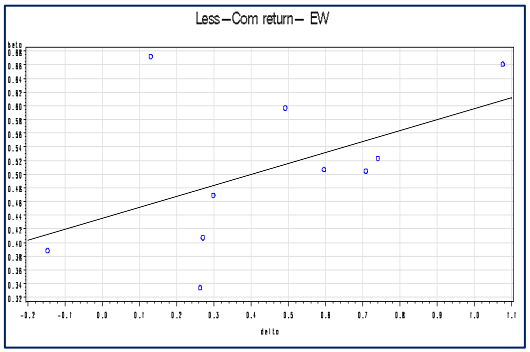
APPENDIX

Panel C: Estimated results for the third 5-year period (2004-2008)

(1) The *Less-Com* Group (EW)

β_i = 0.436 + **0.160** θ_i

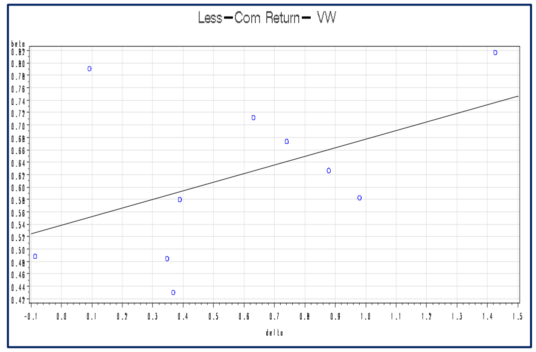
Slope = **0.160**; p-value = 0.143; R^2= 0.248; Adj R^2= 0.154



(2) The *Less-Com* Group (VW)

β_i = 0.539 + **0.139** θ_i

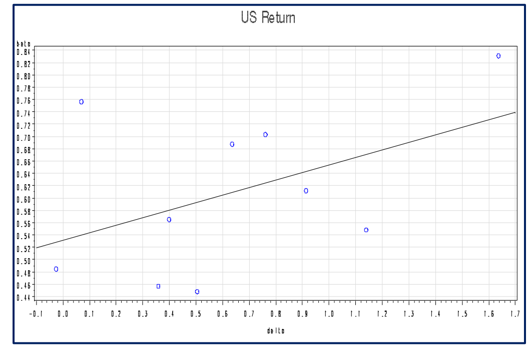
Slope = **0.139**; p-value = 0.165; R^2 = 0.226; Adj R^2= 0.129



(3) The US Return

β_i = 0.531 + **0.123** θ_i

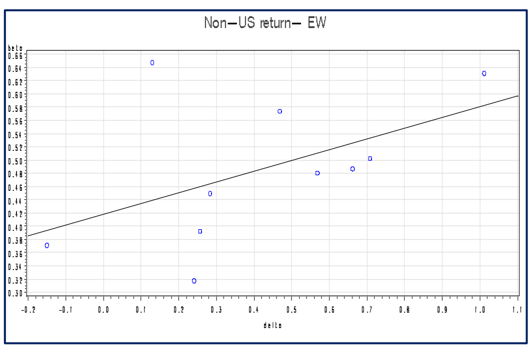
Slope = **0.123**; p-value = 0.175; R^2 = 0.217; Adj R^2 = 0.119



(4) The *Non-US* Group (EW)

β_i = 0.417 + **0.163** θ_i

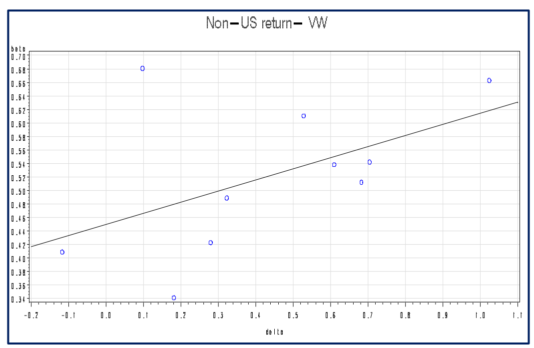
Slope = **0.163**; p-value = 0.142; R^2 = 0.249; Adj R^2 = 0.155



(5) The *Non-US* Group (VW)

β_i = 0.450 + **0.165** θ_i

Slope = **0.165**; p-value = 0.136; R^2 = 0.255; Adj R^2 = 0.162



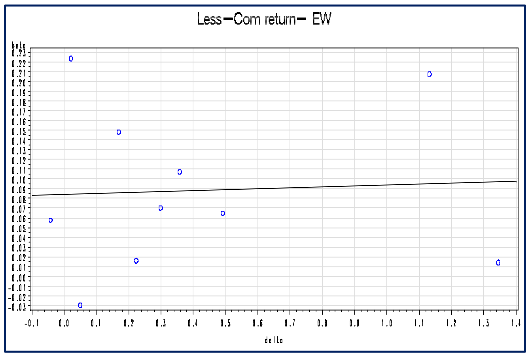
APPENDIX

Panel D: Estimated results for the last 5-year period (2008-2013)

(1) The *Less-Com* Group (EW)

β_i = 0.084 + **0.009** θ_i

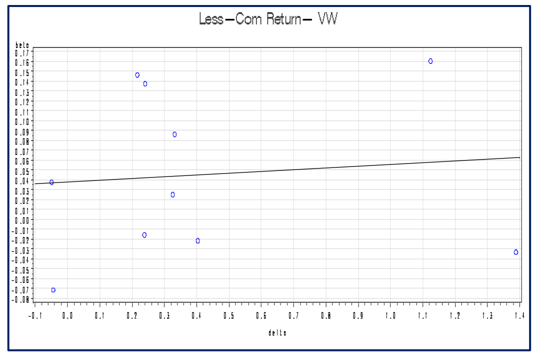
Slope = **0.009**; p-value = 0.884; R^2= 0.003; Adj R^2= -0.121



(2) The *Less-Com* Group (VW)

β_i = 0.038 + **0.018** θ_i

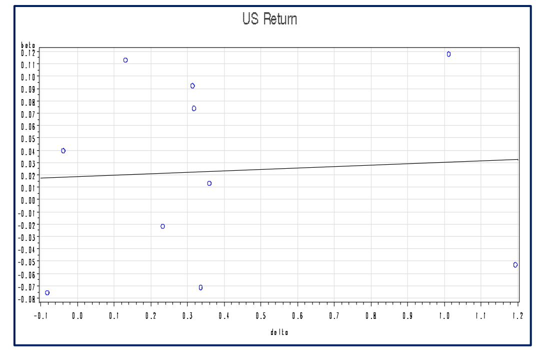
Slope = **0.018**; p-value = 0.778; R^2 = 0.011; Adj R^2= - 0.113



(3) The US Return

β_i = 0.019 + **0.011** θ_i

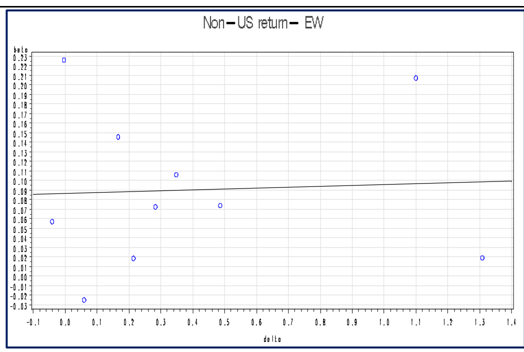
Slope = **0.011**; p-value = 0.864; R^2 = 0.004; Adj R^2 = -0.121



(4) The *Non-US* Group (EW)

β_i = 0.087 + **0.009** θ_i

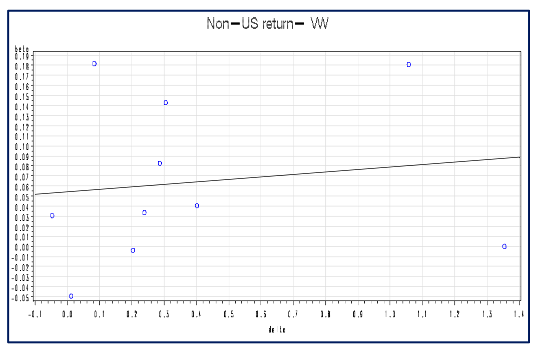
Slope = **0.009**; p-value = 0.892; R^2 = 0.002; Adj R^2 = -0.122



(5) The *Non-US* Group (VW)

β_i = 0.055 + **0.024** θ_i

Slope = **0.024**; p-value = 0.703; R^2 = 0.019; R^2 = -0.103



APPENDIX

Appendix I: Correlation between the *US* return and Return for the *Non-US* Less Complicated Group

Appendix I presents the correlation between the US return and return for the *Non-US* group, (both equally-weighted and value-weighted return).

US return vs *Non-US* return (EW)	US return vs *Non-US* return (VW)